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THE INFLUENCE OF FINANCIAL STRESS ON DYNAMIC CONNECTEDNESS BETWEEN FOSSIL ENERGY COMMODITIES AND GREEN ENERGY MARKETS[1]

Finansal Stresin Fosil Enerji Emtiaları ile Yeşil Enerji Piyasaları Arasındaki Dinamik Bağlantılılığa Etkisi

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Keywords:
Financial Stress, Green Markets, Fossil Energy, Connectedness

JEL Codes:
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Abstract

This paper aims to examine the impacts of selected stress variables, such as FSI (Financial Stress Index), VIX (Volatility Index), and EPU (Economic Policy Uncertainty), on dynamic connectedness between green markets (stocks and bonds) and fossil energy commodities. We employ the TVP-VAR model to measure connectedness and the Fourier Cumulative Granger Causality test to investigate the impacts of these stress variables on this connectedness from November 1, 2012, to November 15, 2022. The results indicate moderate return connectedness, mainly from short-term dynamics, suggesting that diversification may be more beneficial for long-term investments. We observe high connectedness during the COVID-19 pandemic. The connectedness is high among fossil energy commodities but low among green stock and bond markets, except for water company stocks. Water stocks have a significant impact on markets, followed by oil. Our causality test results indicate that the FSI and VIX impact the connectedness between them.

Anahtar Kelimeler:
Finansal Stres
Yeşil Piyasalar
Fosil Enerji
Bağlantılılık

JEL Kodları:
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Öz

Bu makale, FSI (Finansal Stres Endeksi), VIX (Volatilite Endeksi) ve EPU (Ekonomik Politika Belirsizliği) gibi seçili stres değişkenlerinin yeşil piyasalar (hisse senetleri ve tahviller) ile fosil enerji emtiaları arasındaki dinamik bağlantılılık üzerindeki etkilerini incelemeyi amaçlamaktadır. Bağlantılılığı ölçmek için TVP-VAR modelini ve bu stres değişkenlerinin 1 Kasım 2012'den 15 Kasım 2022'ye kadar bu bağlantı üzerindeki etkilerini araştırmak için Fourier Kümülatif Granger Nedensellik testini kullanıyoruz. Sonuçlar, esas olarak kısa vadeli dinamiklerden kaynaklanan orta düzeyde getiri bağlantılılığı olduğunu gösteriyor ve bu da çeşitlendirmenin uzun vadeli yatırımlar için daha faydalı olabileceğini gösteriyor. COVID-19 salgını sırasında yüksek bağlantılılık gözlemliyoruz. Bağlantılılık, su şirketi hisseleri hariç, fosil enerji emtiaları arasında yüksek ancak yeşil hisse senedi ve tahvil piyasaları arasında düşüktür. Su hisselerinin piyasalar üzerinde önemli bir etkisi vardır, bunu petrol takip eder. Nedensellik test sonuçlarımız, FSI ve VIX'in bunların arasındaki bağlantılılığı etkilediğini göstermektedir.

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1. Introduction

Stress in financial markets has increased due to greater volatility, deterioration in economic indicators, and uncertainty in future economic policies. This paper explores the impact of financial stress (FS) indicators on interactions between fossil energy and green markets. Our motivation for focusing on these markets is the increasing trend in investments in fossil energy commodities and green markets consisting of green stocks and bonds.

The financialization of energy commodities has increased interaction with other financial markets, especially stock markets. There are many studies investigating the influence of oil price shocks on equity markets (see, Sadorsky, 1999; Park and Ratti, 2008; Kilian and Park, 2009; Wang et al., 2013). The increasing interaction between energy and stock markets causes financial and economic indicators to affect stock markets and fossil energy prices. (Reboredo and Uddin, 2016). In addition, there is a transition from fossils to green energy. Besides the environmental and climatic concerns, volatility in fossil energy prices is driving this transition (Shinwari et al., 2022; Ari et al., 2022). Understanding the drivers of fossil energy commodities and green markets is essential for policymakers to ensure sustainable growth and stability in inflation and develop policies for energy security and climate change. It is also necessary for investors to assess the level of risks and determine the diversification potential associated with their investments in energy commodities and green markets.

The increase in fossil energy prices increases the costs and decreases the profitability of highly fossil energy-dependent companies. As a result, their market values are affected. In contrast, the market values of the companies using green energy are affected positively. Many studies examine the interactions between fossil and green markets, and a few discuss the effect of FS on these markets. Nonetheless, there remains a lack of studies analyzing the impact of FS on connectedness between them (see the literature review part). In parallel with many other studies, we expect an increasing connectedness, especially during stressful periods (Ang and Bekaert, 2002). This stress increases the relationship between these two markets, decreasing investors' diversification opportunities.

Within this scope, first, we assess the interrelationship and spillover among the green energy (solar, wind, geothermal, bio/clean fuels, and water), green bonds, and fossil energy (oil, natural gas, heating oil, and gasoline) assets, employing a time-varying parameter-based vector autoregressive model (TVP-VAR) over November 1, 2012, to November 15, 2022. Second, we use the Fourier Cumulative Granger Causality Test to examine whether some selected stress variables increase this connectedness. In addition to the Financial Stress Index (FSI) developed by the Federal Reserve Bank of St. Louis, we consider the CBOE Volatility Index (VIX) and the Economic Policy Index (EPU) developed by Baker et al. (2016).

This paper contributes to the literature in many aspects. First, as well as much studied crude oil prices, we additionally consider natural gas, gasoline, and heating oil prices, which are rarely discussed. Second, many papers consider green markets on an aggregate/global level. Here, we extend the scope of data by considering the sectoral level and examining a large scale of green energy markets such as wind, solar, water, geothermal, and bio-clean markets. Third, we included green bonds as an essential part of the green market. Fourth, this paper differs from the related literature regarding methodology; unlike the studies investigating the correlation between these two markets, we employ a TVP-VAR model. This econometric framework does not follow the sliding windows procedure according to standard models. Therefore, there is no observation loss, making robust parameter estimation even in the presence of outliers. Fifth and finally, to the best of our knowledge, this is the first paper focusing on the role of FS on time-varying (TV) connectedness between fossil energy commodities and green markets. In this context, the paper makes a potential contribution to literature.

After the introduction, the paper continues with documentation of the relevant literature, a description of the data and econometric framework, a report and discussion of the findings, and a summary of the main findings.

2. Literature Review

We categorize the related literature into two groups: studies investigating the connection between fossil and clean energy markets and studies examining the influence of FS on these markets.

Most of the first papers focus on oil and consider green markets at the aggregate level. These studies argue that changes in oil prices influence clean energy stocks (see Bondia et al., 2016; Dawar et al., 2021; Attarzadeh and Balcilar, 2022; Hanif et al., 2023, Ren et al., 2024; Tang et al., 2023). Hanif et al. (2023) discussed the green stock market was not sufficiently developed to diverge from the traditional energy market. On the other hand, Lucey and Ren (2023) found that green stocks were persisting volatility transmitters, while green bonds and energy commodities were tail volatility receivers. However, there are a few papers at the sectoral level. Reboredo (2015) analyzed the link between oil and renewable energies (wind and solar) stock prices and found a strong interdependence. However, Pham (2019) found that the price of oil affected wind, geothermal, and fuel cells slightly. Foglia and Angelini (2020) argued that the connection between renewable energy and oil rose during the COVID-19 pandemic.

