Energy 335 (2025) 138267

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Dynamics of extreme spillovers between clean energy stocks and fossil fuels: The role of climate policy uncertainty and geopolitical risks

Ismail O. Fasanya *, Darren T. Mubaiwa

School of Economics and Finance, University of the Witwatersrand, 1 Jan Smuts Avenue, Braamfontein, 2000, South Africa

A R T I C L E I N F O

JEL classification:
C22
P48
Q40
Q58

Keywords:
Clean energy stocks
Fossil fuels
Climate policy
Geopolitical risk
Non-parametric techniques

A B S T R A C T

The study examines the effect of climate policy uncertainty and geopolitical risk on the intermarket spillovers among clean energy stocks and fossil fuels. Based on US data between December 2000 and August 2023, we first analyse volatility spillovers among clean energy stocks and fossil fuels using the TVP-VAR model. Our empirical analyses demonstrate that there is strong connectedness between clean energy stocks and fossil fuels. Notwithstanding, we observe that the spillovers among fossil fuels (crude oil, diesel, jet fuel etc.) are stronger than the intermarket spillovers between these energy commodities and the clean energy stock market. Furthermore, using the causality-in-quantiles and Quantile-on-Quantile regression techniques, we find that both climate policy uncertainty and geopolitical risk have a formidable impact on clean energy stock and fossil fuel intermarket spillovers. Moreover, the effects among these phenomena are heterogeneous across each of their distributions. These findings constitute important information for investment practitioners and policymakers.

1. Introduction

Rising awareness among investors of the detrimental impact of the continued use of dirty energy sources on the environment has led to the emergence of green finance with the aim of encouraging sustainable energy generation and a low carbon economy. Along with this development, the Paris Climate Agreement has strengthened the resolve to progress to a clean economy, leading to the adoption of goals that include, among others, to prevent the increase in global temperatures from exceeding 2° C above pre-industrial levels [1]. Amid these changing perceptions about the environment, clean energy stocks are among several financial instruments that have gained prominence in recent years. These assets represent interests in companies involved in wind, hydro, solar and other renewable sources, as well as those companies concerned with energy efficiency.

In recognition of the increasing attention on these clean energy stocks from environmentally conscious investors, and in pursuit of a deeper understanding of their behavioural characteristics, several studies have sought to examine the connection between these assets and several commodities (see, [2–8]). The interest behind such research has been, in part, driven by the fact that some fossil fuels like crude oil are substitutes for clean energy sources [9], a relation which is crucial for understanding the dynamics among energy commodities. Certainly, in the United States, of the 100.41 quadrillion British thermal units (Btu) consumed in 2022, renewables accounted for 13 % of total primary energy consumption. In comparison, petroleum and natural gas accounted for 36 % and 33 %, respectively [10]. The predominance of these two fossil fuels was gained between 1925 and 1950. Since then, petroleum (crude oil, diesel, heating oil etc.) and natural gas have come to dominate U.S. energy consumption. Moreover, their combined share reached its zenith at 73.2 % of total energy consumed in 1975 [10].

While the energy sources which underlie clean energy stocks (solar, wind, hydro etc.) are substitutes for fossil fuels, essential commodities like crude oil can affect expected inflation and real interest rates [11]. Pertinently, this relation is further complicated by two issues. First, uncertainty connected to climate policies may have an impact on the decision-making of firms and investors alike. Specifically, climate policy uncertainty may diminish the incentive for investing in sustainable energy projects. Therefore, from a portfolio management perspective, it is imperative to understand the extent of the exposure of investments in clean energy stocks not only to other markets (fossil fuels) but to changes in climate policy uncertainty. Whereas the first consideration is purely concerned with regulation, the second, geopolitical risk, involves the supply of key inputs for production. A quintessential example is the political fallout from the war in Ukraine which resulted in disruptions in the supply of fossil fuels which were crucial for European energy

* Corresponding author.
E-mail addresses: ismail.fasanya@wits.ac.za, fascojnr@yahoo.com, fasanyaismail@gmail.com (I.O. Fasanya), darrenmubaiwa@gmail.com (D.T. Mubaiwa).

https://doi.org/10.1016/j.energy.2025.138267
Received 22 September 2024; Received in revised form 16 April 2025; Accepted 30 August 2025
Available online 2 September 2025
0360-5442/

security. Certainly, the immediate imperative was to seek out other sources of energy at home and abroad. This occurrence is instructive as it clearly demonstrates that potential and realized geopolitical risks may wreak havoc in energy commodity markets. Furthermore, given the fact that clean energy (solar and wind, for example) tends to be locally produced, it is less vulnerable (at least in the short run) to the risk that an important input may be withheld or become unavailable.

