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Volatility spillovers and frequency dependence between oil price shocks and green stock markets

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ABSTRACT

This study uses wavelet coherence and frequency connectedness techniques to examine the time-frequency dependence and risk connectivity between oil shocks and green stocks. The results show that on mid-term and long-term scales, the dependence relationships between the oil and green stock markets are tighter while lead-lag patterns are mixed and time-varying. Total risk spillovers between the oil and green stock markets are mostly conveyed over time. Risk spillovers from the oil market are substantially larger in the green stock market. Furthermore, global crises such as the Great Recession, the oil price collapse, and the COVID-19 pandemic have substantially amplified the magnitude of risk spillovers. Overall, the green stock market has not yet developed enough potential for a larger independence from the conventional energy market. Hence, for participants in the energy and financial markets who have different time horizons for asset allocation and risk management and for committed investors in particular, the examination of time-frequency dependence and risk spillovers can be quite beneficial.

1. Introduction

The last decade has largely reshaped the experience of the investment community. Two fundamental processes have impacted personal and professional investment practices. One of them is the intertwining of technologies commonly referred to as the 4th Industrial Revolution. The other one is the green transition that encompasses a set of consistent actions driven by a growth in environmental awareness and social responsibility of the society. As stated by the European Securities and Markets Authority, "… investor preferences are shifting towards an interest in financial products that incorporate environmental, social, and governance factors, which have increased rapidly over the last few years" (ESMA, 2020).

There are two ways financial markets are affected by the green transition. (*i*) Infrastructural and technological shifts resulting from the implementation of sustainable development programs may impact positively some businesses and negatively other businesses in terms of future performance. (*ii*) Financial markets are venues to channel funds for sustainable development. The green transition translates into the finance world partitioning cash flows into green and brown. According to Climate Transparency, green cash flows are used to finance "low carbon and climate-resilient solutions from both public and private sources" while brown cash flows serve to support "carbon-intensive projects or activities and pathways that do not sufficiently consider future climate risks" (Watson and Schindle, 2017).

Financial markets evolve in line with social and economic trends. Sound investment practice nowadays is hardly feasible without embracing green investing.[1] However, green assets are associated with opportunities and risks that mostly remain undiscovered by scholars and practitioners. It is true that, with the proliferation of the ESG agenda, green investing is frequently viewed from a utility perspective within which the investor is not merely rational but growingly responsible.

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[1] Throughout the paper, the terms 'green' and 'ESG' (Environmental, Social, and Governance) are used interchangeably.

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However, this must not undermine an earthier view of green portfolios, i.e., the extent to which they might serve as rewarding opportunities or safe harbors.

Our research objective is to enhance the knowledge and understanding of the contribution green investing makes to institutional and retail portfolios in terms of cross-market effects. We do not pursue the ambition of mapping a complete risk profile of the global green portfolio but rather focus on the exposure of the global green portfolio to a critical systemic risk by which we assume oil price shocks. This macroeconomic variable is of utmost importance given that the green transition stimulates the growth of such industries as alternative fuels, renewable energies, and clean technologies, which are directly affected by developments in the oil market. Scholars, practitioners, and policymakers share a growing interest in the causes and consequences of price deviations in the oil market (Fueki et al., 2018).

Modeling price deviations in the oil market suggests the consideration of both demand- and supply-induced shocks, though the presently prevailing hypothesis favors demand-based factors (Kilian, 2014; Kilian and Hicks, 2013) rather than supply-based factors (Hamilton, 1983, 1985, 2003). Yet, there is evidence that supply-induced shocks may manifest themselves in driving oil prices (Baumeister and Kilian, 2016). To refine our research approach, we follow the technique of Ready (2018) and differentiate oil price shocks with respect to where they originate: demand-induced, supply-induced, and risk-induced shocks.

An enormous surge in green investing and a strong conviction in further promotion of the ESG agenda give the basis for motivation and relevance of our research. Over the past decade, a series of ESG initiatives and programs at a supranational level have been adopted that establish a partnership between public and private signatories, e.g., the Paris Agreement, the UN Sustainable Development Goals (UN SDG), the Network for Greening the Financial System (NGFS), the UN Principles for Responsible Investment (UN PRI). According to Climate Transparency, in addition to public bodies that introduce ESG principles in public finance, fiscal policy, and financial regulation, professional participants such as rating agencies and securities exchanges take a proactive approach to promoting climate-related objectives in the investment community (Watson and Schindle, 2017). For example, KLD Research & Analytics was the first to launch a socially responsible investment index, KLD 400, as far back as 1990. In 2016, the Luxembourg Stock Exchange was the first to introduce a platform for trading green assets, the Luxembourg Green Exchange. Institutional investors have committed themselves to green investing by joining sustainable development initiatives and programs. Figure A1 in Appendix A illustrates one facet of the development of green investing: as of 2019, more than 2250 institutional investors were UN PRI signatories, a 70% increase since 2015. Altogether, they held AUM in excess of USD80 trillion, a 40% increase since 2015.

With growing ESG awareness, the investment community is seeking more clarity about the vulnerability of green portfolios which motivates us to expand the research in the area. For example, Görgen et al. (2020) advanced a remarkable idea of assessing transition risk with ‘carbon beta’ and ‘carbon premium’ based on the Fama and French multifactor model. The idea was further developed by CARIMA. In our research, we attempt to assess the responsiveness of green portfolios to price disturbance in the oil market which further reverberates across other markets through cross-market risk spillovers and amplified shocks. By risk spillover, we mean that a shock to the volatility of one market is transmitted to the volatility of another market. Green portfolios are less diversified compared to their brown peers; hence, they appear to be more vulnerable to systemic shocks (Chegut et al., 2011).

The contribution and novelty of the research are summarized as follows. Though the ESG topic is not novel in academic literature, previous papers have focused predominantly on finding ‘Greenium’. This paper focuses on risk attributes of green portfolios and contributes to the available knowledge which is not yet comprehensive. (*i*) To fully reveal the perplexity of the processes underlying cross-market behavior, we enhance wavelet analysis with a multi-resolution connectedness analysis using techniques for measuring connectedness both in the time domain (Diebold and Yilmaz, 2012, 2014) and in the frequency domain (Baruník and Křehlík, 2018). Additionally, we apply the shock decomposition procedure of Ready (2018) to partition shocks based on where they originate. Shock decomposition of Ready (2018) or Kilian (2009), routinely applied in studies on the conventional stock market, has been neglected in research on the green stock market. Meanwhile, oil shocks of different types heterogeneously affect green assets. We document a strong negative impact of risk-based shocks similar to the case of conventional assets (Umar et al., 2021), while the impact of supply-based shocks appears positive at low frequencies which goes against observations for conventional assets (Das et al., 2020). An explanation could be a special link between the two markets when clean energy gains in relative attractiveness following manipulative cuts in oil supply.

(*ii*) In terms of data, the research is different in two respects. First, we do not constrain the sample data to clean and renewable energy indices as in earlier works (Sadorsky, 2012; Reboredo et al., 2017; Shahbaz et al., 2021) and add MSCI and S&P green indices as alternative proxies for the global green portfolio that include a vaster universe of green assets selected on a broader basis of ESG criteria. Index providers employ proprietary methodologies for selecting green assets. As noted in Statman (2006), they emphasize different features of sustainable development. This translates into our empirical findings in that the performance of broadly diversified ESG benchmarks is more tightly linked to demand- and risk-based shocks while the performance of narrower benchmarks of clean and renewable energy stocks is significantly affected by supply-based shocks. In general, however, none of the considered green indices is independent enough from oil shocks of any type; hence, we do find support for the conclusion of Dutta et al. (2020) on limited dependence between the oil market and eco-friendly firms.

Second, our observations span from 2007 to 2021 covering major crisis events including the COVID-19-triggered financial turbulence. Hence, we are able to capture both equilibrium properties of connectedness and spillover in the oil-green stock system and properties that change in stressful market conditions. For instance, supply-based shocks appear to be sensitive to the nature of the crisis event as they “exchanged” spillovers with demand-based shocks only during the period of the oil crisis/Brexit. The Great Recession strengthened connectedness and spillover within the oil-green stock system to a greater extent than the COVID-19 pandemic. And during the period of the COVID-19 pandemic, oil shocks (green portfolios) were unambiguous net transmitters (net recipients) of spillovers which, interestingly enough, depicts a situation quite different from that in China where Duan et al. (2023) find an opposite net transmitter-net receiver relationship during the pandemic.

Our overall conclusion is as follows. The green stock market is weakly responsive to oil price shocks at high frequencies of less than a week. This points to the non-speculative nature of its participants. At lower frequencies, greater coherence suggests the presence of long-term players in the green transition whose economic outlook incorporates multiple projections. The dependency structure between the oil and green stock market possesses many properties earlier documented for the conventional stock market. Hence, green portfolios are ineffective as an insurance tool. In this sense, green portfolios are rather ‘fragile’ and may require more incentives for capital to retain invested.

Benchmarking our research findings against the existing knowledge of the risk profile of green portfolios, we believe that we have provided an opportunity for investors and policy makers to augment their evaluation, planning, and decision-making processes with useful input. This can lead to better manageability of green portfolios, especially when they are not a stand-alone investment choice but a part of larger diversified portfolios. This, in turn, will increase investor confidence in dealing with green assets and improve the current balance of weights between underweighted sustainable and overweighted unsustainable investment.

The paper is structured as follows: Section 2 reviews relevant literature findings. Section 3 outlines the research design, detailing the empirical techniques employed and presenting summary statistics. Section 4 gives presentation of empirical results. Finally, conclusion is given in Section 5.

2. Literature review

Knowledge of market interconnectedness and cross-market behavior is core both to asset managers in pursuing effective portfolio risk management and to policymakers in identifying targets in financial regulation. The latter, for example, could use it to work out measures to smooth green cash flows during times of high and low oil prices. There is a solid body of academic literature that addresses cross-market behaviour; in particular, those related to developments in the oil market. Over the past couple of decades, the existence of cross-market effects has been confirmed with many pieces of empirical evidence. Unlike Greenium, there is presently an unambiguous conclusion on the existence of cross-market effects in the green stock market. We only provide an exemplary literature review for both conventional and green stock markets.

Das et al. (2020) conjecture that a response to oil price shocks is heterogeneous and is dependent on the origin of the shock, the market condition, and whether the nation is a net oil exporter or importer. The authors adopt the shock decomposition procedure of Ready (2018) and apply the Markov regime-switching approach and quantile regressions. For emerging markets, they find that demand-based (supply- and risk-based) oil price shocks positively (negatively) affect the stock market of some oil-exporting nations and the interconnectedness is particularly pronounced in bearish markets.

Enwereuzoh et al. (2021) use Structural Vector Autoregression to structure oil price shocks and Smooth Transition Regression to detect spillovers in African nations. They find that the majority of the stock markets are irresponsive to supply-induced shocks but react to oil-specific demand-induced shocks. Global demand-induced shocks appear to be insignificant for the stock markets of oil-importing nations and barely significant for the stock markets of oil-exporting nations. Adrangi et al. (2021) use Structural Vector Autoregression and Spectral Analysis to study Latin American markets. They confirm interconnectedness with the oil market and a negative response to positive shocks to oil prices with a varying degree of responsiveness across all markets.

Umar et al. (2021) consider the stock markets of the Gulf region and the BRIC countries from 2005 to 2020 and conjecture that the response to oil price shocks varies for the two regions, over time, and depending on where the shock originates. It is additionally hypothesized that the Great Recession and the COVID-based financial turmoil altered the nature of interconnectedness between the oil market and the stock market. The authors adopt the approach of Ready (2018) to partition oil price shocks and the Forecast Error Variance Decomposition technique of Diebold and Yilmaz (2014) to study interconnectedness. The authors confirm that the stock markets of the two regions have notable differences in the direction and degree of responsiveness to oil price shocks. Among the BRIC countries, most shocks are generated in Russia and Brazil while in the Gulf region, they come from the UAE. The impact of demand-based and risk-based shocks on the stock markets exceeds that of supply-based shocks. During financial distress, the impact of risk-based shocks tends to be the most prolonged. The authors find support for the hypothesis of the time-varying nature of interconnectedness. Another conclusion is that shocks in the oil market may have predictive power for the stock market.

In a paper by Ziadat et al. (2022), the authors apply Structural Vector Autoregression and quantile regressions to a geographically diverse market sample that includes the US, Canada, the UK, Continental Europe, Russia, the Gulf countries, India, China, and Asian-Pacific countries from 2002 to 2018. The authors confirm that stock markets exhibit a varying degree of responsiveness to oil price shocks depending on their origin, the market condition, and whether the nation is a net oil exporter or importer.

Over the past decade, the issue of cross-market behavior has received some attention in studies of green assets. Sadorsky (2012) develops a variable beta model with multiple systemic risk factors for stock returns of renewable energy companies: the market factor is complemented with firm size, the debt-to-equity ratio, the R&D expenditure to sales ratio, the growth of sales, and oil price returns. Panel regression is applied to the constituent companies of the Wilderhill Clean Energy ETF. His findings are that price deviations in the oil market contribute to the volatility of renewable energy stocks by reinforcing the effect of market risk.

In a paper by Reboredo et al. (2017), the authors use Wavelet Analysis to check whether dependence between the oil market and renewable energy stocks varies over time and across frequencies and apply linear as well as non-linear Granger causality tests to identify the direction of causality for different time horizons. Interconnectedness is found to be growing in strength from the short-run to the long-run. The authors find unidirectional and bidirectional linear causality at lower frequencies only. At the same time, non-linear causality is observed at both low and high frequencies.