Among the papers, which included other fossil fuels, Song et al. (2019) found static and dynamic connections among renewable energy index, oil, gas, and coal. Similarly, Jiang et al. (2021) found that renewable energy indices positively influenced oil and coal but not gas. However, Umar et al. (2022) found a slight volatility connectedness between clean and dirty energy. Corbet et al. (2020) found risk transmission from oil to clean energy and coal when the oil prices became negative. Zhou et al. (2022) found that extreme volatility spillover highly impacted the clean energy market, especially in the bullish market. Among the papers focused on green bonds, Reboredo (2018) and Reboredo et al. (2020) revealed a weak link between energy commodities and green bonds, while Hammoudeh et al. (2020) reported bounded causality from renewable energy to green bonds. Using time and frequency-domain analyses, Naeem et al. (2021a) showed a vital link between green bonds and oil. Naeem et al. (2021b) documented green bonds had a remarkable negative connection with all energy commodities other than natural gas. Nguyen et al. (2021) found that green bonds had a negative or limited correlation with commodities and stocks, making these assets suitable for diversification. Saeed et al. (2021) investigated the connectedness among indices of green energy, green bonds oil, and energy ETFs and revealed that return shocks were transmitted principally from clean energy to oil. Among all variables, green bonds were the most diminutive receiver and contributor in the return connectedness system. Lee et al. (2021) documented a dualistic link between oil and green bonds in lower quantiles. Naeem et al. (2021c) reported that bearish market conditions in energy commodities result in a fall in return on green bonds. Mensi et al. (2022) showed that oil and green bonds are the net recipients of all the G7 stock markets, except for Japan's. Tiwari et al. (2022) revealed that green energy is the most significant sender of information to green bonds. Umar et al. (2024) investigated the influence of oil price shocks on green bonds and found a low degree of connection, implying potential diversification benefits.

The second stream of papers explores the influences of risks and uncertainties on energy markets, including the FS factor. Nazlioglu et al. (2015) considered the Cleveland FS index. They found a volatility transmission from crude oil prices to this index before the crises and in the opposite direction after them. On the other hand, after the crisis, there was a causal direction from oil prices to FS, and during the crises, from FS to oil prices. In a similar paper, unlike the previous paper, Das et al. (2022) considered the categorical stress components in addition to a composite FS index. They used oil price uncertainty (OVX) instead of oil prices, showing the presence of co-movement between these during economic turmoil. The relationship was mainly positive, with OVX generally leading to FS.

In a more comprehensive paper, in addition to the FS index (STLFSI), Reboredo and Uddin (2016) examined the effects of VIX and EPU on dirty energy commodities, precious metals, and copper futures using a quantile regression model. They observed that STLFSI affected all return quantiles other than lower quantiles for all commodities. He et al. (2021) found a meaningful negative impact of FS on green energy stocks when the markets were bullish. In a similar paper, Fu et al. (2022) suggested that an increased FS index depressed the renewable energy stocks' performances in all periods.

Elsayed et al. (2022) focused on green bonds. They examined the linkage between green bonds and other traditional and green markets using multiple correlations and dynamic connectedness techniques. Their analysis also considered the economic activity index, the VIX, the world FSI, and the Twitter Economic Uncertainty Index. Their results indicated low interdependence in the short run but high integration in the long run. The static connectedness results revealed that the green bond market received more volatility than it transmitted. On the other hand, dynamic connectedness results showed that the traditional stock and energy, green energy, and VIX were contributors to shocks. In contrast, both the conventional and green bonds, business conditions, FSI, and TEU were the recipients of shocks.

Tiwari et al. (2024) analyzed the dependence between oil, the stock market, and FSI and found that oil prices influenced stock prices positively during extreme market conditions. Additionally, the link became stronger after they considered policy uncertainty and FS, indicating that uncertainties also led the stock price returns. Elsayed et al. (2024a) investigated the connection between the FS indexes of the GCC economies and oil prices. They found vital interconnectedness and risk transmission patterns in time and frequency areas. Elsayed et al. (2024b) examined the relationship between FS and shocks, including oil supply and demand and financial risk shocks in MENA countries. They found FS particularly strong during exceptional oil demand and supply shocks for exporter countries and extended periods.

3. Methodology

We first employ the frequency connectedness approach of Chatziantoniou et al. (2023), based on the TVP-VAR. This approach integrates research by Baruník and Křehlík (2018) and Antonakakis et al. (2020), considering the frequency and TVP-VAR connectivity, respectively.

We analyze the connectivity in the short (1 day – 5 days) and long (5 days - Infinity) terms. The advantages of the TVP-VAR model are (i) no loss of observations, (ii) no arbitrarily selected rolling window sizes, and (iii) resistance to outliers. Second, we conduct the Fourier cumulative Granger causality framework to assess the potential effect of FS on interconnectivity.

3.1. TVP-VAR-Based Connectedness in the Time and Frequency Domain

The TVP-VAR(p) model can be written as:

$$x_t = \Phi_{1t}x_{t-1} + \Phi_{2t}x_{t-2} + \cdots + \Phi_{pt}x_{t-p} + \epsilon_t \qquad \epsilon_t \sim N(0, \Sigma_t) \tag{1}$$

here, Φ_{it} and Σ_t denote the TV coefficients and the TV variance-covariance matrix, respectively, and x_t and ϵ_t are the N × 1 dimensional vectors. The generalized forecast error variance decomposition (GFEVD), as described by Koop et al. (1996) and Pesaran and Shin (1998), is formulated as follows:

$$\theta_{ijt}(H) = \left. (\Sigma_t)_{jj}^{-1} \sum_{h=0}^{H} ((\Psi_h \Sigma_t)_{ijt})^2 \middle/ \sum_{h=0}^{H} (\Psi_h \Sigma_t \Psi_h')_{ii} \right. \tag{2}$$

$$\tilde{\theta}_{ijt}(H) = \left. \theta_{ijt}(H) \middle/ \sum_{k=1}^{N} \theta_{ijt}(H) \right. \tag{3}$$

where $\tilde{\theta}_{ijt}(H)$ represent the impact of variable j to the "forecast error variance" of variable i at horizon H. Based on the above, the following measures can be computed:

$$TO_{it}(H) = \sum_{\mathrm{i}=1,\mathrm{i}\neq j}^{N} \tilde{\theta}_{jit}(H) \tag{4}$$

$$FROM_{it}(H) = \sum_{j=1,\mathrm{i}\neq j}^{N} \tilde{\theta}_{ijt}(H) \tag{5}$$

$$NPDC_{ijt}(H) = \tilde{\theta}_{ijt}(H) - \tilde{\theta}_{jit}(H) \tag{6}$$

TO and FROM represent the extent to which variable i transmits shocks to or receives shocks from all other variables, respectively. NPDC stands for net pairwise directional connectedness, which measures whether variable j exerts more influence on variable i or vice versa. Using the TO and FROM, we compute the following connectedness measures:

$$TCI_t(H) = N^{-1} \sum_{i=1}^{N} TO_{it}(H) = N^{-1} \sum_{i=1}^{N} FROM_{it}(H) \tag{7}$$

$$NET_{it}(H) = TO_{it}(H) - FROM_{it}(H) \tag{8}$$

Here, TCI represents the level of connectedness among variables within the VAR system; NET stands for the net directional connectedness, indicating whether a variable exerts more influence on all other variables than it receives from them.

The above measures can be decomposed into frequencies exploiting the Stiassny's (1996) spectral decomposition. The density of x_t at a given frequency ω can be expressed as the Fourier transform of the TVP-VMA (∞) model:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x_{t-h}') e^{-i\omega h} = \Psi(e^{-i\omega h}) \Sigma_t \Psi'(e^{+i\omega h}) \tag{9}$$

where the frequency response function is expressed as $\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega}\, \Psi_h$ with $i = \sqrt{-1}$. The GFEVD in frequency domain is derived by aggregating the spectral density and GFEVD, and is expressed through normalization as follows:

$$\theta_{ijt}(\omega) = \frac{(\Sigma_t)_{jj}^{-1} \left| \Sigma_{h=0}^{\infty} \left(\Psi(\mathrm{e}^{-\mathrm{i}\omega h}) \Sigma_t \right)_{\mathrm{i}jt} \right|^2}{\Sigma_{h=0}^{\infty} \left(\Psi(\mathrm{e}^{-\mathrm{i}\omega h}) \Sigma_t \Psi(\mathrm{e}^{\mathrm{i}\omega h}) \right)_{\mathrm{ii}}} \tag{10}$$

$$\tilde{\theta}_{ijt}(\omega) = \frac{\theta_{ijt}(\omega)}{\sum_{k=1}^{N} \theta_{ijt}(\omega)} \tag{11}$$

We compute the high and low frequency interconnectedness by aggregating frequencies over defined ranges.

$$N\tilde{\theta}_{ijt}(d) = \int_a^b \tilde{\theta}_{ijt}(\omega)\, d\omega \tag{12}$$

where $d = (a, b): a, b \in (-\pi, \pi), a < b$.