Notwithstanding these issues, to the best of our knowledge, no study has yet endeavoured to fully examine the effect of geopolitical risk (GPR) and climate policy uncertainty (CPU) on the direction and strength of volatility spillovers among fossil fuels and clean energy stocks. It is against this background that the current study presents an explicit exposition of the links that exist among these phenomena. Following this, we assess the impact of CPU and GPR on the spillovers among clean energy stocks and several non-green energy commodities. Consequently, and foreshadowing the results of the study, we demonstrate that climate policy uncertainty and geopolitical risk are not only non-trivial but have a significant impact on the dynamic connectedness between clean energy stock and fossil fuel markets.

The study has six sections. The present section has described the specific gap in the literature. Section 2 gives an account of relevant literature. Thereafter, section 3 describes the analytical framework that accounts for the associations among clean energy stocks, fossil fuels, CPU, and GPR. Following this, section 4 gives an exposition of the methodologies employed in the study. Meanwhile, section 5 discusses the results of the study. Lastly, section 6 concludes with some recommendations.

2. Literature review

Prior studies on the connection between clean energy stocks and energy commodity markets have differed in scope and methodologies employed. For example, in one of the earlier studies, Ferrer et al. [2] observed that clean energy stocks were net-transmitters of return and volatility spillovers in a system with crude oil and other financial assets for most of the period of assessment (January 2, 2003 to September 29, 2017). Using the Baruník and Křehlík [12] frequency framework, their results showed that return spillovers to and from clean energy stocks worked in opposite directions between higher and lower frequencies for large stretches of the period. Meanwhile, in the case of volatility spillovers, this effect was less pronounced. They also found that the intensity in the connectedness among markets had increased since the onset of the global financial crisis of 2007. Meanwhile, Ding et al. [8] examined the effect of attention on climate change on the connectedness among carbon, fossil fuel, and clean energy markets. Using the Google Search Volume Index (GSVI) as their proxy, they uncovered that attention on climate change had a significant effect on the spillovers among these markets. Moreover, they observed that this effect increased at the onset of the COVID-19 pandemic. Similarly, Coskun et al. [3] analysed the spillover connectedness among clean energy stocks, commodities, global stocks, and geopolitical oil price risk. They uncovered that the volatility spillovers intensified at the onset of various events like the Arab Spring and the COVID-19 pandemic. Surprisingly, Umar et al. [9] found that there were weak volatility spillovers among fossil fuel markets and clean energy stocks, which may entail potential diversification benefits. Furthermore, they observed that the connectedness among petroleum markets was particularly strong.

Interestingly, there has been a stream of studies that have sought to examine clean energy stocks at the firm or subsector level (see, inter alia, [4–7]). For example, Tiwari et al. [4] examined the return connectedness among clean energy stocks (proxied by S&P Global Clean Energy Index, Solactive Global Wind, and Solactive Global Solar), green bonds, and CO2 emission prices. They observed that clean energy stocks (S&P Global Clean Energy Index) were the biggest transmitter of shocks to green bonds. Moreover, they uncovered that the clean energy indices were more susceptible to network spillovers than green bonds. From the dynamic total connectedness, they showed that connectedness reached its greatest extent during the COVID-19 period. Similarly, looking at the dynamic spillovers among clean energy stock markets and non-green energy commodities, Qi et al. [5] found that clean energy stock indices (nuclear, photovoltaic, and wind) were the greatest transmitters and receivers in the system. This relation was maintained in both the short and long frequencies. Where these respectively entail the finest and coarsest intervals. However, there was only a marginal decrease in the level of connectedness from the short to the long frequency. Similarly, Chen et al. [6] examined the strength and direction of spillovers among sectoral clean energy stocks and non-ferrous metals. They found that spillovers in the time domain were mostly driven by short-term (high frequency) factors as opposed to long-term (low frequency) factors. They also observed that events such as the European debt crisis, the signing of the Paris Agreement and the COVID-19 pandemic all markedly increased the connectedness among clean energy markets and non-ferrous metals. Furthermore, in the time domain, the greatest spillover transmitters were the energy management and smart grid clean energy sub-sector stocks. Moreover, not only were non-ferrous metals the greatest receivers of spillovers, but they remained net-receivers in both the short and long frequency domain. Meanwhile, in a study focusing on China, Deng et al. [7] used the Diebold and Yılmaz [13] and Baruník and Křehlík [12] techniques to assess the spillover dynamics among several clean energy sub-sectors and non-ferrous metals markets. They found that the connectivity among clean energy market sub-sectors was stronger than the connectivity between this market and non-ferrous metals. In addition, they observed that the connectedness among these markets changed significantly during the COVID-19 pandemic. During this period, the strength of the connectedness between clean energy markets and non-ferrous metals weakened, but intra-connectivity among the clean energy sub-sectors strengthened. Overall, Deng et al. [7] show that net spillovers are transmitted from clean energy markets to non-ferrous markets.