Pham (2019) considers heterogeneity of the clean energy sector within the context of interconnectedness. The author seeks to answer the question of whether different types of clean energy stocks respond differently to shocks to oil prices. Sub-sectoral proxies are selected from the NASDAQ OMX Green Economy index family. The author adopts the technique of Diebold and Yilmaz (2014) to assess the strength and direction of spillovers and uses multivariate GARCH models. The author confirms heterogeneous links in that biofuel and energy management stocks exhibit the greatest connection with oil prices while geothermal, wind, and fuel cell stocks tend to be more independent from oil prices. The spillover effect is reported to be stronger for oil prices which means that the oil market is a net receiver of shocks.

Dutta et al. (2020) study interconnectedness between the green stock market and the oil stock market applying the Markov regime-switching (MRS) approach that allows for identifying distinctions in responses under different market conditions. The authors conclude that green stocks are similar to conventional stocks in that they possess the regime-switching property. An interesting insight is that green stocks are impacted by the volatility of the oil market, as measured by the Crude Oil Volatility Index (OVX), rather than by oil price fluctuations. The impact is negative and this means that implied volatility is a more effective tool for diversifying and hedging purposes. Shahbaz et al. (2021) use modified GC tests to study interconnectedness and causality among the oil market, the clean energy stock market, and the conventional stock market. The authors find evidence of predictive power of oil prices for clean energy stock prices in bear and bull markets. Similar to Shahbaz et al. (2021), Duan et al. (2023) study interconnectedness among multiple conventional and green markets but confine their study to Chinese securities and the period of the COVID-19 pandemic only. The authors' findings are that spillovers substantially intensified during the COVID-19 pandemic and featured new energy and clean energy stocks as net contributors and green bonds and crude oil stocks as net recipients of spillovers.

It should be noted that for green bonds, the issue of cross-market behavior has also been addressed in a series of research papers. However, for green bonds, the starting point was the examination of their association with conventional fixed-income securities (Treasuries, corporate high-quality and high-yield bonds), currencies, and clean energy stocks with a subsequent inclusion of the oil market into consideration. In a study by Kanamura (2020), the author reports that green bond prices are negatively associated with WTI and Brent prices. Long et al. (2022) examine spillovers among the oil market, the clean energy stock market, and the conventional stock market but consider market volatilities instead of price fluctuations for all markets. The authors' findings are that spillover processes intensify in stressful market conditions and that there is "regional specialization" in spillovers within green markets, with the US being the net transmitter and China being the net receiver of spillovers. Dai et al. (2023) find asymmetric spillover effects for bullish and bearish periods among green bonds, "brown" stocks, and the oil market. In a recent paper by Khalfoui et al. (2023), the focus again shifts away from the oil market: it is reported that in bear markets during the COVID-19 pandemic period, fake news about the disease and cryptocurrencies were net transmitters of spillovers and green bonds were net receivers.

In Table 1, we summarize methods and findings from those papers reviewed in this section that examine spillover and connectedness between the oil market and both conventional and green stocks.

3. Data and summary statistics

As proxies for the global green portfolio, we select five green indices from the ESG index families of IWR, MSCI, S&P, and WilderHill. These providers have a long experience in applying ESG principles to the products they offer which makes their green indices reliable benchmarks for investors and regulators. Two of the indices, the Dow Jones Sustainability World Index (DJSI WORLD) and the World ESG Leaders Index (MSWESG), are broadly diversified sustainability benchmarks. The other three indices, the Global Clean Energy Index (SPGCLE), the Clean Energy Index (ECO), the Renewable Energy Industrial Index (RENIXX), represent portfolios of alternative energy stocks.

The sample period spans from 2007 to 2021 providing an opportunity to study the performance of the green stock market over a diverse set of critically important economic, geopolitical, and health events (the Great Recession, the European debt crisis, civil conflicts in the Middle East, the coronavirus pandemic). Over this period, oil prices exhibited vast fluctuations with a rise to a historical maximum in 2008, crashes by more than 50% in 2009 and 2014, a dive into a negative zone in 2020, and a growth afterwards.

The rough data have been retrieved from DataStream. We compute a time series of continuously compounded returns on each index with a daily frequency. Table 2 contains the descriptive statistics for green portfolio returns series (Panel A) and oil shock series (Panel B). Green assets produced a mean return close to zero over the period considered. The World ESG Leaders Index and the Dow Jones Sustainability World Index are representative of a broader set of green assets not constrained to the clean and renewable energy sector. Judging by the level of their unconditional volatility and the spread between the maximum and minimum values, they appear to be less risky. In contrast, RENIXX, the narrowest considered index, is the most volatile. Among oil shocks, risk shocks are the most volatile. All the series under consideration exhibit non-normal distribution, as evidenced by their skewness, kurtosis, and the Jarque Bera test. Additionally, all series are stationary as indicated by the ADF, PP, and KPSS tests.[2]

Table 3 summarizes unconditional correlations among all series. All green portfolios are positively correlated with demand-based oil shocks and negatively correlated with both supply-based and risk-based oil shocks. Also, we observe strong correlation among green portfolios and a very weak correlation among oil shocks.

Fig. 1 displays the dynamics of green stock prices. The graphical evidence shows that SPGCLE, ECO, and IWR Renewable Energy share the same patterns. Specifically, they experience a decrease during the Global Recession followed by a stable period until the COVID-19 outbreak when the markets experience a second downward move. MSCI World ESG Leaders and Dow Jones World Sustainability have an upward trend between the two events. Fig. 2 illustrates the dynamics of green portfolio returns and oil shocks. We observe significant volatility clustering and a fat-tailed distribution for all series.

[2] In fact, the wavelet analysis deals with non-stationary time series equally well. See Roueff and Von Sachs (2011) and Crowley (2005).

4. Empirical methods

4.1. Wavelet coherence model

In applied economics, wavelet analysis[3] was first proposed by Ramsey and Lampart (1998) in a study of interconnectedness between macroeconomic variables. For a finite time series $x(t)$, we define the continuous wavelet transform $W_x(\tau, s)$ as

$$W_x(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t) \overline{\psi}\left(\frac{t-\tau}{s}\right) dt, \tag{1}$$

where $\psi(t)$ denotes the mother wavelet function with $\tau, s \in R, s \neq 0$ representing location and scale, respectively, t denotes dimensionless time, and the bar symbol denotes the operation of complex conjugate. Parameter τ specifies time interval, parameter s specifies the stretch of the wavelet. The cross wavelet transform $W_{x,y}$ for oil shocks $x(t)$ and green stock returns $y(t)$ is given by

$$W_{x,y}(\tau, s) = W_x(\tau, s) \overline{W}_y(\tau, s). \tag{2}$$

To capture co-movement between the green stock market and the oil market we compute the wavelet coherence coefficient R_y^2 as

$$R_y^2(\tau, s) = \frac{\left|S\left(s^{-1} W_{x,y}(\tau, s)\right)\right|^2}{S\left(\left(s^{-1}|W_x(\tau, s)|^2\right)\right) S\left(\left(s^{-1}|W_y(\tau, s)|^2\right)\right)}. \tag{3}$$

The wavelet coherence coefficient resembles the conventional correlation coefficient in that it measures localized correlation between the two time series at location τ and scale s. Its value ranges from 0 to 1. The closer the value to 1, the stronger the linear association between oil shocks and green stock returns. Because R_y^2 is a squared term, it does not distinguish between positive and negative linear association and does not convey information on a delay between the two time series. For this purpose, the phase difference $\varphi_{x,y}$ based on the signs of deferments in the oscillating of time series is used:

$$\varphi_{x,y}(\tau, s) = \tan^{-1}\left(\frac{\Im\left\{S\left(s^{-1} W_{x,y}(\tau, s)\right)\right\}}{\Re\left\{S\left(s^{-1} W_{x,y}(\tau, s)\right)\right\}}\right), \tag{4}$$

Where $\Im$ and $\Re$ are imaginary and real part operators, respectively.

4.2. Frequency connectedness approach

To analyze volatility spillovers and interconnectedness between the oil market and the green stock markets in the time domain, we employ the approach proposed by Diebold and Yilmaz (2012). Within the structural $VAR(p)$ model, the n-variate process $x_t = (x_{t,1}, x_{t,2}, \ldots, x_{t,n})$ at $t = 1, 2, \ldots, T$ can be expressed as:

$$\varnothing(L) x_t = \varepsilon_t, \tag{5}$$

where $\varnothing(L) = \sum_h \varnothing_h L^h$ denotes an $n \, x \, n$ lag polynomial of order p and ε_t denotes white noise. The VAR model can be expressed as a moving average process:

$$x_t = \Psi(L) \varepsilon_t, \tag{6}$$

where $\Psi(L)$ is an $n \, x \, n$ infinite lag polynomial matrix of coefficients. The generalized forecast error variance decompositions are defined as:

[3] To gain a comprehensive understanding of the application of wavelet analysis in the fields of economics and finance, see Percival and Walden (2000), Serroukh et al. (2000), Gençay et al. (2002).

Table 1
Summary of previous research methods and findings.

Paper	Period	Shock by origin	Methods	Findings
Conventional stocks				
Das et al. (2020)	2002–2018	Demand-based, supply-based, risk-based shocks from Ready (2018) decomposition	Markov regime-switching framework, quantile regressions	Demand-based (supply-based, risk-based) shocks positively (negatively) affect the stock market of oil-exporting nations; connectedness is particularly strong during crisis periods.
Enwereuzoh et al. (2021)	2000–2018	Supply-based, aggregate demand-based, oil-specific demand-based shocks from Kilian (2009) SVAR decomposition	Two-state regime smooth transition regression framework	Stock markets are irresponsive to supply-based shocks, weakly responsive to aggregate demand-based shocks but react to oil-specific demand-based shocks.
Adrangi et al. (2021)	2000–2016	No decomposition by origin; decomposition following SVAR, measurement following Kilian and Park (2009)	Spectral density functions and co-spectral analysis; smooth transition regression (STAR)	Evidence for connectedness; stock markets response negatively to positive oil shocks.
Umar et al. (2021)	2005–2020	Demand-based, supply-based, risk-based shocks from Ready (2018) decomposition	Forecast error variance decomposition (Diebold and Yilmaz, 2012, 2014)	Medium degree of connectedness in a normal market environment; unpreceded degree of connectedness during the COVID-19 pandemic; the impact of demand- and risk-based shocks exceeds that of supply-based shocks with the impact of risk-based shocks being most prolonged during the COVID-19 pandemic.
Ziadat et al. (2022)	2002–2018	Supply-based, aggregate demand-based, oil-specific demand-based shocks from Kilian (2009) SVAR decomposition	Quantile regressions	Oil demand shocks impact oil-exporting stock markets positively, while oil-importing markets show no consistent response to oil shocks.
Green stocks				
Reboredo et al. (2017)	2006–2015	No shock decomposition	Wavelet coherence and phase analysis; linear and non-linear Granger causality	Weak short-run association, strengthening in the long-run; linear causality at lower frequencies, non-linear causality at both low and high frequencies.
Pham (2019)	2010–2018	No shock decomposition	Forecast error variance decomposition (Diebold and Yilmaz, 2012, 2014), multivariate GARCH	Association varies based on green portfolio; oil market is a net receiver of stronger spillover shocks.
Dutta et al. (2020)	2010–2018	No shock decomposition; implied volatility as an alternative factor under consideration	Markov regime-switching framework	Crude oil prices have an insignificant positive impact, while implied volatility impact is significant but negative.
Shahbaz et al. (2021)	2005–2021	No shock decomposition	Granger-causality tests in the time and quantile domains	Association depends on the market regime.
Duan et al. (2023)	2019–2022	No shock decomposition	Vector parameter autoregression, Forecast error variance decomposition (Diebold and Yilmaz, 2012, 2014)	During the COVID-19 pandemic, the intensity of spillovers between different markets significantly escalated. New energy and clean energy stocks, including green bonds and crude oil stocks, emerged as net contributors to volatility spillovers, transmitting shocks and exhibiting heightened volatility. Conversely, certain sectors within the new energy and clean energy space acted as net recipients of volatility spillovers, experiencing increased vulnerability to external shocks and greater volatility

Table 2
Summary statistics.