3.2. Fourier Cumulative Granger Causality Test

Nazlioglu et al. (2016, 2019) enhance the Granger causality framework of Enders and Jones (2016) with Fourier approximation, incorporating the Toda and Yamamoto (1995) procedure (TY) to consider the structural breaks:

$$y_t = a(t) + \beta_1 y_{t-1} + \cdots + \beta_{p+d} y_{t-(p+d)} + \varepsilon_t \tag{13}$$

where y_t is endogenous variables vector in the VAR(*p*+*d*) model, β is the matrix of parameters, *d* represents the highest integration level, and ε_t is error terms vector. $a(t)$ denotes the Fourier approximation, designed to capture structural shifts of unknown timing, quantity, and form, expressed as a function of time, relaxing the constant intercept assumption:

$$a(t) \cong a_0 + \sum_{k=1}^{n} \gamma_{1k} \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \gamma_{2k} \cos\left(\frac{2\pi kt}{T}\right) \tag{14}$$

where n and T are the quantity of frequency and observations, respectively, k is a specific frequency, γ_{1k} and γ_{2k} represent frequency magnitude and shift, respectively (see Enders and Lee, 2012: 197; Nazlioglu et al., 2019). The final model, gathered by substituting equation (13) into equation (14), can be estimated by setting n greater than unity, indicating cumulative frequencies:

$$y_t = a_0 + \sum_{k=1}^{n} \gamma_{1k} \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \gamma_{2k} \cos\left(\frac{2\pi kt}{T}\right) + \beta_1 y_{t-1} + \cdots + \beta_{p+d} y_{t-(p+d)} + \varepsilon_t \tag{15}$$

4. Data and Descriptive Analysis

In the first phase, to analyze the dynamic connectedness between fossil energy commodities and green energy markets, we obtained daily data on the indices of various green energy (sub) sectors, the green bond index, and the prices of different fossil energy commodities.

The green energy (sub)sectoral indices include solar (SOL), wind (WND), geothermal (GEO), bio/clean fuels (BIO), and water (WAT), as well as the green bonds index (BND). Fossil energy commodities include oil (OIL), natural gas (NGS), heating oil (HOI), and gasoline (GAS). All data, except for the S&P Green Bond Index (BND), was extracted from Thomson Reuters DataStream. The BND was obtained from the S&P Global Website. The study period spans from November 1, 2012, to November 15, 2022, dictated by the data availability and regularity on Thomson Reuters DataStream. All data used in this study was denominated in USD. The data was transformed into a natural logarithm return series. Figure 1 depicts the movements of the time series. The variables exhibited similar behavior during the 2020 pandemic period. In the second phase, to analyze the impact of FS on the connectedness above (LONG), (SHORT), and (TOTAL), we collected weekly data on the FS index (FSI), the Chicago Board of Exchange (CBOE) volatility index, and the economic policy uncertainty index for the US (EPU) from the FRED website.

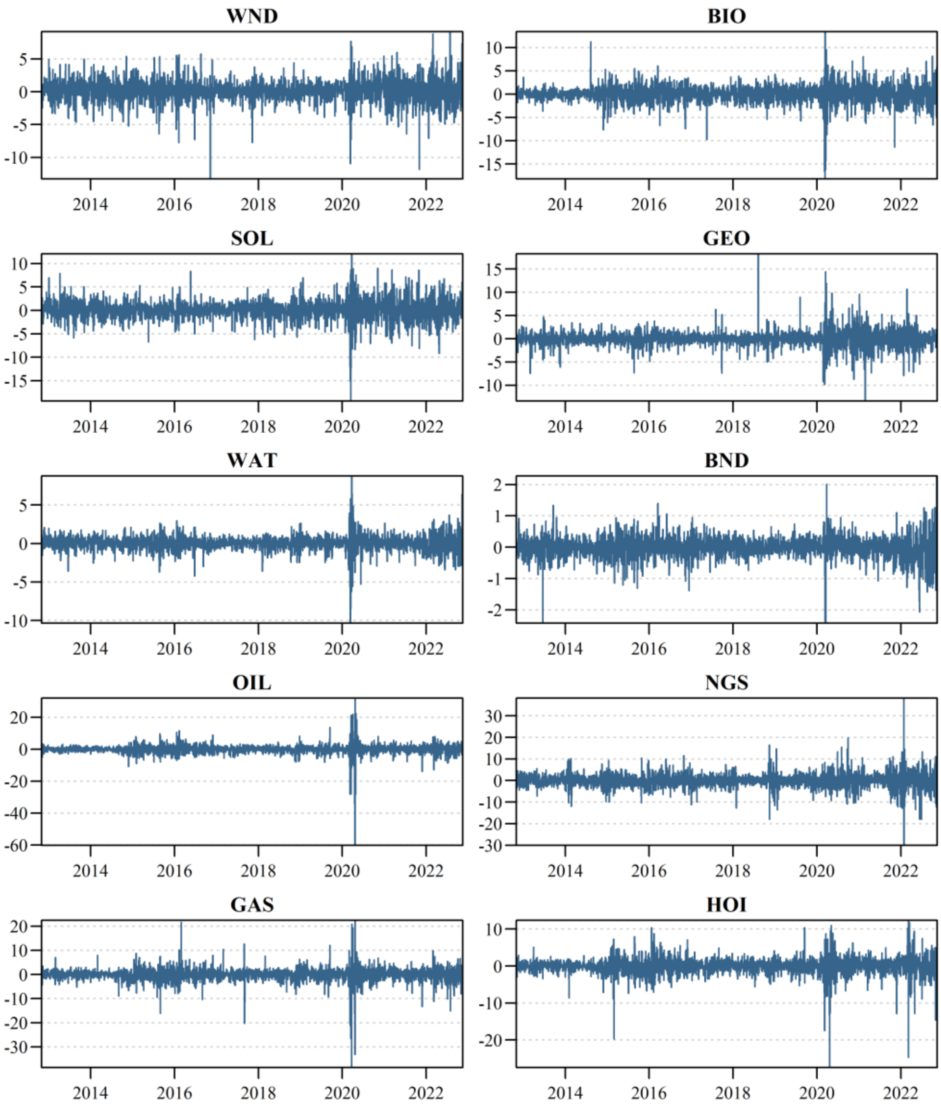

Figure 1. The Return Series Plots of Green Energy Indices, Green Bonds, and Fossil Energy Commodities

Hata! Başvuru kaynağı bulunamadı. shows the descriptive statistics of the log return series. According to Jarque and Bera (1980), from now on referred to as JB, the test results indicate that the null hypothesis is rejected at a 1% significance level for all series. Therefore, data is not normally distributed. The unit root test proposed by Elliott et al. (1996), referred to as ERS, was used to assess the stationarity of the data. The result shows that the entire data set is stationary at the 1% significance level. Fisher and Gallagher (2012) developed the tests for the serial correlation, from now on referred to as $Q\ and\ Q^2$. At a 1% significance level, the time series is autocorrelated up to 20 lags.