As the preceding literature shows, much work has been dedicated to assessing the possibility of contagion among clean energy markets and various commodities. However, the shortcoming of these previous studies, in our view, has been the failure to account for climate policy uncertainty arising from unclear or changing regulation on environmental issues as well as geopolitical risk. Specifically, the question of how these phenomena affect the connectedness between fossil fuels and clean energy stocks has not been sufficiently addressed.

3. Analytical framework

3.1. Microeconomic foundations of clean and dirty energy markets

To establish the link between clean energy stocks and fossil fuels, we take our starting point to be a firm that uses both clean energy materials (for wind, hydro, solar etc.) and non-green energy commodities (fossil fuels like crude oil) to generate energy for its production process. We do this to explain the demand for these materials/commodities which, along with the supply side, determines the prices of these materials/commodities. Moreover, it is important to stress that "the firm" is any company or organization that is involved in some aspect of energy generation and consumption. Its end-product may be the energy itself or equipment used to generate power for industrial, transportation or household needs. Thus, we can account for those firms involved in electric vehicle production and energy efficiency. Admittedly, this is a broad classification, but this is done to focus on the relationships that matter most to us. We assume the firm has the capacity to use both inputs in the production process. That is, clean energy materials (X_{CE}) and non-green commodities (X_{NG}) are substitutes.

In this framework, firms may invest in new capacity to produce with one input or another, increasing its relative proportion, which, given enough time, may then affect the relative prices of these inputs. Furthermore, in addition to changes in the relative prices of the inputs,

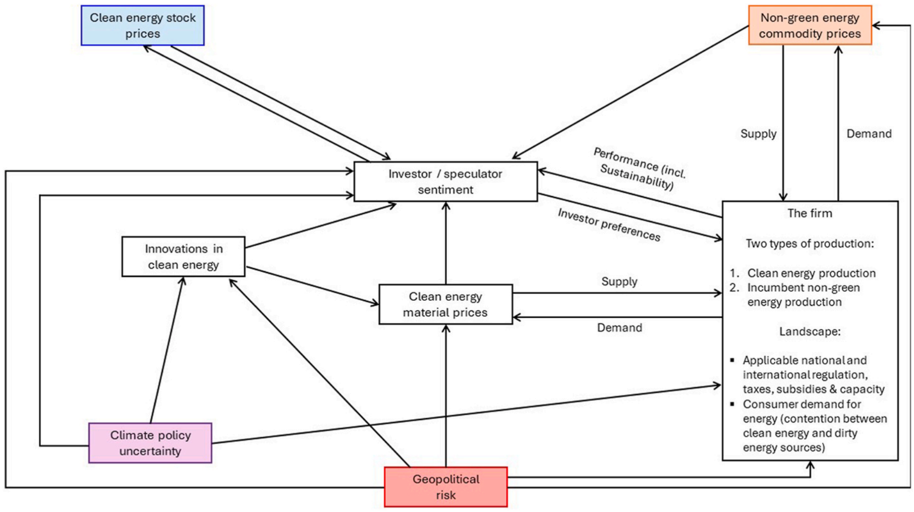

Fig. 1. The framework
Note: Figure shows the associations among clean energy stocks, non-green energy commodities, climate policy uncertainty and geopolitical risk. These primary variables are shaded. Except where specified, the arrows represent signals.
Source: Authors' own compilation.

Fig. 2. Series price levels.
Note: Figure shows series price levels (P_t) between December 2000 and August 2023. The price level (P_t) is cast on the y-axis.
Source: Authors' compilation.

(i) government regulation may limit the maximum quantity of an input that is permissible for a firm to use in its production process, while (ii) consumers may have a strong preference for one input being used in the production process, and (iii) falling short of sustainability thresholds would limit the firm's ability to raise capital. However, these preceding considerations may be tempered by the fact that (iv) holding fast to incumbent production processes, which are geared toward dirty energy generation, require little, if any, capital investments. These facts would reasonably weigh on the decision-making of the firm's managers.