	Mean	STD	Min	Max	Skewness	Kurtosis	J.B. test	ADF	PP	KPSS
Panel A: Green stock market returns										
SPGCLE	−0.023	1.941	−14.973	18.093	−0.572	12.542	24000***	−14***	−3000***	0.66
ECO	−0.011	2.227	−16.239	14.519	−0.457	5.805	5200***	−14***	−3600***	0.65
RENIXX	0.001	2.457	−41.627	42.217	−0.402	80.031	960000***	−14***	−3900***	0.84
MSWESG	0.017	1.097	−10.269	8.623	−0.74	12.367	23000***	−15***	−3400***	0.30
DJSI World	0.011	1.17	−10.604	8.838	−0.58	10.726	18000***	−15***	−3200***	0.29
Panel B: Oil shocks										
Supply shock	0.000	2.221	−29.759	24.380	0.050	22.023	72946***	−14***	−3761***	0.15
Demand shock	0.000	1.283	−13.989	14.062	−0.192	17.262	44837***	−16***	−3382***	0.18
Risk shock	0.002	7.569	−31.384	78.984	1.274	7.0570	8469***	−16***	−3273***	0.79

Notes: *** stands for significance level at 0.01.

$$(\Theta_H)_{j,k} = \frac{\sigma_{k,k}^{-1} \sum_{h=0}^{H} \left((\Psi_h \Sigma)_{j,k} \right)^2}{\sum_{h=0}^{H} (\Psi_h \Sigma \Psi_h^{'})_{j,j}}, \tag{7}$$

where Ψ_h denotes $n\,x\,n$ matrix of coefficients corresponding to lag h. Variable $(\Theta_H)_{j,k}$ estimates the contribution of market k to the forecast error variance of market j. A normalized version of equation (7) is given by:

$$(\widetilde{\Theta}_H)_{j,k} = \frac{(\Theta_H)_{j,k}}{\sum_{k=1}^{N} (\Theta_H)_{j,k}}, \tag{8}$$

Where $\sum_{k=1}^{N} (\widetilde{\Theta}_H)_{j,k} = 1$ and $\sum_{j,k=1}^{N} (\widetilde{\Theta}_H)_{j,k} = N$. The connectedness measure C_H is computed as a percentage of the sum of the off-diagonal elements to the sum of the whole matrix

$$C_H = \left(\frac{\sum_{j \neq k} (\widetilde{\Theta}_H)_{j,k}}{\sum (\widetilde{\Theta}_H)_{j,k}} \right) \times 100 = \left(1 - \frac{\mathrm{T_r}\{\widetilde{\Theta}_H\}}{\sum (\widetilde{\Theta}_H)_{j,k}} \right) \times 100, \tag{9}$$

Table 3
Correlations.

	SPGCLE	ECO	RENIXX	MSWESG	DJSI WORLD	Supply Shock	Demand Shock	Risk Shock
SPGCLE	1							
ECO	0.826	1						
RENIXX	0.637	0.504	1					
MSWESG	0.778	0.753	0.478	1				
DJSI WORLD	0.761	0.663	0.498	0.962	1			
Supply Shock	−0.067	−0.007	−0.048	−0.106	−0.122	1		
Demand Shock	0.525	0.371	0.347	0.561	0.625	−0.014	1	
Risk Shock	−0.483	−0.598	−0.275	−0.675	−0.598	0.019	0.00	1

Notes: This table shows Pearson's correlation.

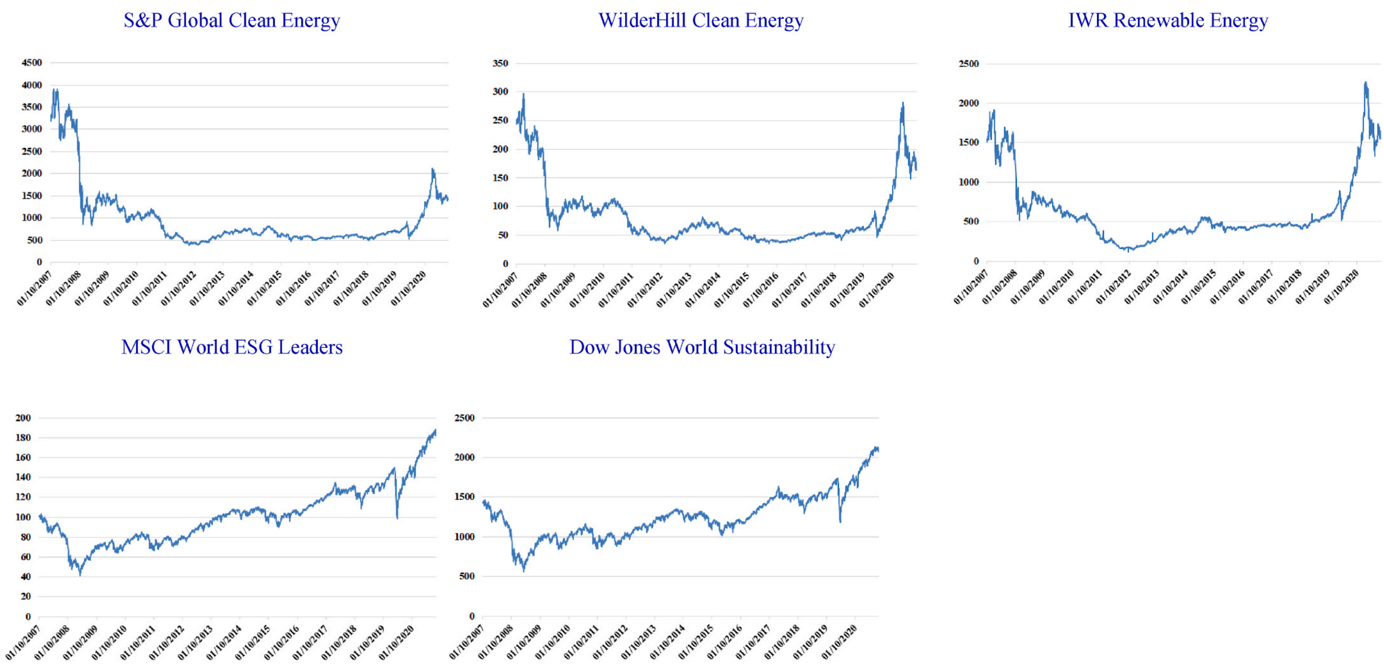

Fig. 1. Price dynamics of green stock markets.

where T_r represents the trace operator. In addition, to further measure the connectedness in the frequency domain, we utilize the approach introduced by Baruník and Křehlík (2018).The spectral representation of the coefficient matrix Ψ_h is given by the Fourier transform by $\Psi(e^{-iw}) = \sum_h e^{-iwh}\Psi_h$ with $i = \sqrt{-1}$. The generalized causation spectrum over frequencies $\omega \in (-\pi, \pi)$ is given by:

$$(f(\omega))_{j,k} = \frac{\sigma_{k,k}^{-1}\left|\left(\Psi(\mathrm{e}^{-\mathrm{i}w})\Sigma\right)_{j,k}\right|^2}{\left(\Psi(\mathrm{e}^{-\mathrm{i}w})\Sigma\Psi'(\mathrm{e}^{+\mathrm{i}w})\right)_{j,j}}. \tag{10}$$

At frequency ω, $(f(\omega))_{j,k}$ computes the portion of the spectrum of market j due to shocks in market k. The frequency band d is defined as $d = (a,b)$, a, $b \in (-\pi, \pi)$, $a < b$. The generalized forecast error variance decompositions on the frequency band d are computed as

$$(\Theta_d)_{j,k} = \frac{1}{2\pi}\int_d \Gamma_j(\omega)(f(\omega))_{j,k}d\omega. \tag{11}$$

A scaled version of (11) is given by

$$(\widetilde{\Theta}_d)_{j,k} = \frac{(\Theta_d)_{j,k}}{\sum_k(\Theta_\infty)_{j,k}}. \tag{12}$$

Overall connectedness is measured as:

$$C_d^F = \left(\frac{\sum_{j\neq k}(\widetilde{\Theta}_d)_{j,k}}{\sum(\widetilde{\Theta}_\infty)_{j,k}} - \frac{\mathrm{T_r}\{\widetilde{\Theta}_d\}}{\sum(\widetilde{\Theta}_\infty)_{j,k}}\right) \times 100, \tag{13}$$

$$C_d^W = \left(1 - \frac{\mathrm{T_r}\{\widetilde{\Theta}_d\}}{\sum(\widetilde{\Theta}_\infty)_{j,k}}\right) \times 100, \tag{14}$$

Within the frequency connectedness measure, volatility spillovers are calculated at.certain frequencies. When the frequency connectedness measure is summed up over all frequency bands, the time connectedness measure is obtained: $C_H = \sum_d C_d^F$.

5. Empirical results

5.1. Wavelet coherence analysis

In line with Singh et al. (2019), we partition the frequency scale into three categories: short (high) frequencies (2–4 days), medium frequencies (8–16 days), and long (low) frequencies (over one month). Additionally, specific frequencies such as 128, 256, 512, and 1024 days correspond to intervals of half a year, one year, two years, and four years, respectively. Fig. 3 presents the co-movement and lead-lag patterns, allowing for the assessment of the interdependency structure.

For demand-based shocks, the inspection of Panel A reveals many instances of strong co-movement across time and frequency. Co-

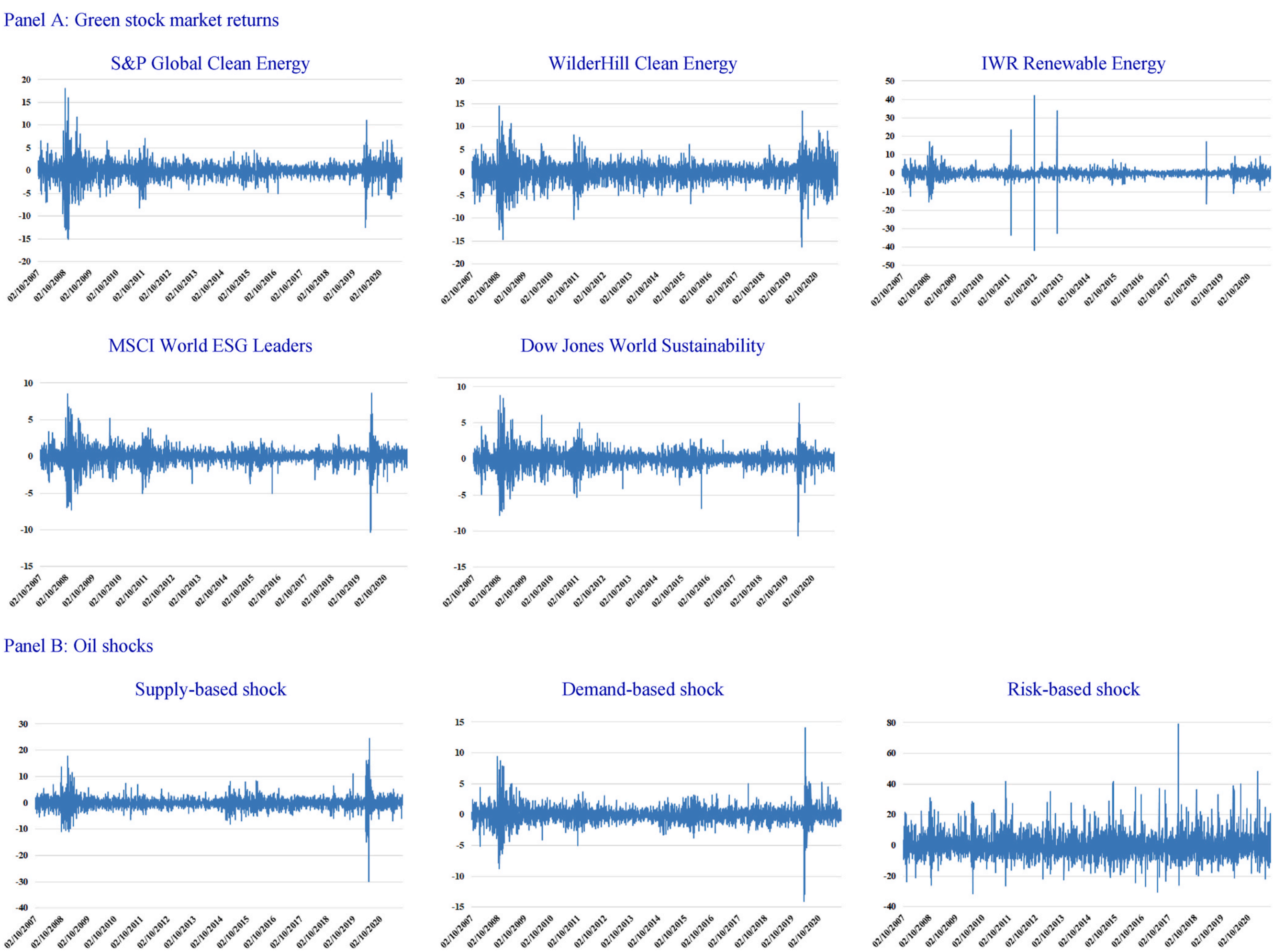

Fig. 2. Returns dynamics.