Table 1. Summary Statistics of Return Series

	Mean	Variance	Skewness	Ex. Kurtosis	JB	ERS	Q(20)	$Q^2(20)$
WND	0.066*	2.913***	-0.331***	5.069***	2753.51***	-19.996***	25.164***	196.98***
BIO	-0.001	3.847***	-0.877***	10.801***	12616.50***	-15.792***	66.714***	2179.16***
SOL	0.103**	4.506***	-0.498***	6.392***	4409.82***	-13.606***	58.391***	1368.22***
GEO	0.015	3.123***	0.369***	12.231***	15821.41***	-12.479***	27.031***	339.16***
WAT	0.035*	1.019***	-0.587***	12.812***	17441.36***	-8.310***	138.967***	2681.71***
BND	-0.005	0.124***	-0.505***	5.228***	2987.196***	-15.726***	51.968***	607.93***
OIL	0.000	9.472***	-2.857***	74.911***	594768.24***	-16.182***	108.499***	538.81***
NGS	0.019	11.916***	0.234***	10.841***	12406.65***	-23.562***	41.718***	506.89***
GAS	-0.004	8.219***	-1.884***	31.322***	104877.57***	-5.041***	25.140***	571.26***
HOI	0.007	5.628***	-1.458***	17.928***	34763.79***	-14.576***	22.300***	302.54***

Notes: *** $\mathbf{p < 0.01}$; ** $\mathbf{p < 0.05}$;* $\mathbf{p < 0.1}$ imply significance levels at 1%, 5%, and 10%. JB (Jarque Bera (1980)) is the normality test. ERS stands for the Elliot et al. (1996) unit root test. $\mathbf{Q(20)}$and $\mathbf{Q^2(20)}$ are for the Fisher and Gallagher (2012) portmanteau statistics.

5. Empirical Results

5.1. TVP-VAR-based Frequency Connectedness

We estimate the TVP-VAR model with one lag—as determined by the Schwarz Information Criterion—and employ a 10-day forecast horizon. To test the robustness of these results, we extend the forecast horizon to 20 and 30 days. The outcomes across these alternative horizons remain qualitatively similar, confirming the reliability of the original model's outputs. Consequently, we present the findings based on the original model. Table 2 presents the static return connectedness results in both time and frequency domains. Panel A shows time connectedness, while other panels illustrate frequency connectedness with short (1-5 days) and long (5-Inf) terms. The first panel's average total connectedness index (TCI) is 43.68%, indicating that 43.68% of the variation in the variables is attributable to network connectedness. In the other panels, analysis reveals that total connectedness is driven by short-term connectedness (39.06%), while the effect of long-term connectedness is less pronounced (4.61%). The rest of TCI (56.32%) is derived from its own variable (idiosyncratic) shocks. NGS exhibits the highest autocorrelation within the network and, thus, the lowest cross-correlation effects. For instance, 88.57% of future return shocks in natural gas can be attributable to own previous shocks. On the other hand, other energy commodities, including OIL, GAS, and HOI, show the lowest autocorrelation and the highest cross-correlation effects. Thus, future return shocks for these commodities are less influenced by the shocks in others in the network.

The diagonal values in Table 2 indicate idiosyncratic shocks, while off-diagonal values represent pairwise spillover. According to Panel A, the most considerable average pairwise spillovers are found between the fossil energy futures from OIL to HOI, HOI to OIL, OIL to GAS, and HOI to GAS (25.36%, 21.18%, 20.93%, and 19.88%, respectively). However, the lowest average pairwise spillover is found from NGS to WAT (0.44%). One of the highest pairwise spillovers other than fossils and BND is seen from WAT to other green markets (from WAT to SOL with 15.39%). Similar to the findings of Umar et al. (2022) like oil, other fossil energy commodities also have low connectedness with green markets, indicating diversification opportunities. Our findings on green bonds support the conclusions of Reboredo (2018), Reboredo et al. (2020), and Nguyen et al. (2021), indicating a low relationship between green bonds and fossil energy markets and parallel to the findings of Tiwari et al. (2022), the return transmissions from green stocks to green bonds are greater compared to others.

Net directional connectedness is displayed at the bottom of each panel. A positive (negative) value represents the net shock transmitter (receiver), which means the transmitters (receivers) influence (influenced by) other variables. Amongst the greens, WAT, BIO, and SOL are the net shock transmitters, and the most dominant net transmitter is WAT (13.53%), followed by BIO (2.92%). In contrast, the primary net receiver among these is BND (-9.15%), followed by WND (-8.13%). Furthermore, except NGS and GAS, fossil energy commodities act as net shock transmitters. The leading net transmitter is OIL (7.27%), followed by HOI (4.32%). In contrast to Reboredo (2015) and consistent with Pham (2019), we find that oil has low effects on wind and geothermal stocks. In contrast to Saeed et al. (2021), the return shock spillover from oil to green markets is more significant in parallel to our expectations. However, NGS (5.14%) is the primary net receiver among fossil energy commodities. Panels B and C illustrate the average short-term and long-term connectedness, respectively. We observe that short-term drives the overall return connectedness. When we look at the pairwise contribution, we observe that most of it is short-term, other than BIO. In addition, while HOI is a transmitter in the short term, it turns into a receiver in the long term.

Table 2. The Average Time and Frequency Connectedness

Panel A: Total	**WND**	**BIO**	**SOL**	**GEO**	**WAT**	**BND**	**OIL**	**NGS**	**GAS**	**HOI**	**FROM**
WND	58.36	5.96	8.91	4.26	13.20	3.74	1.85	0.58	1.61	1.54	41.64
BIO	4.58	51.95	8.57	5.34	12.20	2.03	5.75	0.92	3.80	4.86	48.05
SOL	6.75	9.19	52.81	6.20	15.39	1.09	3.06	0.77	2.46	2.28	47.19
GEO	4.40	6.63	7.34	62.44	10.96	1.11	2.59	0.77	1.76	2.00	37.56
WAT	9.20	11.13	13.33	7.63	45.74	3.51	3.47	0.44	3.01	2.53	54.26
BND	4.98	3.76	2.03	1.62	6.09	76.28	1.99	0.52	1.43	1.32	23.72
OIL	0.95	4.68	2.74	1.75	3.20	1.06	40.58	0.72	19.39	24.92	59.42
NGS	0.72	1.75	1.16	1.13	1.02	0.58	1.69	88.57	1.65	1.72	11.43
GAS	1.10	3.68	2.66	1.33	3.21	0.64	20.93	0.75	44.53	21.18	55.47
HOI	0.82	4.21	2.21	1.41	2.52	0.81	25.36	0.81	19.88	41.97	58.03
TO	33.50	50.98	48.95	30.66	67.78	14.58	66.69	6.28	54.99	62.35	436.76
Inc.Own	91.87	102.92	101.75	93.10	113.5	90.85	107.27	94.86	99.53	104.32	cTCI/TCI
Net	-8.13	2.92	1.75	-6.90	13.53	-9.15	7.27	-5.1	-0.4	4.32	48.53/43.68
NPDC	3	5	5	2	7	1	9	0	5	8	
Panel B: Short Term	**WND**	**BIO**	**SOL**	**GEO**	**WAT**	**BND**	**OIL**	**NGS**	**GAS**	**HOI**	**FROM**
WND	52.62	5.00	7.56	3.62	11.36	3.38	1.65	0.49	1.49	1.41	35.97
BIO	4.05	46.76	7.69	4.70	10.89	1.84	5.21	0.81	3.47	4.45	43.10
SOL	5.93	8.02	47.24	5.55	13.68	0.98	2.73	0.66	2.25	2.04	41.86
GEO	3.83	5.82	6.41	56.37	9.64	0.98	2.27	0.69	1.65	1.78	33.06
WAT	8.22	9.74	11.80	6.82	40.88	3.13	3.10	0.40	2.79	2.28	48.29
BND	4.34	3.09	1.66	1.40	5.07	68.75	1.75	0.46	1.21	1.15	20.14
OIL	0.88	4.22	2.53	1.57	2.93	1.01	37.33	0.65	17.86	22.93	54.60
NGS	0.66	1.57	1.05	1.02	0.93	0.53	1.57	81.07	1.51	1.58	10.42
GAS	0.96	3.26	2.40	1.19	2.84	0.59	19.25	0.66	40.58	19.42	50.55
HOI	0.73	3.75	2.00	1.26	2.26	0.76	23.11	0.71	18.07	38.19	52.65
TO	29.61	44.48	43.09	27.14	59.59	13.19	60.64	5.54	50.32	57.04	390.64
Inc.Own	82.22	91.25	90.32	83.51	100.48	81.94	97.97	86.61	90.89	95.23	cTCI/TCI
Net	-6.36	1.39	1.23	-5.92	11.31	-6.96	6.04	-4.88	-0.24	4.39	43.40/39.06
NPDC	3	5	5	2	7	1	9	0	5	8	