This flexible microeconomic foundation allows for both incumbent dirty energy and clean energy firms. The latter includes those energy producers who, of their own volition or through regulation, have restricted themselves to exclusively using clean energy sources for energy generation. However, this does not preclude spillovers between the two energy sources. This is because decreased demand for dirty energy sources, in favor of clean energy, would have the effect of generally reducing their prices. On the other hand, at least theoretically speaking, a fall in the prices of non-green energy commodities would make dirty energy producers more competitive. Moreover, any innovations in clean energy technologies, which reduce the prices of clean energy materials, would allow for decreases in clean energy prices.

Geopolitical risk and climate policy uncertainty are to be thought of

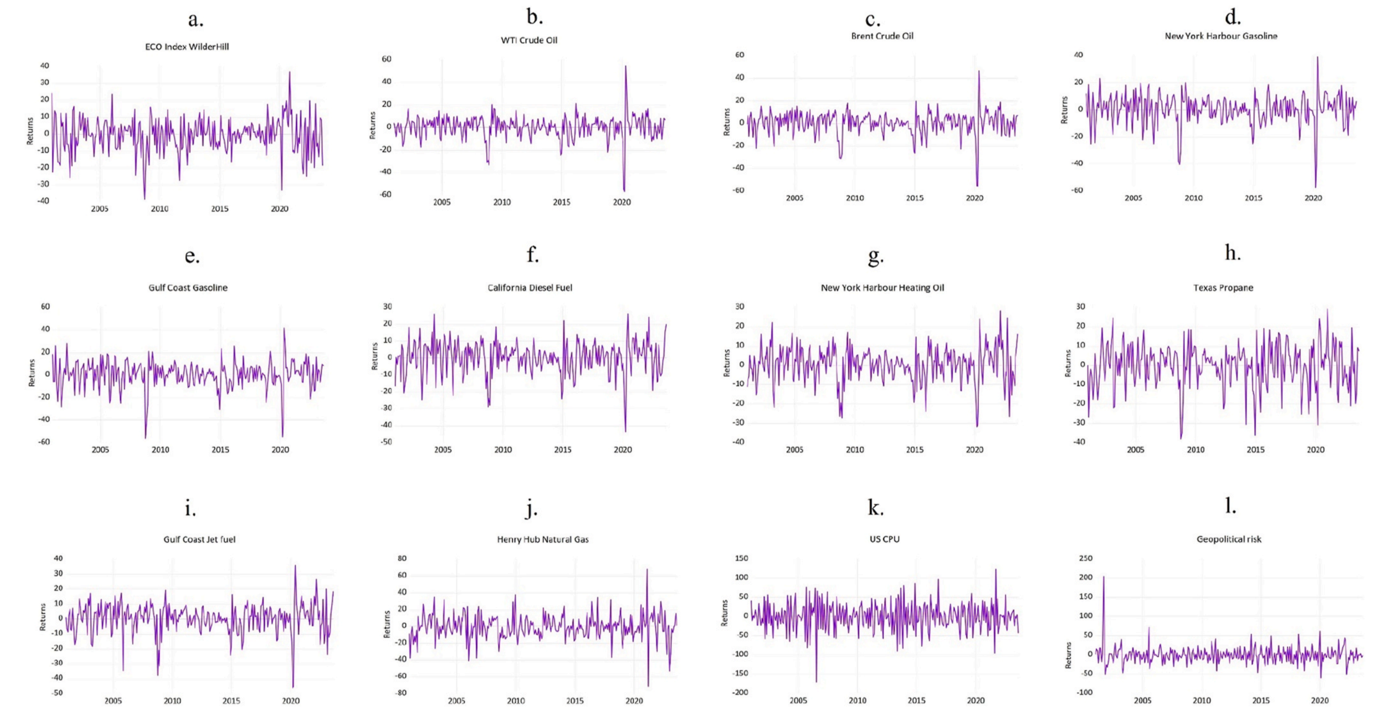

Fig. 3. Series returns.
Note: Figure shows series returns between December 2000 and August 2023. Recall that the returns are calculated using $r_t = (\Delta \ln P_t) \times 100$.
Source: Authors' compilation.

as *threats* to the system. As shown in Fig. 1, these two phenomena may affect firms and the producers of clean energy materials/non-green energy commodities by sending signals that portend future outcomes. By "threats" we mean the risk that market conditions faced by firms and investors may change. This could be in a way that is fortuitous or ruinous. For example, clean energy producers may not enjoy the expected level of favor from regulation. In the case of geopolitical risk, the threat is more immediate and direct. That is, crucial inputs in the production process like crude oil may suddenly become unavailable or reduced in quantity by suppliers on the global stage.