Panel A. Demand shocks and green stock returns

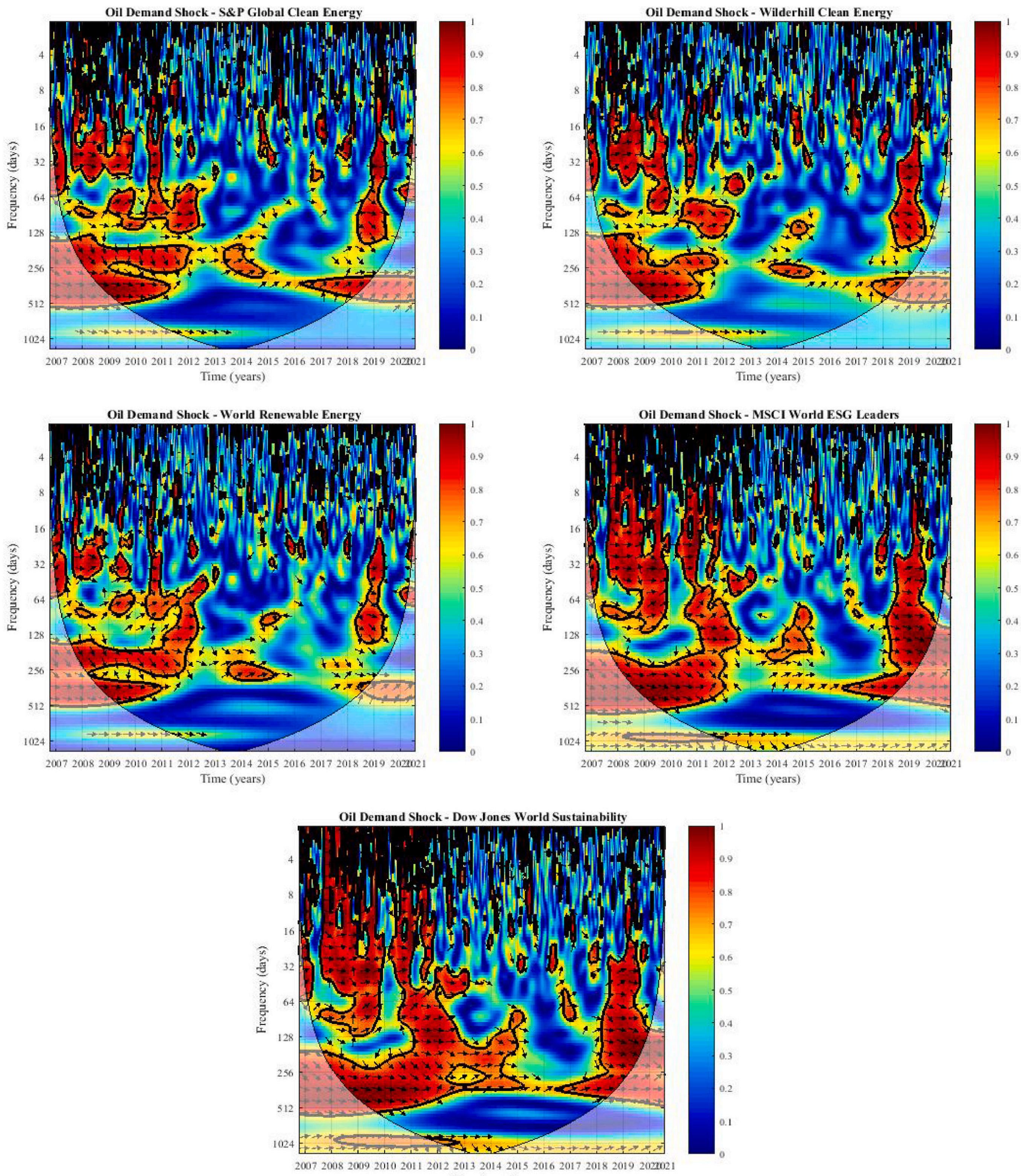

Fig. 3. Wavelet coherence.

Panel B. Supply shocks and green stock returns

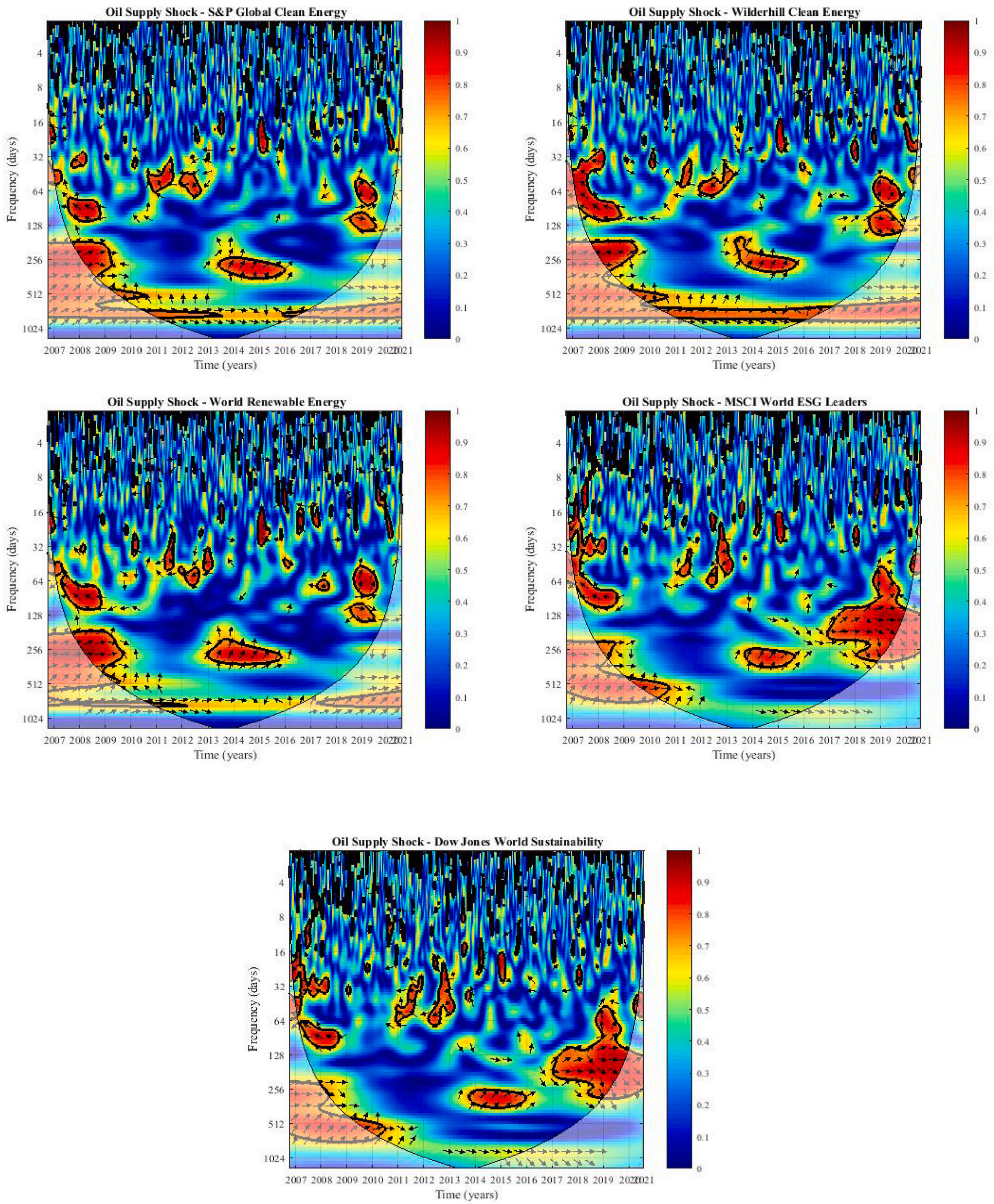

Fig. 3. (*continued*).

Panel C. Risk shocks and green stock returns

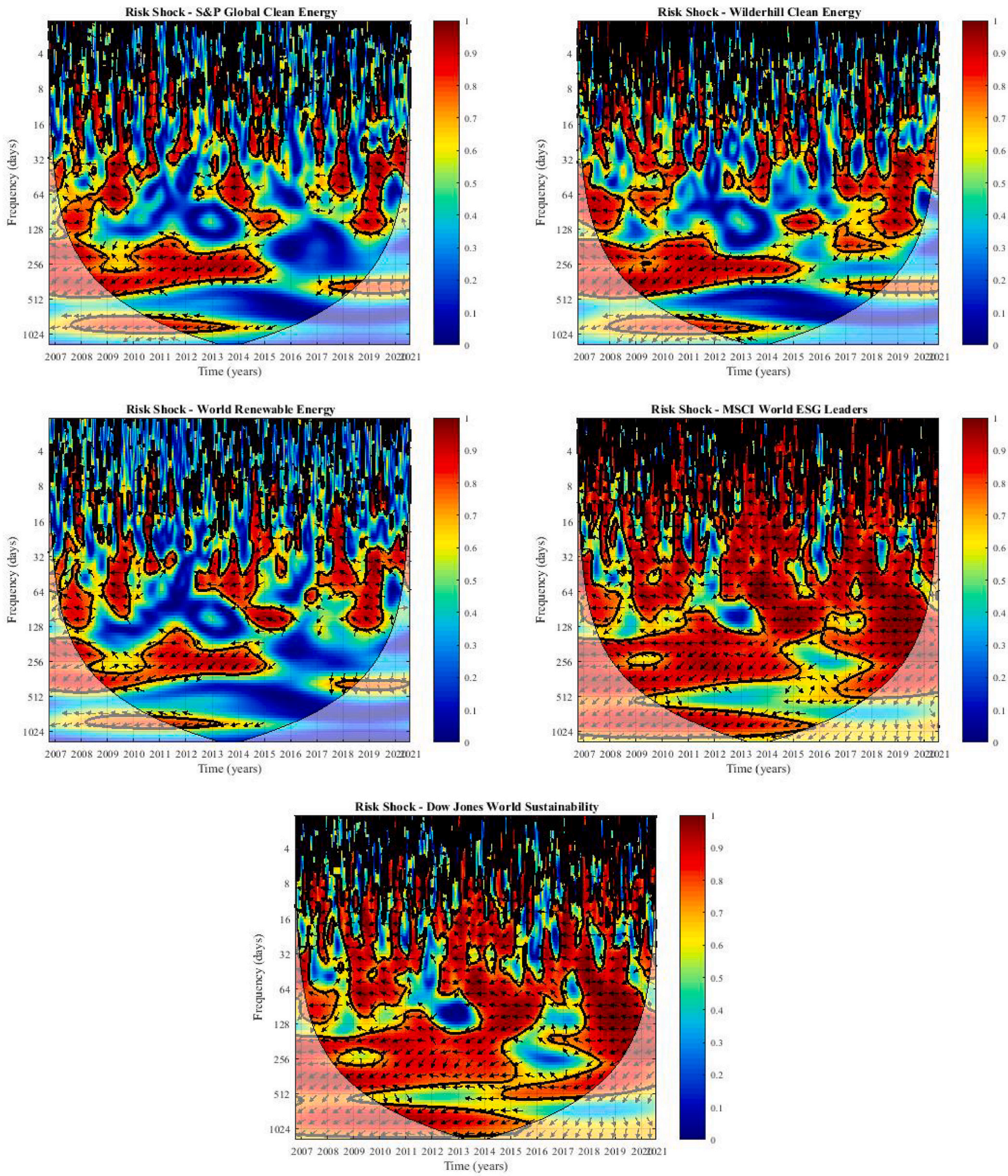

Fig. 3. (*continued*).

movement is evident across all frequencies, except for the high frequencies shorter than a week, which primarily capture transient events. This doesn't come as a surprise given that green portfolios generally attract longer-term players. Indeed, correlation strengthens with a decrease in frequency which is perhaps reflective of the fact that the general economic outlook over a long-term period of non-speculative investors is aligned across the oil and green stock markets. Co-movement is strong for the first and the last third of the sample period but fades out or discontinues between the two periods. The middle period is bounded by periods of financial distress at both ends and may be regarded as relatively stable. Hence, in line with Das et al. (2020), we argue that market interconnectedness grows more pronounced during bear markets.

Reboredo et al. (2017) notice that crude oil price fluctuations exercise an impact on the green market that shifts from weak to strong as time moves towards the end of the sample period which is bounded by 2015. In our study, the sample period extends to 2021 and we discover the resumption of co-movement from 2017 to 2018. Therefore, we support their conclusion of a dynamically changing interdependency structure. However, we point to the fact that the resumption of co-movement from 2017 to 2018 means that it occurred a way earlier than the coronavirus breakout and, because of the nature of the latter event, it cannot be attributed to pessimistic market expectations. Although high correlation at both ends of the sample period reflects growing ties between the oil market and the green stock market under more homogeneous investor sentiments during periods of financial distress, the earlier reversal to co-movement cannot be explained this way.

For supply-induced shocks, Panel B reveals that the mapping of co-movement patterns is, by far and away, a scaled down version of that for demand-induced shocks. Co-movement holds across a smaller range of frequencies and for shorter time spans. This is in line with previous findings for the conventional stock market that supply-induced shocks receive no cross-market response or a weaker cross-market response than demand-induced shocks (Enwereuzoh et al., 2021; Umar et al., 2021). Though negative correlation is occasionally observed for frequencies ranging from one to two months, it is still of a transient nature given long-term objectives of green investing.

Finally, for risk-based shocks, Panel C demonstrates the most salient interdependency structure and unambiguously negative association across time and frequency: innovations in implied volatility appear to be a more significant factor that links the crude oil market and the green stock market. In this respect, the green stock market is no different from the conventional stock market (Das et al., 2020).

We re-inspect Panels A, B, C in Fig. 3 to identify lead-lag patterns. The oil market and the green stock market are sometimes desynchronized but there is no unambiguous leader or lagger. During the Great Recession of 2008–2009, innovations in the global green portfolio tended to precede demand-based shocks and be preceded by supply-based and risk-based shocks in the oil market. This lead-lag pattern fades out afterwards except for risk-based shocks which, as noted above, establish the most stable interdependency structure with green stocks.

Consistent with our conjecture, the interdependency structure of broadly diversified ESG benchmarks somewhat differs from that of narrower benchmarks of clean and renewable energy stocks only. The World ESG Leaders portfolio and the Dow Jones Sustainability portfolio appear to contribute more actively to a positive (negative) association with demand-induced (risk-induced) shocks. At the lowest frequency of four years, only these green portfolios exhibit a persistent relationship with the oil market over the entire sample period.

In contrast, for supply-based shocks, clean and renewable energy indices (SPGCLE, ECO, RENIXX) exhibit a more pronounced, medium to strong, positive correlation at low frequencies. Low frequency corresponds to a time interval which better reflects the nature of sustainable development projects. In this respect, positive correlation seems to convey a straightforward message: supply-based shocks increase the attention to and the urgency of future substitution of oil by cleaner sources of energy.