Table 2. Continue

Panel C: Long Term											
WND	5.75	0.95	1.34	0.63	1.85	0.37	0.20	0.08	0.11	0.13	5.67
BIO	0.53	5.18	0.88	0.63	1.31	0.19	0.55	0.11	0.33	0.42	4.96
SOL	0.81	1.16	5.57	0.65	1.71	0.12	0.33	0.10	0.21	0.24	5.33
GEO	0.57	0.81	0.93	6.07	1.32	0.13	0.32	0.08	0.12	0.22	4.50
WAT	0.99	1.39	1.53	0.81	4.86	0.38	0.37	0.04	0.22	0.24	5.97
BND	0.63	0.67	0.37	0.21	1.02	7.53	0.23	0.06	0.22	0.17	3.58
OIL	0.07	0.45	0.21	0.18	0.26	0.05	3.25	0.07	1.53	1.99	4.82
NGS	0.06	0.18	0.11	0.11	0.09	0.05	0.12	7.51	0.14	0.14	1.00
GAS	0.15	0.42	0.27	0.14	0.37	0.05	1.68	0.09	3.96	1.76	4.91
HOI	0.09	0.46	0.21	0.15	0.26	0.05	2.24	0.11	1.81	3.77	5.38
TO	3.90	6.49	5.86	3.52	8.19	1.39	6.05	0.74	4.68	5.31	46.13
Inc.Own	9.64	11.68	11.43	9.59	13.05	8.92	9.30	8.25	8.63	9.08	cTCI/TCI
Net	-1.77	1.54	0.52	-0.98	2.22	-2.19	1.23	-0.26	-0.24	-0.07	5.13/4.61
NPDC	2	8	5	4	7	0	9	2	3	5	

Notes: The outcomes are derived from the TVP-VAR (1), where the forgetting factors are set to 0.99, and a Bayesian prior is applied, as in Chatziantoniou et al. (2023). TO denotes the transmission from one variable to others. FROM shows the level of return spillover one variable receives from others. Net implies the subtraction of TO from FROM, reflecting the net transmission. TCI denotes the total connectedness index. cTCI denotes corrected TCI. NPDC represents the net pairwise directional connectedness, quantifying the number of bilateral relationships in which a variable exerts greater influence over other variables.

The visual representation of the static relations can be seen in Figure 2. From left to right, networks depict the total, high (1 day - 5 days) and low (5 days - Infinity) frequencies, respectively. The larger the nodes, the more pronounced the degree of transmission and vice versa. Thicker arrows represent the more substantial effect from the primary variable to the target variable, and the blue (yellow) color shows that the assets are net information sources (net recipients).

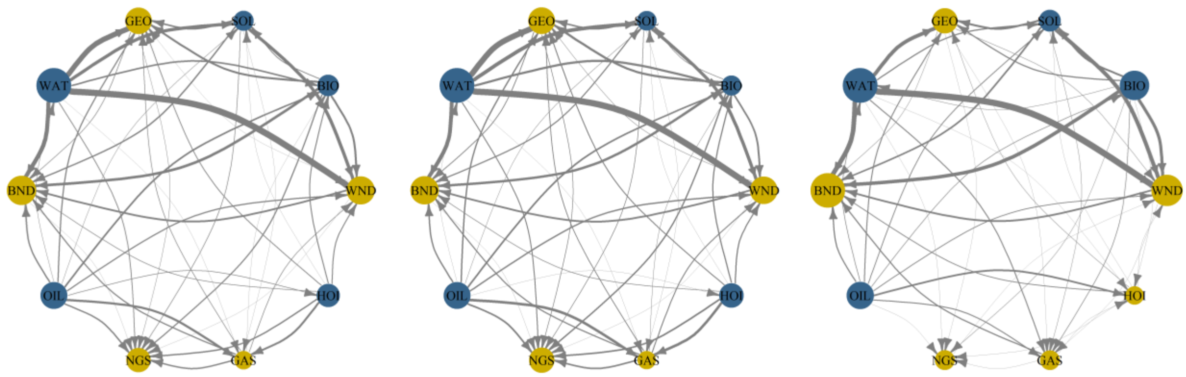

Figure 2. Time and Frequency Connectedness Network
Notes: The outcomes are derived from the TVP-VAR (1).

Figure 3 depicts the time and frequency connectedness indices. The black, red, and green-shaded areas show the time, short (1 day - 5 days), and long-term (5 days - Infinity) connectivity indices, respectively. The sharp rise in short-term and long-term frequency connectedness indices, and hence the total, may be related to the COVID-19 outbreak at the beginning of 2020. Consistent with the findings of Foglia and Angelini (2020), we observe high connectedness during the COVID-19 pandemic, indicating that connectedness increased during uncertainty periods. Figure 4 illustrates the net directional time and frequency connectedness and reveals that certain variables, including WAT, OIL, and HOI, act as net transmitters. Over time, changes in direction and magnitude are observed. For instance, BIO and SOL shifted from net receivers to net transmitters after 2020. In contrast, OIL previously acted as a net transmitter but temporarily switched to a net receiver after 2020. Additionally, certain variables, such as WAT and BND, experienced an increase in magnitude. Next, we investigate the bilateral dynamics among the assets by drawing on two complementary measures: net pairwise directional connectedness indices in Figure 5 and pairwise connectedness indices in Figure 6. The former captures which asset dominates (transmits shocks to) the other, while the latter reflects the degree of interdependence between the two assets. From Figure 5 WAT, OIL, and HOI emerge as persistent transmitters, although OIL and HOI briefly shift to net receivers in the post-2020 environment. Likewise, BIO and SOL have begun transmitting shocks to other green energy and fossil-based assets, aside from WAT, following the COVID-19 outbreak. By contrast, WND and NGS consistently receive shocks from nearly all other assets (except BND) throughout the sample period, suggesting that they generally act as receivers of shocks. Turning to Figure 6, the pairwise connectedness indices underscore stronger bilateral linkages within the same asset classes compared to those across different categories (e.g., green vs. fossil), which further intensified during the COVID-19 outbreak. Notable exceptions include the WAT-fossil and BIO-fossil pairs (excluding NGS), which exhibit higher interconnectedness and thus challenge the notion of clear market segmentation. Overall, this relatively low interconnectivity across green and fossil energy assets may imply potential diversification opportunities since shocks do not fully propagate between these two market segments.