3.2. The market prices of clean energy stocks

Although the discussion taken up till now accounts for how clean energy firms behave in relation to non-green energy commodities and consumer preference for sustainable energy generation, it still does not account for the firm's stock. To make this leap, we appeal to the seminal work of Williams [14], wherein he undertook an accounting of stock prices and stated that because no investor can be sure their estimate of the stock's fundamental value is correct, the current market price of stocks reflects today's opinion (or sentiment). Certainly, positive/-negative news and the accompanying change in business outlook causes shifts in the demand curve for stocks. Where this demand curve is thought to come from a cumulative frequency of each stockholder's valuation of the price of a stock and the market price is the marginal valuation.

As Williams [14]'s discussion clarifies, although fundamental value, which also entails the present value of dividends, is central to investors, there exists a separate group, given the moniker of speculators, for whom market sentiment, as well as how to anticipate it, instead of intrinsic value, is the foremost concern. From Fig. 1, we observe that investor sentiment is affected by climate policy uncertainty, geopolitical risk, the underlying business of the firm, any innovations in clean energy production, the prices of clean energy materials and non-green energy commodity prices. As the arrows in Fig. 1 show, changes in CPU and GPR are taken as signals by investors/speculators. That is, changes in climate policy uncertainty affect the expectations of investors and speculators with respect to business viability and/or profitability. Moreover, investors and speculators may feel strongly about ESG (on climate change) or are at least aware that other investors, speculators, and consumers have such preferences/beliefs. On the other hand, given the localized nature of clean energy (solar and wind, for example), the risk that crucial fossil fuels may not be supplied in sufficient quantities or simply withheld presents an opportunity for clean energy to fill the vacuum. These considerations translate into fluctuations in clean energy stock prices.

4. Methodology

4.1. Time-varying connectedness framework

To analyse the connectedness among fossil fuels and clean energy stocks, we employ Antonakakis et al. [15]'s TVP-VAR framework. The technique improves the standard connectedness framework of Diebold and Yılmaz [13,16] by allowing the variances to evolve across time. Following Antonakakis et al. [15], we compute the GFEVD ($\widetilde{\psi}_{ij,t}(H)$) that entails the pairwise directional spillovers from variable j to variable i. That is, its influence on this variable in terms of forecast error variance share. Subscript t should be taken to indicate time.

$$\widetilde{\psi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1}\theta_{ij,t}^{2}}{\sum_{j=1}^{m}\sum_{t=1}^{H-1}\theta_{ij,t}^{2}} \tag{1}$$

Where $\sum_{j=1}^{m}\widetilde{\psi}_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{m}\widetilde{\psi}_{ij,t}(H) = m$. The denominator of Equation (1) characterizes the cumulative effect of all shocks, while the numerator shows the cumulative effect of the shock in variable i. After, the total spillover index is derived through the GFEVD.

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m}\widetilde{\psi}_{ij,t}(H)}{\sum_{i,j=1}^{m}\widetilde{\psi}_{ij,t}(H)}*100 = \frac{\sum_{i,j=1,i\neq j}^{m}\widetilde{\psi}_{ij,t}(H)}{m}*100 \tag{2}$$

Equation (2) captures how shocks in one variable spill over to other variables. Furthermore, we measure the total directional spillovers transmitted by variable i through Equation (3).

$$C_{i\rightarrow j,t}(H)=\frac{\sum_{i,j=1,i\neq j}^{m}\widetilde{\psi}_{ji,t}\ (H)}{\sum_{i,j=1}^{m}\widetilde{\psi}_{ji,t}\ (H)}*100 \tag{3}$$

Meanwhile, the total directional spillovers received from other variables j by variable i are measured by Equation (4).

$$C_{i\leftarrow j,t}(H)=\frac{\sum_{i,j=1,i\neq j}^{m}\widetilde{\psi}_{ij,t}\ (H)}{\sum_{i,j=1}^{m}\widetilde{\psi}_{ij,t}\ (H)}*100 \tag{4}$$

The difference between Equations (3) and (4) is the net total connectedness. If positive (negative), it means variable i is an overall net transmitter (receiver) of spillovers in the system. This is shown in Equation (5).

$$C_{i,t}=C_{i\rightarrow j,t}(H)-C_{i\leftarrow j,t}(H) \tag{5}$$

Meanwhile, the net pairwise directional connectedness (NPDC) is obtained in Equation (6). If the NPDC is positive, it means variable i dominates variable j. However, if it is negative, it means variable i is dominated by variable j.

$$NPDC_{ij}(H)=\left(\widetilde{\psi}_{jit}\ (H)-\widetilde{\psi}_{ijt}\ (H)\right)*100 \tag{6}$$