5.2. Time-frequency risk connectedness analysis

Table 4 provides the results of static connectedness analysis, while Table 5 presents the risk connectedness across different frequency bands: short-term (1–5 days), medium-term (5–22 days), and long-term (22-infinity days). To capture volatility characteristics, an autoregressive moving average structure with the ARMA (1,1)-GJR-GARCH (1,1) model is employed, considering various combinations of lag parameters (p, q, r, and m) ranging from 0 to 5. The model with the skewed-t distribution is chosen based on the minimum AIC value. In Table 4, the total volatility connectedness between oil shocks and the green stock market is reported as 46.97%. The SPGCLE and MSWESG portfolios contribute the most to the overall connectedness of the oil-green stock system, accounting for 11.32% and 7.63%, respectively. The DJSI World, ECO, and MSWESG portfolios exhibit relatively higher levels of risk connectedness. Furthermore, most portfolios show a significant contribution to risk spillovers stemming from their own shocks.

In Table 5, the majority of total volatility spillovers between the oil market and green portfolios occur in the long run (over 22 days), contributing to 72.71% of the overall volatility connectedness. Indeed, the dominance of volatility spillover transmissions in the long run (over 22 days) between the oil market and the green stock market reinforces the conclusions drawn from the preceding subsection. This indicates that long-term market factors play a significant role in driving the volatility spillovers observed between these markets. The sum of the risk connectedness values across three-time horizons is equal to the time-domain connectedness result, satisfying the condition $C_H = \sum_d C_d^F$. The "TO_ABS" and "FROM_ABS" (or "TO_WTH" and "FROM_WTH") rows represent the total volatility connectedness transmitted to or received from the entire system within the specific frequency band, measured in absolute terms. These values capture the overall magnitude of volatility spillovers within the frequency range being considered. We find that the MSWESG portfolio (demand-based shock) makes (receives) a relatively larger contribution “TO” (“FROM”) the oil-green stock system in the frequency bands d_1 (1–5 days) and d_2 (5–22 days). As for longer time horizons (over 22 days), the SPGCLE portfolio and risk-based shock (ECO and DJSI World) make (receive) relatively larger contributions “TO” (“FROM”) the whole system.

Table 4
Static connectedness.

Variables	SPGCLE	ECO	RENIXX	MSWESG	DJSI World	SS	DS	RS	From
SPGCLE	34.85	10.12	12.15	14.95	10.78	0.00	5.94	11.21	8.14
ECO	27.94	20.38	10.16	14.97	7.66	0.00	5.05	13.83	9.95
RENIXX	25.35	6.90	35.08	11.35	8.14	0.04	4.12	9.03	8.12
MSWESG	18.28	4.92	6.11	20.90	14.53	0.08	11.32	23.86	9.89
DJSI World	18.57	3.02	6.59	19.45	18.14	0.08	12.43	21.72	10.23
SS	0.04	0.00	0.06	0.18	0.12	98.52	0.57	0.50	0.19
DS	0.06	0.07	0.16	0.04	0.47	0.43	97.16	1.61	0.35
RS	0.29	0.17	0.06	0.09	0.05	0.08	0.04	99.22	0.10
To	11.32	3.15	4.41	7.63	5.22	0.09	4.93	10.22	**46.97%**
Net	3.17	−6.80	−3.70	−2.26	−5.01	−0.10	4.58	10.12	

Notes: "From" column shows total received connectedness, "To" row shows total transmitted connectedness, and "Net" row shows net connectedness. Positive net values indicate net transmission, while negative net values indicate net reception.

Table 5
Frequency connectedness.

Variables	SPGCLE	ECO	RENIXX	MSWESG	DJSI World	SS	DS	RS	From_ABS	From_WTH
Frequency Domain Short-term: 3.14–0.63 (1 to 5 days)										
SPGCLE	0.19	0.16	0.03	0.04	0.03	0.00	0.04	0.06	0.04	0.14
ECO	0.07	0.36	0.00	0.03	0.01	0.00	0.03	0.13	0.03	0.11
RENIXX	0.08	0.06	0.83	0.02	0.05	0.00	0.05	0.06	0.04	0.13
MSWESG	0.04	0.10	0.01	0.39	0.29	0.01	0.30	0.67	0.18	0.57
DJSI World	0.02	0.04	0.01	0.24	0.34	0.01	0.32	0.45	0.14	0.44
Supply Shock	0.00	0.00	0.04	0.03	0.01	82.35	0.45	0.28	0.10	0.32
Demand Shock	0.01	0.04	0.12	0.00	0.32	0.35	77.15	1.26	0.26	0.85
Risk Shock	0.01	0.13	0.01	0.03	0.01	0.05	0.00	81.04	0.03	0.10
To_ABS	0.03	0.07	0.03	0.05	0.09	0.05	0.15	0.36	0.83	
To_WTH	0.10	0.22	0.09	0.16	0.29	0.17	0.48	1.16		**2.66**
Net	−0.01	0.03	−0.01	−0.13	−0.05	−0.05	−0.12	0.33		
Frequency Domain Medium-term: 0.63–0.14 (5 to 22 days)										
SPGCLE	0.53	0.46	0.08	0.11	0.08	0.00	0.04	0.09	0.11	1.54
ECO	0.22	1.00	0.02	0.11	0.03	0.00	0.03	0.19	0.08	1.08
RENIXX	0.24	0.17	2.25	0.08	0.12	0.01	0.04	0.10	0.10	1.37
MSWESG	0.13	0.26	0.02	1.06	0.72	0.01	0.72	1.74	0.45	6.44
DJSI World	0.07	0.11	0.03	0.68	0.85	0.01	0.67	1.20	0.35	4.96
Supply Shock	0.00	0.00	0.01	0.02	0.01	12.03	0.07	0.12	0.03	0.42
Demand Shock	0.00	0.01	0.02	0.00	0.06	0.06	14.90	0.26	0.05	0.73
Risk Shock	0.01	0.02	0.00	0.02	0.01	0.02	0.01	13.93	0.01	0.17
To_ABS	0.09	0.13	0.02	0.13	0.13	0.01	0.20	0.46	1.17	
To_WTH	1.22	1.83	0.32	1.84	1.85	0.18	2.84	6.61		**16.71**
Net	−0.02	0.05	−0.07	−0.32	−0.22	−0.02	0.15	0.45		
Frequency Domain Long-term: 0.14–0.00 (22 days to infinity)										
SPGCLE	34.14	9.49	12.05	14.80	10.68	0.00	5.86	11.06	7.99	12.92
ECO	27.65	19.03	10.14	14.82	7.61	0.00	4.99	13.52	9.84	15.91
RENIXX	25.03	6.67	32.00	11.24	7.97	0.03	4.03	8.87	7.98	12.90
MSWESG	18.11	4.55	6.08	19.45	13.52	0.06	10.30	21.45	9.26	14.97
DJSI World	18.48	2.87	6.55	18.52	16.95	0.07	11.44	20.07	9.75	15.76
Supply Shock	0.04	0.00	0.02	0.13	0.10	4.14	0.05	0.11	0.06	0.09
Demand Shock	0.04	0.02	0.01	0.03	0.09	0.02	5.11	0.10	0.04	0.06
Risk Shock	0.27	0.02	0.05	0.04	0.03	0.00	0.03	4.25	0.06	0.09
To_ABS	11.20	2.95	4.36	7.45	5.00	0.02	4.59	9.40	44.97	
To_WTH	18.11	4.78	7.05	12.04	8.08	0.04	7.42	15.19		**72.71**
Net	3.21	−6.89	−3.62	−1.81	−4.75	−0.03	4.55	9.34		

Notes: The table shows frequency connectedness over short-, medium-, and long-term periods.

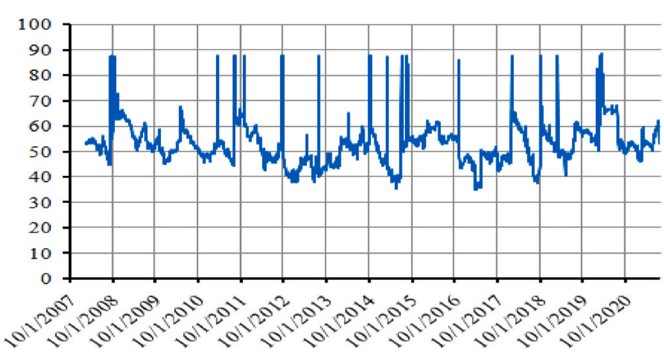

Fig. 4. Total spillover index.

The net risk connectedness results in both tables indicate the role of each component within the oil-green stock system as a net-transmitter or a net-recipient of risk. Based on the static net connectedness results, we can conclude that the SPGCLE portfolio and demand- and risk-based shocks act as net-transmitters of risk connectedness. On the other hand, the other green portfolios and supply-based shocks are net recipients of volatility spillovers. Notably, the ECO portfolio, representing risk-induced shocks, emerges as the largest net-transmitter and recipient of risk spillovers. Analyzing the frequency-domain net connectedness results, we observe that the ECO portfolio and risk-induced shocks function as net-transmitters during the periods of 1–5 days and 5–22 days. However, in higher frequency bands (over 22 days), the ECO portfolio shows a shift in its role and becomes a net-recipient of risk spillovers. This indicates a change in the dynamics of risk transmission over different time horizons within the frequency domain. Across all frequency bands, the green stock market consistently acts as a net-recipient of risk spillovers. However, there is one exception to this pattern, which is observed in the case of the SPGCLE portfolio. In higher frequency bands (over 22 days), the SPGCLE portfolio transitions from being a net-recipient to becoming a net-transmitter of risk spillovers. This highlights the unique behavior of the SPGCLE portfolio in terms of risk transmission dynamics in longer-term frequencies.

The static volatility connectedness measures presented in Table 4 face a fundamental issue in that they remain consistent across different frequency bands. Consequently, these measures may fail to capture price increases that are triggered by crucial macroeconomic events. Such events can have a substantial impact on both the magnitude and direction of risk connectedness across various frequency bands. To enhance our analysis of risk connectedness, we employ a dynamic approach that incorporates spillover effects. Specifically, we utilize a 200-day rolling window with a 100-day forward projection horizon. This methodology, as suggested in previous studies (Mensi et al., 2017; Al-Yahyaee et al., 2019; Mensi et al., 2019; Lovcha and Laborda, 2020), allows us to capture the evolving nature of spillovers over time. By adopting this approach, we aim to provide a more comprehensive understanding of the transmission and interconnectedness of risks in the financial system. Figs. 4 and 5 provide insights into the evolution of dynamic total volatility connectedness in both the time-domain and frequency-domain. These figures allow us to examine how risk interconnectedness fluctuates over time, considering notable events that have had a substantial impact on the financial landscape. Several significant events are taken into account in our analysis, including the global financial crisis, the European debt crisis, the suspension of Libya's oil production, the Arab Spring, China's oil production pricing reform, the collapse of oil prices, the crash of China's stock market, the OPEC oil production cuts, and the

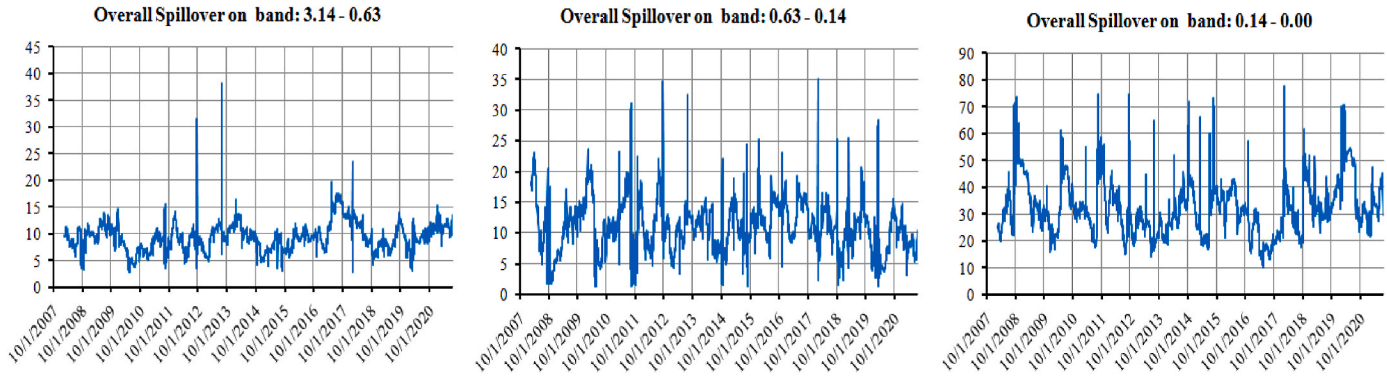

Fig. 5. Total Frequency Spillover Index among oil shocks and green stocks.

outbreak of COVID-19. These events are recognized as pivotal occurrences that have influenced the dynamics of risk connectedness between the oil market and the green stock market. Our findings indicate that dynamic total volatility connectedness, both in the time-domain and across different frequency bands, demonstrates significant time-varying characteristics throughout the sample period. In particular, we observe a substantial increase in risk connectedness during three distinct periods: 2008–2009, corresponding to the Great Recession; 2014–2016, associated with the decline in oil prices; and post-2019, coinciding with the outbreak of the COVID-19 pandemic. This suggests that major crisis events have considerably reinforced the interconnectedness of risks between the oil market and the green stock market. The analysis underscores the importance of understanding the time-varying nature of risk transmission and highlights the intensified connections between these markets during times of economic turbulence and crisis situations. In addition to the previous observations, our analysis reveals that dynamic total volatility spillovers predominantly occur over longer time horizons, specifically beyond 22 days. This finding aligns with the static connectedness results discussed earlier. The implication is that during significant crisis events, strategic investors who maintain unhedged investments in green portfolios may face significant adverse effects. The transfer of total volatility spillovers between the oil market and the green stock market has been amplified by a range of global financial, economic, and geopolitical events. These events have had the effect of diminishing the diversification benefits that green portfolios traditionally provide. The reinforced spillovers observed during major crisis events highlight the importance of risk management and hedging strategies for investors in green portfolios. Without appropriate hedging measures, strategic investors may experience heightened vulnerability and exposure to the risks arising from the interconnectedness between the oil market and the green stock market. It becomes crucial for these investors to carefully consider and implement hedging strategies to mitigate potential losses and protect their portfolios during times of economic turbulence and crisis.