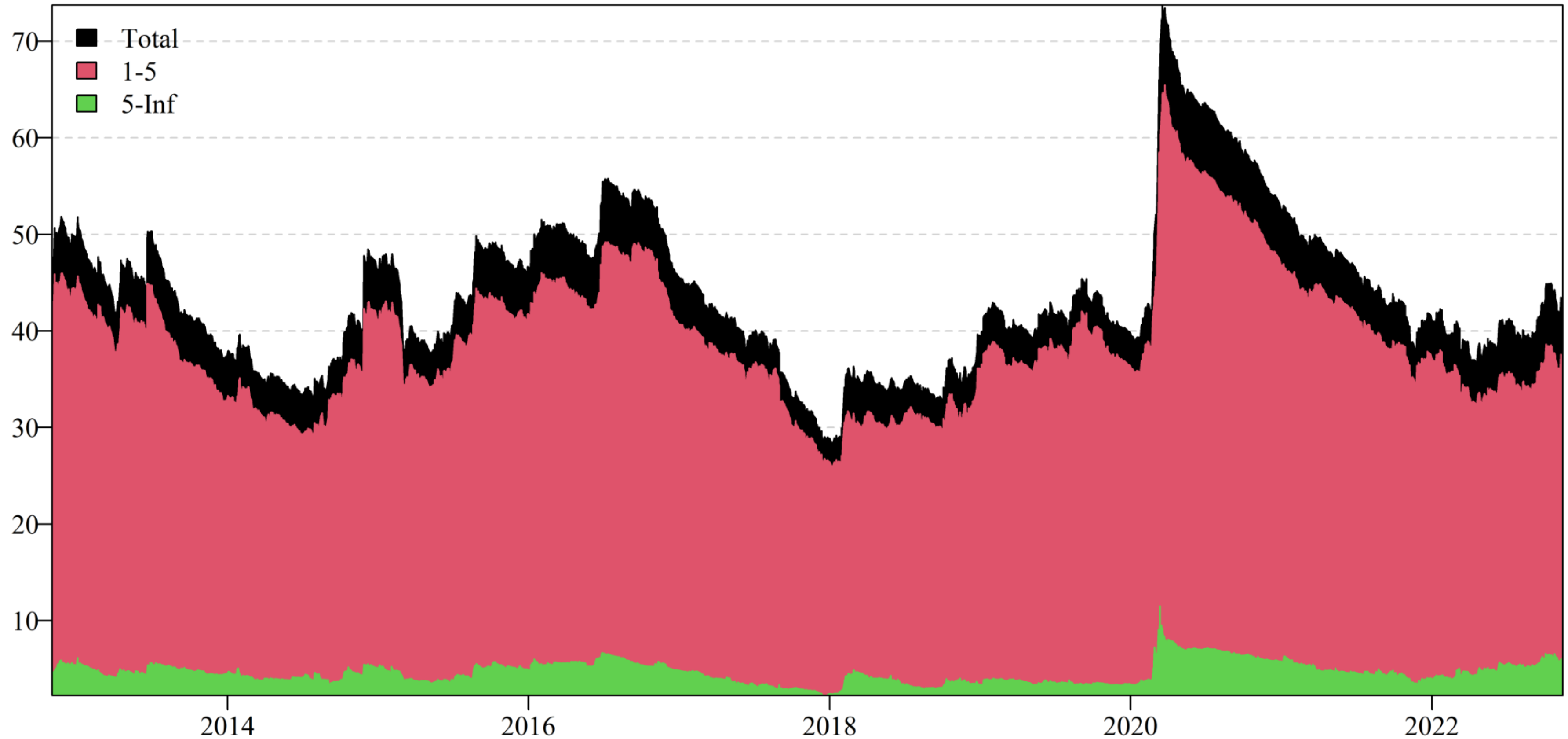

Figure 3. Dynamic Time and Frequency Connectedness Indices

Notes: The outcomes are derived from the TVP-VAR (1). The black, red, and green regions show total (Diebold and Yilmaz, 2012), high (1 day - 5 days), and low (5 days - Infinity) frequency (Baruník and Křehlík, 2018) TCI, respectively.

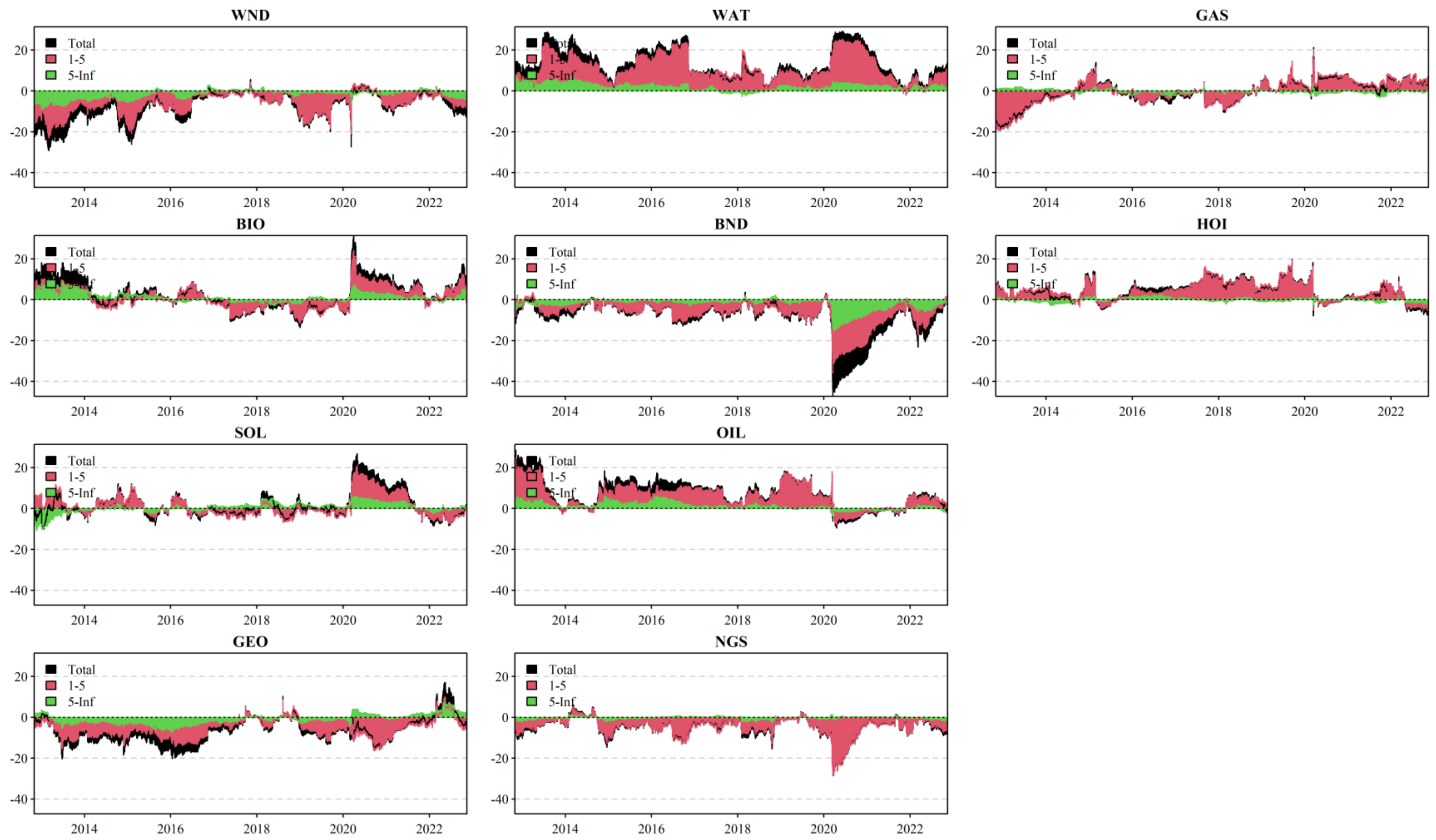

Figure 4. Net Directional Time and Frequency Connectedness

Notes: The outcomes are derived from the TVP-VAR (1). The black, red, and green regions show the total, high (1 day - 5 days) and low (5 days - Infinity) frequency net directional connectedness, respectively.