4.2. Nonlinear causality-in-quantile technique

To analyse the effect of CPU and GPR on the connectedness between fossil fuels and clean energy stocks, we apply the causality methodology of Balcilar et al. [17]. This technique builds on the work of Jeong et al. [18] and Nishiyama et al. [19]. The variable c_t (CPU or GPR) is designated as the predictor which does not cause the predicted variable a_t (in our case, intermarket spillovers) in the φth quantile considering $\{a_{t-1},\ldots,a_{t-w},c_{t-1},\ldots,c_{t-w}\}$ if:

$$K_{\varphi}(a_t|a_{t-1},\ldots,a_{t-w},c_{t-1},\ldots,c_{t-w})=K_{\varphi}(a_t|a_{t-1},\ldots,a_{t-w}) \tag{7}$$

Where $K_{\varphi}(a_t|\cdot)$ is the φ th quantile of a_t. While c_t causes a_t in the φ th quantile if:

$$K_{\varphi}(a_t|a_{t-1},\ldots,a_{t-w},c_{t-1},\ldots,c_{t-w})\neq K_{\varphi}(a_t|a_{t-1},\ldots,a_{t-w}) \tag{8}$$

Causality in higher order moments is explained by Balcilar et al. [17] using the following model:

$$a_t=f(A_{t-1},C_{t-1})+\mu_t, \tag{9}$$

Therefore, the generalized quantile causality, which accounts for higher order moments, is given by:

$$H_0=P\left\{F_{a_t^n|U_{t-1}}\{K_{\varphi}(A_t|U_{t-1})\}=\varphi\right\}=1, for\ n=1,2,..,N, \tag{10}$$

$$H_1=P\left\{F_{a_t^n\ |U_{t-1}}\{K_{\varphi}(A_t|U_{t-1})\}=\varphi\right\}<1, for\ n=1,2,\ldots,N. \tag{11}$$

Where $U_t=(A_t,C_t)$ is the historical values of both the variables.

Using Equation (10), we can create test statistics of the null for each n. In general, we can then test causality from c_t to a_t across quantiles (φ). Considering this, we test for the existence of causality from US CPU and GPR to intermarket spillovers. The bandwidth is selected using the SJ method.

4.3. Quantile-on-quantile regression

To better understand the causality from CPU or GPR to the clean energy stock - fossil fuel nexus, we appeal to the Quantile-on-Quantile (QQ) regression technique of Sim and Zhou [20]. This technique enables us to examine the effects of different quantiles of one variable (say CPU) on different quantiles of another variable (intermarket spillovers). The QQ is expressed as follows:

$$CFIS_t=\beta_0\ (\theta,\tau)+\beta_1\ (\theta,\tau)(CPU_t-CPU^{\tau})+\mu_t^{\theta} \tag{12}$$

Where *CFISt* represents intermarket spillovers between clean energy stocks and fossil fuels at time t and *CPUt* represents climate policy uncertainty at time t. On account that indexes τ and θ are present in Equation (12), we are able to examine dependence across the quantiles of both CFIS and CPU.

CPU_t *and* CPU^{τ} are replaced with $\widehat{CPU}_t$ *and* $\widehat{CPU}^{\tau}$, their empirical counterparts. We then obtain estimates of the parameters b_0 and b_1 through the following minimization problem:

$$\min_{b0,b1}\sum_{k=0}^{n}\rho_{\theta}\left[CFIS_t-b_0-b_1\left(\widehat{CPU}_t-\widehat{CPU}^{\tau}\right)\right]K\left(\frac{F_n(\widehat{CPU}_t)-\tau}{h}\right) \tag{13}$$

Where:

$$F_n(\widehat{CPU}_t)=\frac{1}{n}\sum_{k=1}^{n}(\widehat{CPU}_k<\widehat{CPU}_t) \tag{14}$$

ρ_{θ} represents the quantile loss function. Observations are weighted in proximity of $\widehat{CPU}^{\tau}$ using the gaussian kernel denoted by $K(\cdot)$. We do this for the purpose of examining the local impact of CPU's τ th quantile. Following Sim and Zhou [20], we choose 0.05 as our bandwidth.