To assess the directional volatility spillovers between the oil market and green portfolios, we calculate dynamic net risk connectedness by subtracting the directional spillovers "TO" and "FROM." This calculation allows us to illustrate the net transmission of risk in a particular direction. Positive dynamic net connectedness values indicate that the market acts as a net-transmitter of risk spillovers, while negative values suggest that it serves as a net-recipient. Figure B1 in Appendix B provides a visual representation of the dynamic net volatility spillovers between the oil market and green portfolios across various frequency bands. These spillovers exhibit fluctuating directions, with both positive and negative values observed throughout the sample period. The intensity of these spillovers also varies over time. Our analysis reveals that the SPGCLE portfolio, demand-induced shocks, and risk-induced shocks predominantly act as net transmitters of risk connectedness. On the other hand, the other green portfolios and supply-induced shocks tend to serve as net-receivers of risk connectedness.

Furthermore, we observe distinct positive and negative spikes in dynamic net volatility spillovers during significant macroeconomic events such as the Great Recession, the European debt crisis, and other critical events. These spikes indicate the heightened volatility and dynamic shifts in risk transmission between the oil market and green portfolios during these periods. Overall, the analysis highlights the varying directional dynamics of risk spillovers and underscores the importance of considering not only the magnitude but also the direction of risk transmission. Understanding the net-transmitter and net-recipient roles of different markets and shocks can provide valuable insights for investors and risk managers in formulating effective risk management strategies.

5.3. Network connectedness

Fig. 6 presents a network diagram illustrating the pairwise and net-pairwise directional connectedness between green energy indices, including the DJSI WORLD, the MSWESG, the SPGCLE, the ECO, the RENIXX, and oil supply, demand, and risk-based shocks. The network connectedness based on the DY model, is assessed across two main aspects: pairwise connectedness and net-pairwise connectedness. Pairwise connectedness examines the directional spillovers between each pair of markets, indicating the strength and direction of the linkages. On the other hand, net-pairwise connectedness calculates the net impact of spillovers by subtracting the spillovers in one direction from the spillovers in the opposite direction. This provides a more nuanced understanding of the overall transmission of shocks and identifies the net transmitters and net receivers of shocks within the network. The network connectedness is evaluated across the entire sample period, as well as four distinct subsamples representing different crisis periods. These crisis periods are determined based on key timeline events. Specifically, the Great Recession is defined as spanning from September 12, 2008, to December 31, 2010. The European debt crisis extends from January 01, 2011, to December 31, 2012. The oil crisis/Brexit period covers the timeframe from August 21, 2015, to September 29, 2019. Lastly, the COVID-19 pandemic period starts on December 01, 2019, and concludes on July 27, 2021, which marks the end of the sample period. In the graph, each market or shock is represented by a node, and the connections between them are depicted as arrows. The color of each node carries important information: red-colored nodes represent net transmitters of shocks, indicating that they have a higher propensity to transmit shocks to other markets; green-colored nodes represent net receivers of shocks, indicating that they are more likely to be influenced by shocks from other markets. The size of each node corresponds to the magnitude of connectedness between the paired markets or shocks. Larger nodes indicate stronger interconnectedness, while smaller nodes represent weaker connections. The thickness of the arrows connecting the nodes reflects the strength of the directional connectedness. Thicker arrows indicate a higher degree of spillover from one market or shock to another, while thinner arrows indicate a lower degree of spillover. By

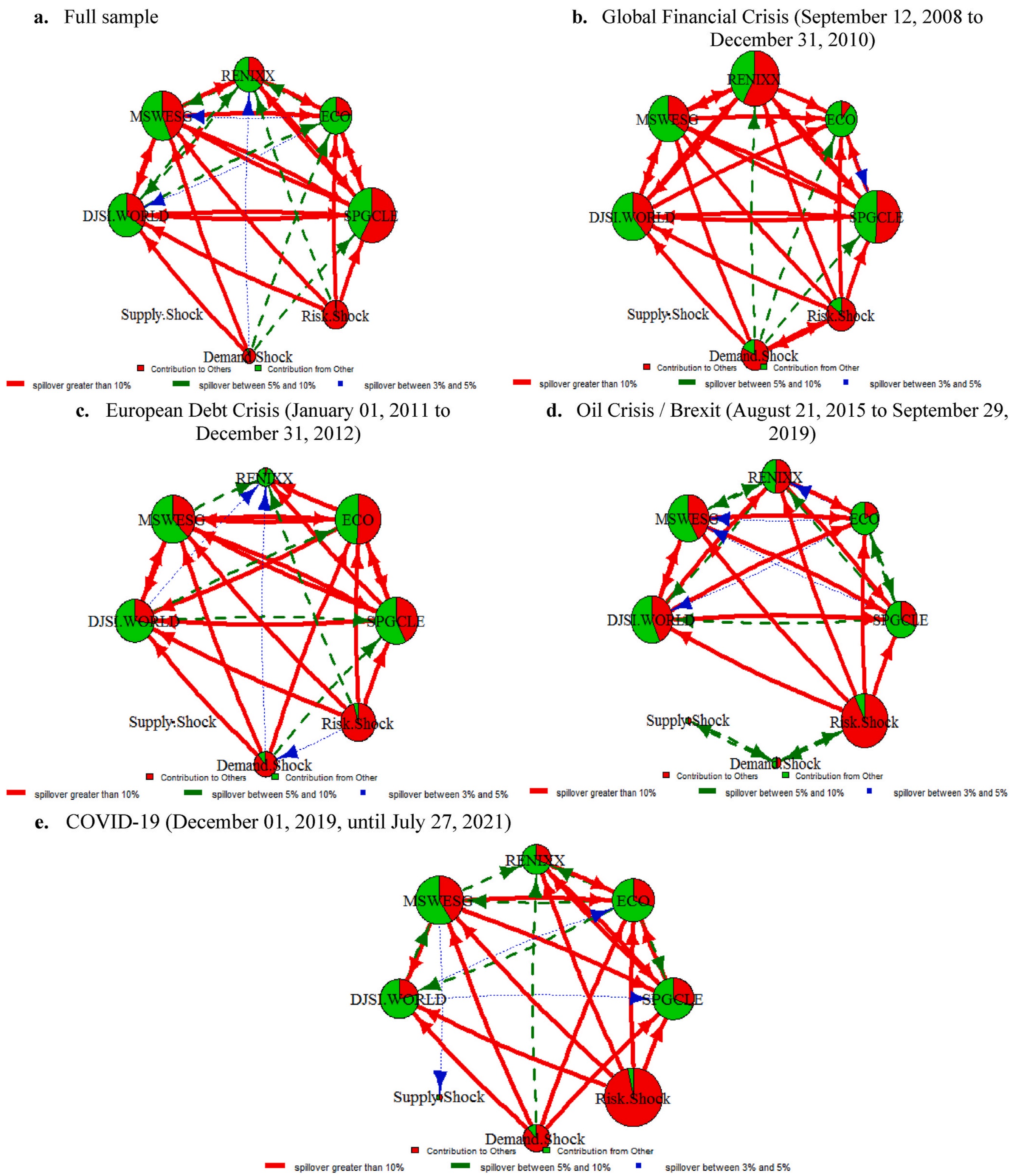

Fig. 6. Net pairwise connectedness networks during major events.

examining the network diagram, one can gain insights into the transmission of shocks and the interconnectedness between different markets and shocks. It reveals which markets tend to act as net transmitters or receivers of shocks, providing a visual representation of the directionality of the spillovers. Additionally, the size of the nodes and the thickness of the arrows provide information about the strength and intensity of the connectedness between the markets. This visual representation is beneficial in understanding the dynamics of risk transmission and the interplay between different markets and shocks. It helps identify the key players in transmitting or receiving shocks and provides an overview of the overall interconnectedness within the network. Such insights can be valuable for portfolio managers, risk analysts, and investors in assessing the potential impact of shocks and designing effective risk management strategies.

During the entire sample period, Fig. 6 reveals that there is a significant level of connectedness between all markets, although the magnitudes of the connectedness may vary. It is important to note that different markets exhibit distinct roles as either net receivers or net contributors to spillovers. In terms of net receivers of spillovers, the RENIXX, the MSWESG, the DJSI WORLD, and the ECO are identified. These indices are depicted as green-colored nodes in the network diagram. This implies that these markets are more likely to be influenced by shocks transmitted from other markets, making them net recipients of spillovers. The magnitudes of the connectedness for these net receivers may vary, indicating differing degrees of sensitivity to external shocks. On the other hand, the remaining series in the analysis, including the SPGCLE and the oil supply, demand, and risk-based shocks, are illustrated as red-colored nodes in the graph. This classification signifies that these markets are net contributors to spillovers. They are more likely to transmit shocks to other markets, acting as net transmitters of risk within the network. It is worth noting that the magnitudes of connectedness for these net contributors may also differ. Some markets may exhibit stronger connectedness and have a more significant impact on transmitting shocks, while others may contribute to a lesser extent.

We observe a strong bidirectional connectedness among all the green portfolios considered (RENIXX, MSWESG, DJSI WORLD, ECO). This indicates that shocks and information flow between these green portfolios in both directions, implying interdependencies and potential contagion effects within the green stock market system. The bidirectional connectedness suggests that changes or shocks in one green portfolio can have spillover effects on other portfolios, indicating a high level of interconnectedness among these markets. When examining the connectedness between the oil market and the green stock market, unidirectional connectedness is observed. Specifically, spillovers are transmitted from the oil market, specifically from oil risk shocks, to the green portfolios. These spillovers exceed 10% for most of the green portfolios, with the exception of RENIXX, which experiences spillovers between 5% and 10%. This suggests that shocks originating from oil risk factors have a significant impact on the green portfolios, influencing their volatility and performance. Similarly, spillovers transmitted from oil demand shocks to the green portfolios vary in magnitude. Some green portfolios experience spillovers of less than 5%, while others have spillovers exceeding 10%. Once again, RENIXX appears to be the least affected green portfolio among those considered. This indicates that shocks related to oil demand factors can also influence the volatility and performance of the green portfolios, although the magnitude of the impact varies across different indices. Interestingly, the analysis shows that oil supply shocks are unconnected with all the other series. This suggests that shocks specific to oil supply do not have a significant direct impact on the green portfolios or their interconnectedness. This finding highlights the differentiated nature of oil supply shocks compared to oil demand and risk shocks, which have a stronger influence on the green portfolios.

During the Great Recession and the oil crisis/Brexit period, there are notable shifts in the connectedness patterns. Specifically, the behavior of the RENIXX changes from being a net receiver of spillovers to a net transmitter of spillovers during the Great Recession and the oil crisis/Brexit period. However, RENIXX reverts back to being a net receiver during the European debt crisis and the pandemic period. This suggests that RENIXX is more susceptible to external shocks during the Great Recession and the oil crisis/Brexit period, while it becomes relatively more resilient during the European debt crisis and the pandemic period. Furthermore, there is evidence of strong bidirectional connectedness among the green portfolios (RENIXX, MSWESG, DJSI WORLD, ECO) during all the turbulent periods analyzed (the Great Recession, the European debt crisis, the oil crisis/Brexit, and the pandemic period). This bidirectional connectedness implies that shocks and information flow between these green portfolios in both directions, indicating interdependencies and potential contagion effects within the green stock market system during turbulent times. Additionally, we find a strong bidirectional spillover between oil demand shocks and oil risk shocks specifically during the Great Recession. This suggests a simultaneous transmission of shocks between oil demand and oil risk factors during this period. However, this connectedness weakens during the European debt crisis and the oil crisis/Brexit period and eventually disappears during the pandemic period. These findings indicate that the relationship between oil demand shocks and oil risk shocks is more pronounced and synchronized during the Great Recession, while it becomes less significant during subsequent crisis periods.These observations regarding the changing features of overall connectedness in the oil-green stock market system during turbulent periods align with findings in other research papers that have examined various markets such as rare earth metals, currency, precious metals, renewable energy stocks, and the oil market (Hanif et al., 2021; Hanif et al., 2023; Hanif et al., 2023; Mensi et al., 2017). These studies have also documented evolving connectedness patterns and interdependencies during periods of market turmoil, providing further support for the dynamic and complex nature of financial markets during crises. In addition, the COVID-19 pandemic has had a more severe and widespread impact than the 2008–2009 financial crisis, affecting not only the financial markets, but also a wide range of industries and socio-economic aspects. Several previous studies have shown that the COVID-19 pandemic has not only impacted human lives and the environment (Ali et al., 2021; Fareed et al., 2020; Iqbal et al., 2020), but it has also had a significant influence on cryptocurrency, insurance and banking sectors, as well as the travel and tourism industry (Fareed et al., 2022a; Fareed et al., 2022b; Iqbal et al., 2021; Wang et al., 2022; Yan et al., 2021). The observed shifts in the magnitude and the direction of spillovers under different nature of the crisis event confirm the complexity of measuring connectedness and the importance of studying spillovers during different crises to gather more insights on the linkages between markets under study.