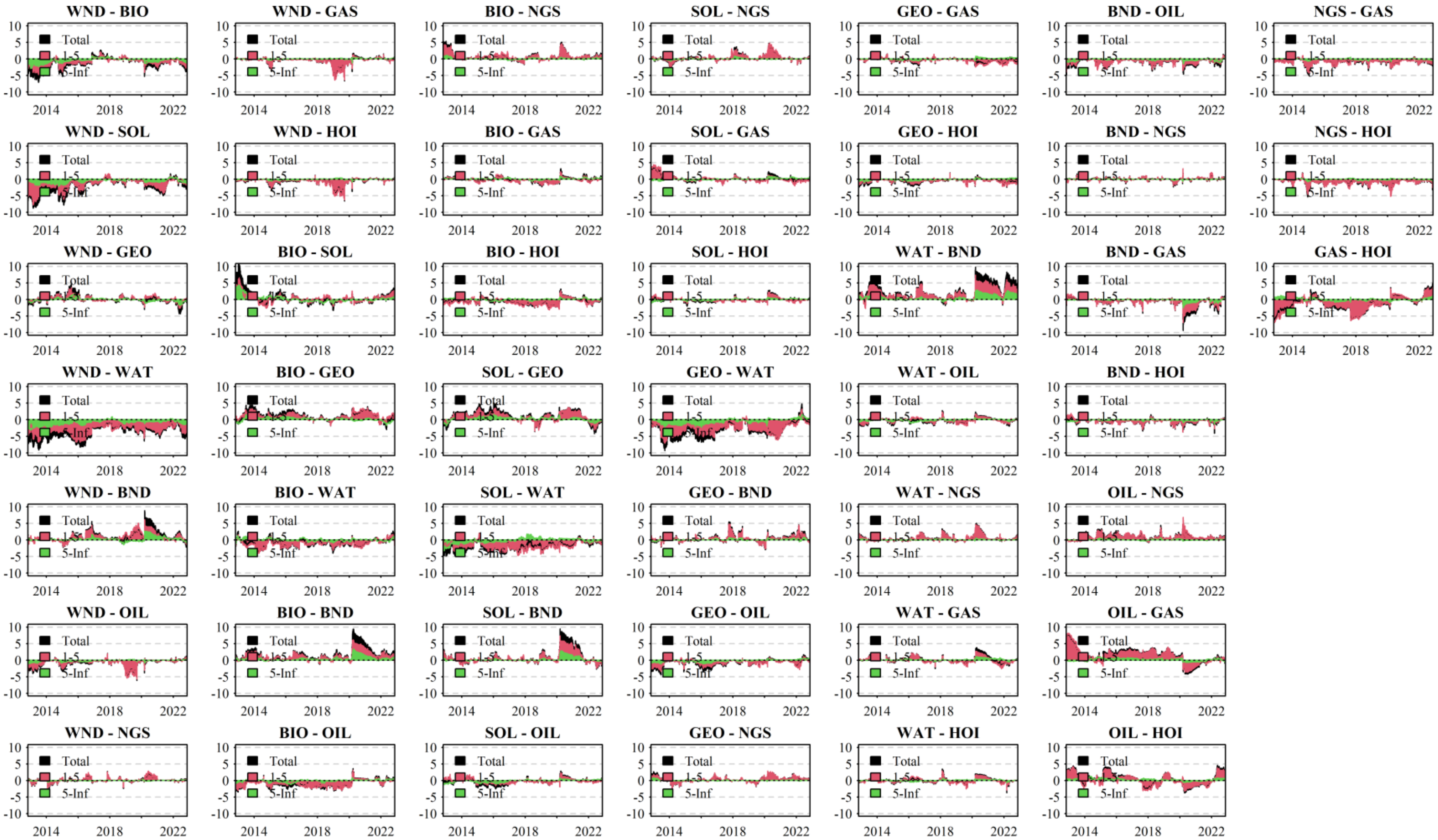

Figure 5. Net Pairwise Directional Time and Frequency Connectedness

Notes: The shaded area above (below) zero means that the first asset spreads (receives) the spillover to (from) the second asset.

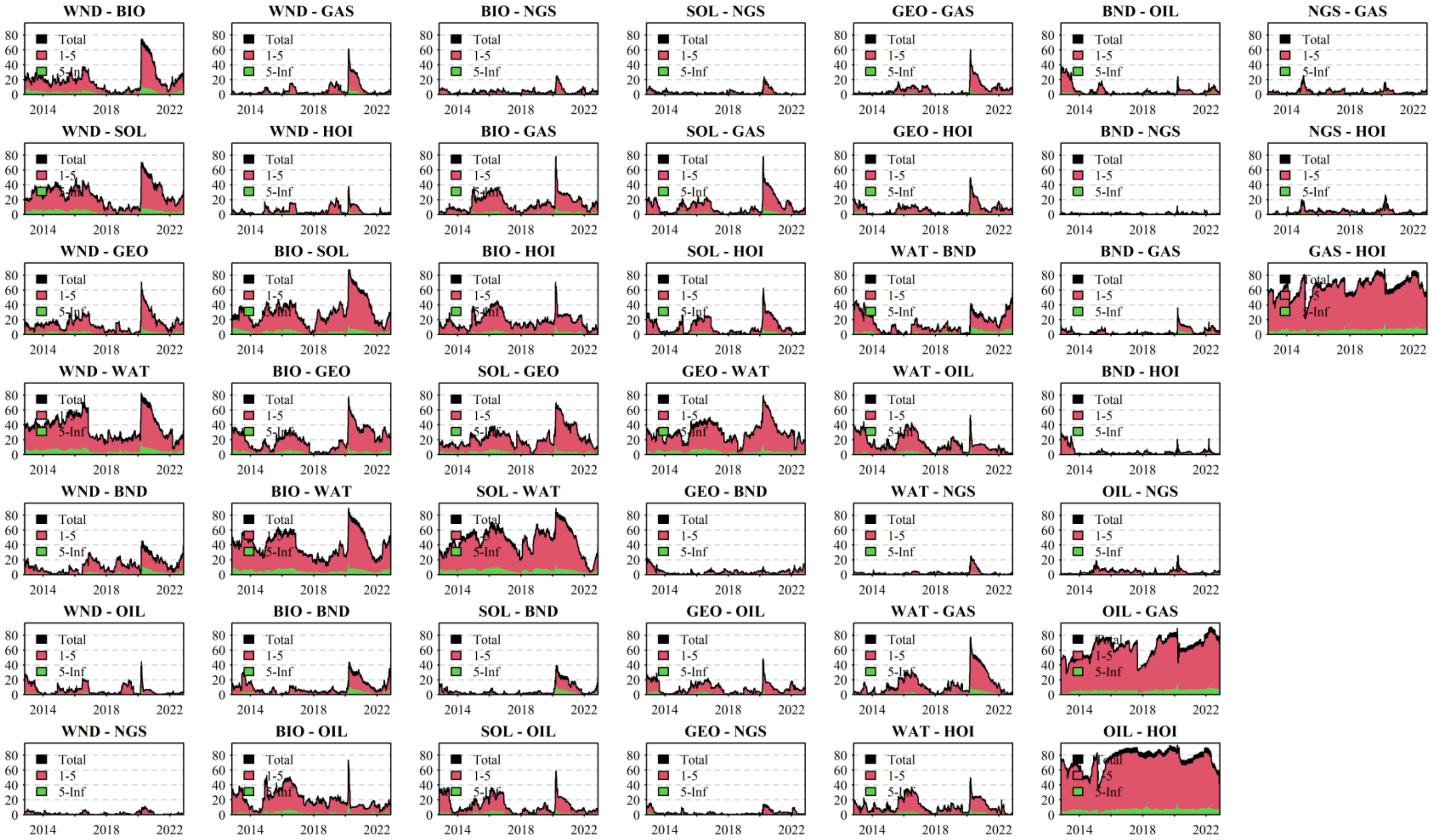

Figure 6. Pairwise Connectedness Indices

Notes: The black, red, and green regions show the total, high (1 day - 5 days) and low (5 days - Infinity) frequency pairwise connectedness indices, respectively.