5. Empirical analysis

5.1. The data

To accomplish the objectives of this study, we select the WilderHill (ECO) index as our measure of the clean energy stock market. This series is sourced from BLOOMBERG. The ECO index includes solar, wind, electric vehicles, energy efficiency, smarter grids, and green hydrogen, among others. Furthermore, it is a modified equal-weight index. Among the various clean energy indices used in the literature, it is the most favored. Its foremost advantage is that it has the earliest date for which data is available when compared to the S&P Global Clean Energy Index (SPGTCED) and the European Renewable Energy Price Index (ERIXP). Pertinently, it is composed of stocks that are publicly traded in the United States. Certainly, several studies we have discussed in the literature review have based their analyses on the ECO index (see, inter alia, [2,3]). In addition, the fossil fuel spot prices are obtained from the United States Energy Information Administration (EIA). These data include WTI crude oil, Brent crude oil, New York Harbor gasoline, U.S. Gulf Coast gasoline, Los Angeles Diesel, New York Harbor Heating oil, Propane, Gulf Coast Jet fuel and Henry Hub Natural gas. Except for crude oil (both WTI and Brent), which is priced in USD per Barrel, the petroleum fuels are priced in USD per Gallon. Natural gas is priced in USD per million Btu. The study also employs the U.S. climate policy uncertainty (US CPU) and geopolitical risk (GPR) indices to consider their effect on the intermarket spillovers among the fossil fuels and clean energy stocks. While the US CPU index was created by Gavriilidis [21], the GPR index was made by Caldara and Iacoviello [22]. These indices are obtained from www.policyuncertainty.com. These are news-based indices that are constructed by searching for specific key-words/terms (relating to climate policy uncertainty or geopolitical risk) in several selected newspapers each month. Monthly data covering the period between December 2000 and August 2023 is selected as the subject of our analysis. This period is chosen on careful consideration of the beginning date of the ECO index, the end date of the US CPU index, and the frequency of the US CPU and GPR indices.

5.2. Preliminary analysis

We derive returns (r_t) by differencing the natural log of the price level (P_t) and multiplying it by 100. This is done for all the variables.

Table 1
Descriptive statistics.

Variable	Mean	Median	Min.	Max.	Std. Dev.	Skewness	Kurtosis	Jacque-Bera	Obs.
ECO WilderHill	−0.342	0.140	−38.657	36.931	10.256	−0.367	4.096	19.721***	272
WTI crude oil	0.387	1.579	−56.813	54.562	10.461	−0.943	10.978	761.630***	272
Brent crude oil	0.445	1.947	−55.479	46.905	10.576	−1.132	9.375	518.588***	272
NY gasoline	0.500	1.172	−57.284	39.017	11.068	−1.043	6.928	224.149***	272
GC gasoline	0.513	1.549	−56.361	41.881	12.064	−0.953	6.808	205.537***	272
Diesel	0.433	1.971	−43.460	26.042	9.858	−0.736	4.710	57.691***	272
Heating oil	0.418	1.078	−31.814	28.375	9.131	−0.477	4.266	28.471***	272
Propane	−0.049	1.101	−38.125	29.272	11.126	−0.563	3.734	20.445***	272
Jet fuel	0.457	1.566	−45.959	35.973	10.213	−1.063	6.666	203.502***	272
US CPU	0.309	−0.385	−170.138	123.268	37.567	−0.234	4.183	18.343***	272
GPR	0.309	−0.575	−60.009	205.130	22.641	2.831	26.940	6858.826***	272