6. Conclusion

Green portfolios are subject to intense debate both in terms of their environmental impact and their investment attractiveness. A solid body of academic literature has been reserved in the performance assessment of green portfolios – the fact that is likely to discourage a profit-seeking investor who pursues a traditional 'buy-hold-sell' strategy. This naturally necessitates the task of enhancing knowledge and understanding of the risk profile of green portfolios that facilitates the development of a proper risk management approach and the identification of the potential to handle green portfolios as diversifying or hedging tools.

In this paper, we consider a single but critically important exposure for green portfolios by which we mean price fluctuations in the oil market which are further processed as demand-, supply-, and risk-induced shocks. To fully capture the interdependence structure of the green stock market and the oil market and to thoroughly identify underlying cross-market processes, we apply wavelet analysis and time and frequency domain connectedness techniques of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), respectively. Previous research has ignored the frequency features of risk transmission patterns as well as the volatility inadequacies in gauging systemic risks. This research seeks to thoroughly address this issue. Both approaches yield consistent findings which are summarized as follows:

i. Over short-term periods that correspond to frequencies less than a week, the green stock market is irresponsive to oil price shocks. This supports the idea that green portfolios are a rare target for speculative traders. The green stock market has been a venue for strategic investors whose inflow and outflow are independent of transient return patterns.
ii. As the length of the period increases, more congruence is observed between the oil market and the green stock market. The strongest co-movements are found for periods over one year. This may be reflective of the activities of seasoned investors who are ready to trade-off between immediate utility and delayed benefits

of green portfolios and whose decision-making is driven by long-term considerations.

iii. Similarly, the overall risk interconnectivity between oil shocks and the green stock market is mostly conveyed over long-term horizons: risk spillovers achieve a maximum of 70% in the lowest frequency band from 22 days to infinity. The green stock market is not necessarily a net-recipient of risk spillovers. It apparently depends on the completeness of a green portfolio. The Global Clean Energy Index (SPGCLE), the largest one among the alternative energy proxies, is weighty enough to be a net-transmitter.

iv. Finally, yet most importantly, positive association with demand-induced shocks and negative association with risk-induced shocks, earlier documented for the conventional stock market, virtually nullify chances for green portfolios to serve as insurance against oil contingency while unambiguous and time-varying lead-lag patterns negate opportunities for market timing with green portfolios. Also, both association and risk interconnectivity between the oil market and the green stock market intensify during periods of financial distress. Overall, the green stock market has not yet developed enough potential for a greater independence from the conventional energy market.

The results of this study have several practical policy consequences for retail and institutional investors, portfolio managers, regulators, and ESG promoters in the stock market. Market participants should be aware of risk spillovers between the oil and green stock markets, particularly during periods of financial distress. Because risk spillovers are primarily transmitted over time, investors with longer investment horizons are expected to keep an eye on long-term risk transmissions between oil shocks and green stock returns and incorporate the frequency-domain features of risk connectedness into their decision-making procedures. Emergency response procedures for disruptive events should be improved further.

Overall, green portfolios prove to be rather ‘fragile’. Uncertainty about their performance and non-transparency of their risk profile make them a less preferred choice for a non-dedicated investor. During periods of market distress, investors may abandon green investing in their ‘flight-to-liquidity’ and, thus, contribute to the deterioration in the green stock market in the short-to medium-run. It is, therefore, utmost important to create favorable long-term conditions for green investing with joint efforts of scholars who elaborate on transparency of the risk profile of green portfolios, of practitioners who work out proper risk management strategies, and regulators who incorporate stimulus packages into environmental projects.

Declaration of competing interest

I certify that there is no conflict of interest.

Data availability

Data will be made available on request.

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Appendix A

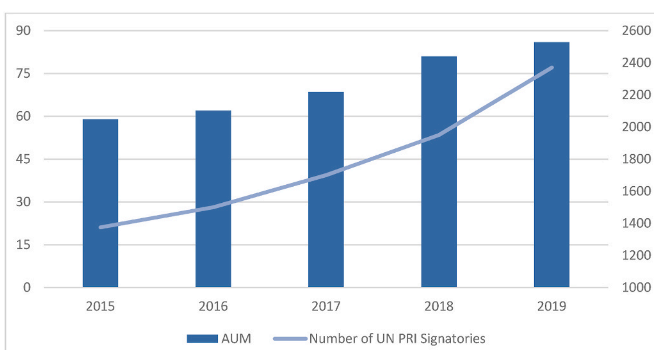

Fig. A1. Increasing relevance of green investing (Liebich et al., 2020).

Appendix B

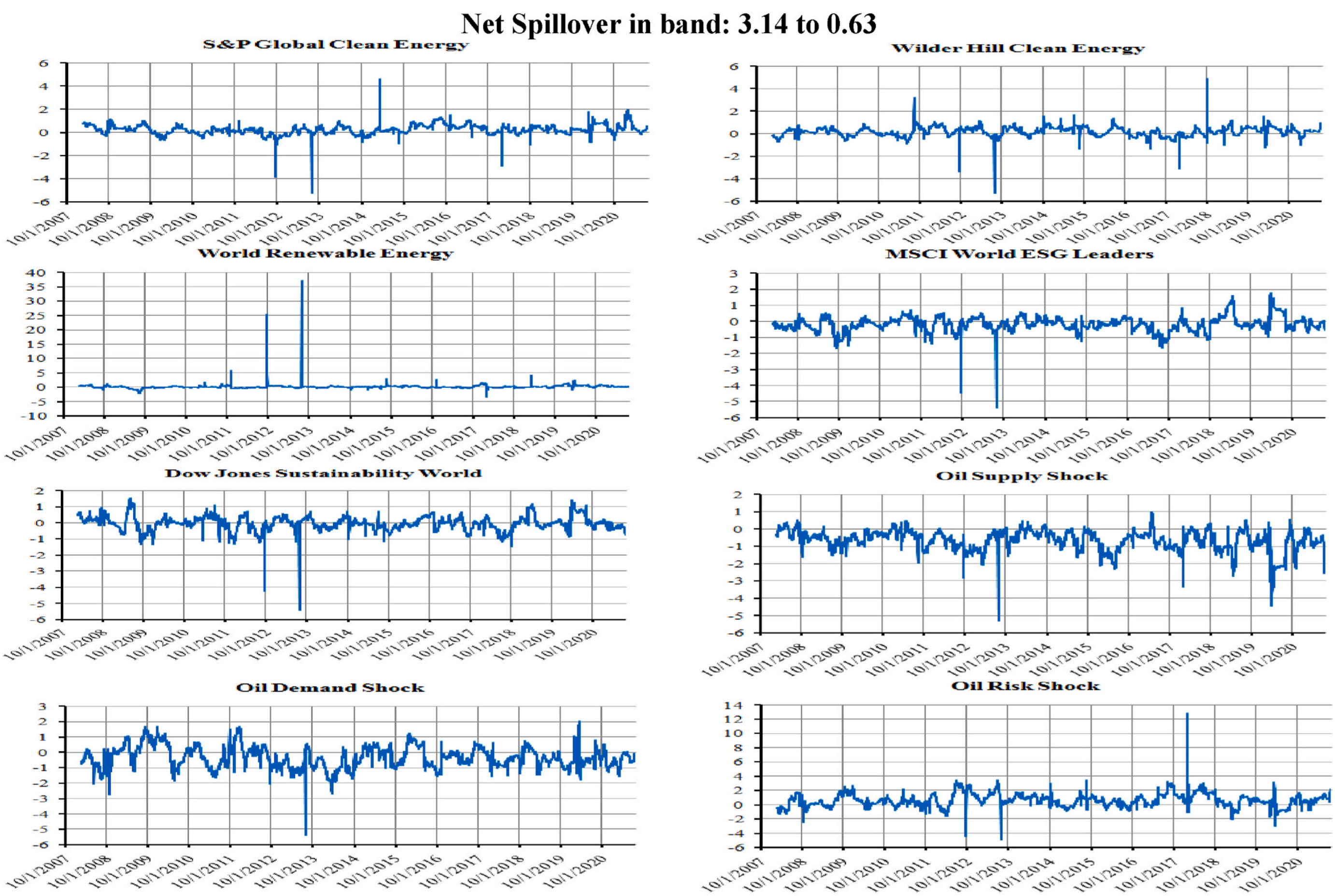

Fig. B1. Dynamic total frequency connectedness.

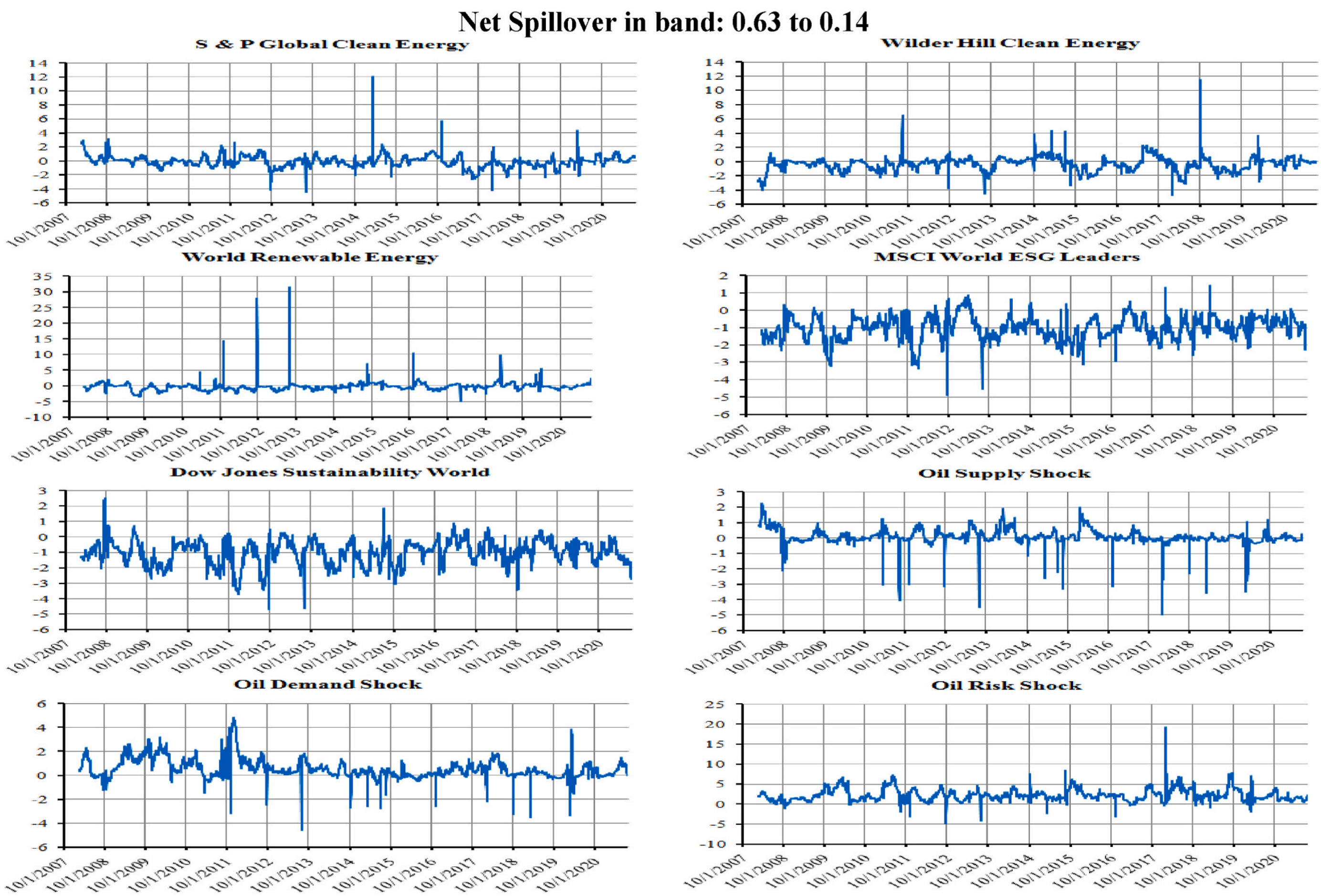

Fig. B1. (*continued*).