5.2. The Fourier Cumulative Granger Causality Test Results

The results of the Fourier ADF (FADF) unit root test proposed by Enders and Lee (2012) are reported in Table 3. It shows that the optimal frequency for TOTAL, SHORT, and LONG is 2. For VIX and EPU, the optimal frequency is set as 1, while for FSI, it is set as 3. According to the results, all series are stationary at the 5% significance level or, even better, at the 1% significance level. This implies the rejection of the null hypothesis of a unit root.

Table 3. Fourier ADF Unit Root Test

	ADF	Lag	Freq
TOTAL	-3.284**	1	2
SHORT	-3.419**	1	2
LONG	-3.495**	2	2
VIX	-6.418***	0	1
EPU	-5.386***	2	1
FSI	-6.712***	1	3

Notes: *** and ** denote the 1% and 5% significance, respectively. The highest number of Fourier frequencies ($\boldsymbol{k_{max}}$) is three; the lag length ($\boldsymbol{p_{max}}$) is 12.

Table 4 shows the test results of the Fourier (cumulative) Granger causality. Based on these findings, we reject the *null* of "*no causality*" for 14 among 18 pairs, thereby indicating the presence of causal linkages between these variables. The causality test provides evidence of bi-directional Granger causality between TOTAL/SHORT/LONG and VIX. In addition, the test results reveal bi-directional Granger causality between TOTAL/SHORT and FSI. On the other hand, a unidirectional causality is observed from TOTAL/SHORT/LONG to EPU, as well as from LONG to FSI.

Table 4. Fourier Cumulative Granger Causality

Direction	Wald	Bootstrap p-value	Lag	Freq.
VIX≠>TOTAL	26.234	0.000*	2	3
TOTAL≠>VIX	12.889	0.000*	2	3
EPU≠>TOTAL	1.546	0.457	2	3
TOTAL≠>EPU	65.028	0.000*	2	3
FSI≠>TOTAL	10.179	0.020*	2	3
TOTAL≠>FSI	57.822	0.000*	2	3
VIX≠>SHORT	28.056	0.000*	2	3
SHORT≠>VIX	15.912	0.000*	2	3
EPU≠>SHORT	2.019	0.367	2	3
SHORT≠>EPU	65.736	0.000*	2	3
FSI≠>SHORT	11.467	0.004*	2	3
SHORT≠>FSI	58.242	0.000*	2	3
VIX≠>LONG	14.106	0.002*	1	3
LONG≠>VIX	4.243	0.042*	1	3
EPU≠>LONG	1.224	0.724	3	3
LONG≠>EPU	38.924	0.000*	3	3
FSI≠>LONG	1.818	0.537	3	3
LONG≠>FSI	64.752	0.000*	3	3

Notes: ≠> represents the null hypothesis of "no Granger causality". The bootstrap-p values were obtained from 1000 repetitions. * represents that values are significant at conventional levels, indicating the presence of causality for the corresponding direction. The highest number of Fourier frequencies (k_{max}) is three; the lag length (p_{max}) is 12. The optimal frequencies (k) and length of lag (p) are suggested by the BIC.

For robustness purposes, we also check the causality between the variables using the framework by Nazlioglu et al. (2019), which follows the TY procedure, accounting for the variables with different integration levels. Based on the results, we obtained results that were very similar to those reported in Table 4.

6. Conclusion and Recommendations

In this paper, first, we investigate return connectedness between the green energy markets (solar, wind, geothermal, bio/clean fuels, and water), green bonds, and fossil energy markets (oil, natural gas, gasoline, and heating oil) and then we measured the impacts of selected stress variables (FSI, VIX, and EPU) on this connectedness to investigate whether they were the drivers of it. The paper contributes to the literature by depicting a broader perspective on the relationship between green and fossil energy markets by considering the effect of FS. As far as we know, this is the first study considering the impact of FS on connectedness between these markets. The findings unveil the dynamics between these markets, with significant implications for decision-making by investors and policymakers.

Our results on time and frequency connectedness indicate a moderate level, which mainly originated from short-term dynamics. This result provides an important implication for investors: diversification opportunities may be more important in long-term investments. Fossil energy commodities, except natural gas, are more connected, whereas green energy markets, except water, are less connected. This finding suggests that there are still benefits from diversification within green stocks and bonds markets, but the diversification benefit within the fossil energy commodities is limited to natural gas.

Since the return spillover from oil to green markets is more significant than vice versa, this might result from the considerable role of oil in financial markets. Our findings indicate a low return connectedness between fossil energy markets and green bonds, and the transmissions from green stocks to green bonds are more pronounced than those from fossil energy commodities. Fossil energy commodities have low connectedness with green markets, indicating diversification opportunities for the portfolios of both green and fossil energy markets. In addition, we find that while water and oil impact the market, the others influence green bonds and wind. This may indicate that investors concerned with optimal portfolio management should consider investing in net transmitters, such as water and oil, and avoid net receivers, such as green bonds and wind, since many risk sources may affect net shock receivers. While short-term main drives return connectedness, the increase in TCI is time and event-dependent.

The causality test results reveal the presence of significant causal relationships between connectedness measures and stress variables. Our findings highlight the presence of bi-directional Granger causality among the connectedness of all frequencies with VIX, indicating that changes in VIX may trigger changes in connectedness measures and vice versa. Similarly, the bi-directional Granger causality between total and short connectedness and FSI implies that changes in the stress index may influence the total and short-term connectedness between fossil and green energy markets and vice versa. Besides, EPU does not impact connectedness measures, while all connectedness measures influence EPU. As a result, FS variables, namely FSI and VIX, lead to the connectedness measures between fossil and green markets. In contrast, the economic variable, namely the EPU, is led by connectedness measures. Therefore, investors holding green and fossil assets should consider FS factors rather than economic ones.

Several policy implications can be suggested from empirical results. First, given the positive connectedness between green energy markets, it is recommended that policymakers encourage investments in green energy sectors. Providing incentives and creating a favorable investment environment will initiate more investment flows to green energy projects. Given that wind, solar, and bio-clean sectors act as net shock transmitters, diversification of the energy sources by emphasizing renewable energy sources could enhance the stability and resilience of the overall energy system. Moreover, policymakers should concentrate on integrating renewable energy sources into the current energy infrastructure to reduce fossil dependence. Both diversifying energy sources and implementing energy efficiency strategies can help reduce the economic and business risks related to volatility in fossil energy prices. The analysis reveals that the network relationship is driven by short-term rather than long-term connectedness. Therefore, policymakers and investors should consider short-term and long-term dynamics when formulating strategies and making investment decisions. Short-term fluctuations may be influenced by market sentiment and immediate shocks, while long-term dynamics indicate structural changes and trends in the energy markets.

The analysis of stress indicators also provides policymakers with various insights. They should consider the impact of VIX as an indicator of stock market risk and volatility on connectedness between green and fossil energy markets to develop risk management strategies and policies to ensure financial stability and sustainability. Similarly, they should consider the influence of the FS index on total and short-term connectedness between green and fossil markets. Policymakers can use this insight to assess systemic risks in the economic system and implement appropriate measures to mitigate the inherent risks in the relationship between green and fossil markets. Additionally, they should consider the influence of connectedness on changes in these stress indicators. This can help detect irregularities and ensure necessary actions are taken to protect investors and maintain market integrity. Policymakers should consider monitoring these measures more closely to understand the impact of market interconnectedness on economic conditions and formulate more appropriate policy responses. These insights can inform the design and implementation of policies and regulations to promote financial stability, mitigate systemic risks, and safeguard the interests of market participants and the broader economy.

Further research is needed to validate and expand upon these findings by including other economic, financial, and political risks and uncertainties, given the evolving nature of the energy markets and the changing nature of green finance instruments.

Declaration of Research and Publication Ethics
This study, which does not require ethics committee approval and/or legal/specific permission, complies with the research and publication ethics.

Researcher’s Contribution Rate Statement
The authors declare that they have contributed equally to the article.

Declaration of Researcher’s Conflict of Interest
There are no potential conflicts of interest in this study

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