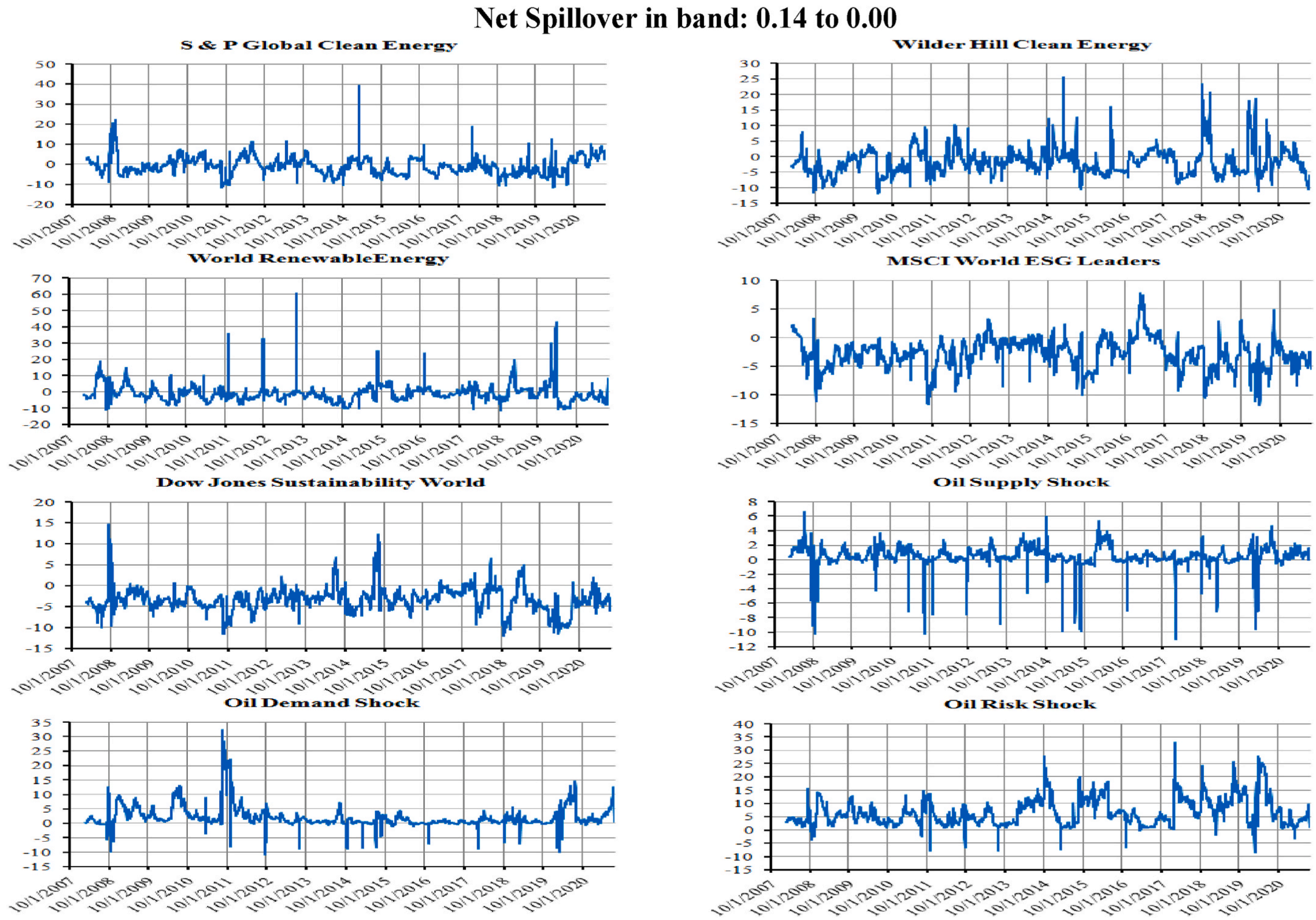

Fig. B1. (*continued*).

References

Adrangi, B., Chatrath, A., Macri, J., Raffiee, K., 2021. Dynamics of crude oil price shocks and major Latin American equity markets: a study in time and frequency domains. Bull. Econ. Res. 73 (3), 432–455.

Ali, H., Yilmaz, G., Fareed, Z., Shahzad, F., Ahmad, M., 2021. Impact of novel coronavirus (COVID-19) on daily routines and air environment: evidence from Turkey. Air Quality, Atmosphere & Health 14 (3), 381–387. https://doi.org/10.1007/s11869-020-00943-2.

Al-Yahyaee, K.H., Mensi, W., Sensoy, A., Kang, S.H., 2019. Energy, precious metals, and GCC stock markets: is there any risk spillover? Pac. Basin Finance J. 56, 45–70.

Baruník, J., Křehlík, T., 2018. Measuring the frequency dynamics of financial connectedness and systemic risk. J. Financ. Econom. 16 (2), 271–296.

Baumeister, C., Kilian, L., 2016. Understanding the decline in the price of oil since june 2014. Journal of the Association of Environmental and Resource Economics 3 (1), 131–158.

Chegut, A., Schenk, H., Scholtens, B., 2011. Assessing SRI fund performance research: best practices in empirical analysis. Sustain. Dev. 19 (2), 77–94.

Crowley, P., 2005. An Intuitive Guide to Wavelets for Economists. Bank of Finland. Research Discussion Papers No.1/2005.

Dai, Z., Zhang, X., Yin, Z., 2023. Extreme time-varying spillovers between high carbon emission stocks, green bond and crude oil: evidence from a quantile-based analysis. Energy Econ. 118, 106511.

Das, D., Kannadhasan, M., Bhattacharyya, M., 2020. Oil price shocks and emerging stock markets revisited. Int. J. Emerg. Mark. 17(6), 1583–1614.

Diebold, F., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.

Diebold, F., Yilmaz, K., 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. J. Econom. 182 (1), 119–134.

Duan, X., Xiao, Y., Ren, X., Taghizadeh-Hesary, F., Duan, K., 2023. Dynamic spillover between traditional energy markets and emerging green markets: implications for sustainable development. Resour. Pol. 82, 103483.

Dutta, A., Jana, R., Das, D., 2020. Do green investments react to oil price shocks? Implications for sustainable development. J. Clean. Prod. 266 (2).

European Securities and Markets Authority (Esma), 2020. Strategy on Sustainable Finance, 06 February 2020.

Enwereuzoh, P.A., Odei-Mensah, J., Owusu Junior, P., 2021. Crude oil shocks and african stock markets. Res. Int. Bus. Finance 55, 101346.

Fareed, Z., Abbas, S., Madureira, L., Wang, Z., 2022a. Green stocks, crypto asset, crude oil and COVID19 pandemic: application of rolling window multiple correlation. Resour. Pol. 79, 102965 https://doi.org/10.1016/j.resourpol.2022.102965.

Fareed, Z., Asl, M.G., Irfan, M., Rashidi, M., Wang, H., 2022b. Exploring the Co-movements between COVID-19 pandemic and international air traffic: a global perspective based on wavelet analysis. Int. Migrat. https://doi.org/10.1111/imig.13026.

Fareed, Z., Iqbal, N., Shahzad, F., Shah, S.a.A., Zulfiqar, B., Shahzad, K., Hashmi, S.H., Shahzad, U., 2020. Co-variance nexus between COVID-19 mortality, humidity, and air quality index in wuhan, China: new insights from partial and multiple wavelet coherence. Air Quality, Atmosphere & Health 13 (6), 673–682. https://doi.org/10.1007/s11869-020-00847-1.

Fueki, T., Higashi, H., Higashio, N., Nakajima, J., Ohyama, S., Tamanyu, Y., 2018. Identifying Oil Price Shocks and Their Consequences: the Role of Expectations in the Crude Oil Market. Bank for International Settlements (BIS). Working Paper No.725.

Gençay, R., Selçuk, F., Whitcher, B., 2002. An Introduction to Wavelets and Other Filtering Methods in Finance and Economics. Academic Press.

Görgen, M., Andrea, J., Nerlinger, M., Riordan, R., Rohleder, M., Wilkens, M., 2020. Carbon risk. Available at SSRN. https://ssrn.com/abstract=2930897.

Hamilton, J., 1983. Oil and the macroeconomy since world war II. J. Polit. Econ. 91, 228–248.

Hamilton, J., 1985. Historical causes of postwar oil shocks and recessions. Energy J. 6, 97–116.

Hamilton, J., 2003. What is an oil shock? J. Econom. 113, 363–398.

Hanif, W., Mensi, W., Gubareva, M., Teplova, T., 2023a. Impacts of COVID-19 on dynamic return and volatility spillovers between rare earth metals and renewable energy stock markets. Resour. Pol. 80, 103196.

Hanif, W., Mensi, W., Alomari, M., Andraz, J.M., 2023b. Downside and upside risk spillovers between precious metals and currency markets: evidence from before and during the COVID-19 crisis. Resour. Pol. 81, 103350.

Hanif, W., Mensi, W., Vo, X.V., 2021. Impacts of COVID-19 outbreak on the spillovers between US and Chinese stock sectors. Finance Res. Lett. 40, 101922.

Iqbal, N., Fareed, Z., Shahzad, F., He, X., Shahzad, U., LiNa, M., 2020. The nexus between COVID-19, temperature and exchange rate in wuhan city: new findings from partial and multiple wavelet coherence. Sci. Total Environ. 729, 138916 https://doi.org/10.1016/j.scitotenv.2020.138916.
Iqbal, N., Fareed, Z., Wan, G., Shahzad, F., 2021. Asymmetric nexus between COVID-19 outbreak in the world and cryptocurrency market. Int. Rev. Financ. Anal. 73, 101613 https://doi.org/10.1016/j.irfa.2020.101613.
Kanamura, T., 2020. Are green bonds environmentally friendly and good performing assets? Energy Econ. 88 (1), 104767.
Khalfoui, R., Mefteh-Wali, S., Dogan, B., Ghosh, S., 2023. Extreme spillover effect of COVID-19 pandemic-related news and cryptocurrencies on green bond markets: a quantile connectedness analysis. Int. Rev. Financ. Anal. 86, 102496.
Kilian, L., 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. Am. Econ. Rev. 99 (3), 1053–1069.
Kilian, L., 2014. Oil price shocks: causes and consequences. Annual Review of Resource Economics 6, 133–154.
Kilian, L., Hicks, B., 2013. Did unexpectedly strong economic growth cause the oil price shock of 2003-2008? J. Forecast. 32 (5), 385–394.
Kilian, L., Park, C., 2009. The impact of oil price shocks on the U.S. Stock market. Int. Econ. Rev. 50 (4), 1267–1287.
Liebich, L., Nöh, L., Rutkowski, F., Schwarz, M., 2020. Current Developments in Green Finance. German Council of Economic Experts. Working Paper 05/2020.
Long, S., Tian, H., Li, Z., 2022. Dynamic spillovers between uncertainties and green bond markets in the US, Europe, and China: evidence from the quantile VAR framework. Int. Rev. Financ. Anal. 84, 102416.
Lovcha, Y., Laborda, A.P., 2020. Dynamic frequency connectedness between oil and natural gas volatilities. Econ. Modell. 84, 181–189.
Mensi, W., Hammoudeh, S., Ai-Jarrah, I.M.W., Sensoy, A., Kang, S.H., 2017. Dynamic risk spillovers between gold, oil price and conventional, sustainability and islamic equity aggregates and sectors with portfolio implications. Energy Econ. 67, 454–475.
Mensi, W., Hammoudeh, S., Ai-Jarrah, I.M.W., Al-Yahyaee, K.H., Kang, S.H., 2019. Risk spillovers and hedging effectiveness between major commodities, and islamic and conventional GCC banks. J. Int. Financ. Mark. Inst. Money 60, 68–88.
Percival, D., Walden, A., 2000. Wavelet Methods for Time Series Analysis. Cambridge University Press.
Pham, L., 2019. Do all clean energy stocks respond homogeneously to oil price? Energy Econ. 81, 355–379.
Ramsey, J., Lampart, C., 1998. Decomposition of economic relationships by timescale using wavelet. Macroecon. Dyn. 2, 49–71.
Ready, R.C., 2018. Oil prices and the stock market. Rev. Finance 22 (1), 155–176.
Reboredo, J.C., Rivera-Castro, M.A., Ugolini, A., 2017. Wavelet-based test of Co-movement and causality between oil and renewable energy stock prices. Energy Econ. 61, 241–252.
Roueff, G., Von Sachs, R., 2011. Locally stationary long memory estimation. Stoch. Process. their Appl. 121 (4), 813–844.
Sadorsky, P., 2012. Modeling renewable energy company risk. Energy Pol. 40, 39–48.
Serroukh, A., Walden, A., Percival, D., 2000. Statistical properties and uses of the wavelet variance estimator for the scale analysis of time series. J. Am. Stat. Assoc. 95 (449), 184–196.
Shahbaz, M., Trabelsi, N., Tiwari, A., Abakah, E., Jiao, Z., 2021. Relationship between green investments, energy markets, and stock markets in the aftermath of the global financial crisis. Energy Econ. 104, 105655.
Singh, J., Ahmad, W., Mishra, A., 2019. Coherence, connectedness and dynamic hedging effectiveness between emerging markets equities and commodity index funds. Resour. Pol. 61, 441–460.
Statman, M., 2006. Socially responsible indexes. J. Portfolio Manag. 32 (3), 100–109.
Umar, Z., Trabelsi, N., Zaremba, A., 2021. Oil shocks and equity markets: the case of GCC and BRICS economies. Energy Econ. 96.
Watson, C., Schindle, H., 2017. Financing the transition from Brown to green: how to track country performance towards low carbon, climate-resilient economies. Climate Transparency. Research Report12/2017.
Wang, Y., Bouri, E., Fareed, Z., Dai, Y., 2022. Geopolitical risk and the systemic risk in the commodity markets under the war in Ukraine. Finance Res. Lett. 49, 103066 https://doi.org/10.1016/j.frl.2022.103066.
Yan, Y., Shah, M.R., Sharma, G.D., Chopra, R., Fareed, Z., Shahzad, U., 2021. Can tourism sustain itself through the pandemic: nexus between tourism, COVID-19 cases and air quality spread in the 'pineapple state' Hawaii. Curr. Issues Tourism 25 (3), 421–440. https://doi.org/10.1080/13683500.2021.1965553.
Ziadat, S., McMillan, D., Herbst, P., 2022. Oil shocks and equity returns during bull and bear markets: the case of oil importing and exporting nations. Resour. Pol. 75, 102461.