Source: Authors' computation

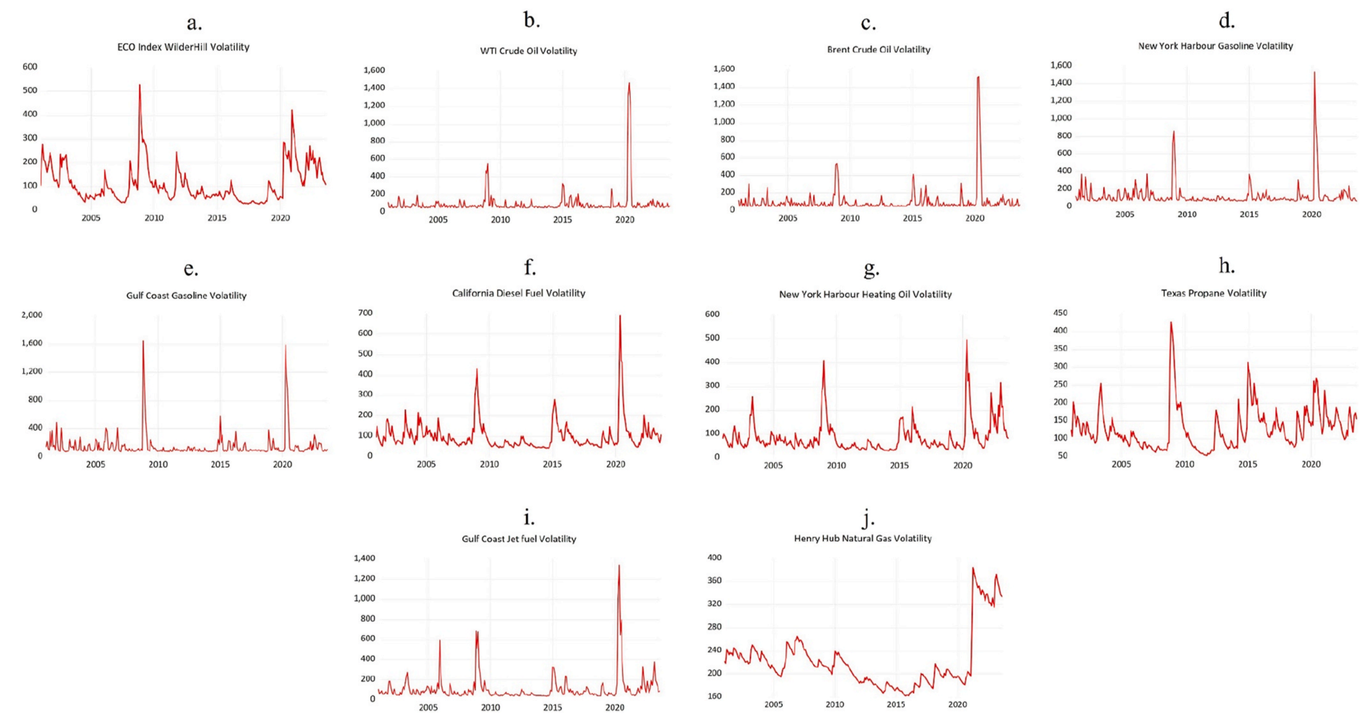

Fig. 4. Series volatility
Note: Figure shows series volatility between December 2000 and August 2023. Generated using a univariate conditional volatility model.
Source: Authors' compilation.

Table 2
Static connectedness.

	ECO	WTI	BRNT	NGLN	GGLN	DSL	HOI	PRP	JETF	NATG	FROM
ECO	**36**	6.9	7.4	6.2	7.6	9.3	11.1	4.5	10.6	0.4	64
WTI	3.1	**19.3**	18	13.5	11.4	9.7	9	4.4	11.5	0	80.7
BRNT	2.9	17.1	**18.8**	13.9	11.9	10	9.1	4.6	11.7	0.1	81.2
NGLN	3.9	13	14.4	**19.3**	17	9	7.8	5.4	10.4	0	80.7
GGLN	5.1	11.4	13	17	**20.4**	8.5	7.4	5.8	11.4	0	79.6
DSL	4.2	11	12.4	11.9	10.8	**16.9**	12.2	7.5	12.9	0	83.1
HOI	5.7	10.7	11.8	9.7	9.1	13.5	**18**	7.6	13.6	0.1	82
PRP	6.7	8.3	9	9.3	11	10.3	11.3	**23.9**	9.6	0.5	76.1
JETF	4.3	11.4	12.5	11.7	12.4	12.1	11.9	5.7	**17.9**	0.1	82.1
NATG	4.5	4	3.9	3.4	2.5	4.1	4.1	4.2	4.1	**65.1**	34.9
TO	40.4	93.8	102.6	96.7	93.8	86.5	83.9	49.7	95.8	1.4	744.5
NET	−23.7	13.2	21.4	16	14.2	3.4	1.9	−26.5	13.7	−33.5	TCI
NPDC	7	4	0	1	2	5	6	8	3	9	**74.4**

Note: NPDC represents net pairwise directional connectedness, which shows how many other variables dominate a particular variable.
Source: Authors' computation.

$r_t = (\Delta ln\, P_t) \times 100$

The results in Table 1 show that, except for the ECO index and Propane, all the series have positive average returns. We also find that, excepting GPR, the rest of the return series have a greater minimum value than maximum value when considered in absolute terms. While Heating oil has the lowest standard deviation (9.1310), US CPU has the highest standard deviation (37.5667). In addition to having, respectively, the highest and second highest standard deviations, we also observe that the US CPU and GPR indices each have the greatest difference between their minimum and maximum return values. This is an indication that climate policy uncertainty and geopolitical risk have fluctuated greatly (see Fig. 3).

Following Ferrer et al. [2], we generate volatility series from the variables using a univariate conditional volatility model. In this endeavor, we appeal to the standard GARCH (1,1) process. The graphs of these volatility series are presented in Fig. 4. Expectedly, we see several large spikes in volatility across the series. This ranges from the 9/11 attacks, the Iraq war, the GFC, the 2015/16 commodity price crash, COVID-19, and the war in Ukraine. Strikingly, we see that the evolution of natural gas' volatility differs greatly from petroleum. Specifically, unlike most of the other fossil fuels, natural gas' volatility reaches its greatest extent at the onset of the Russia-Ukraine war.

Moreover, given the importance of ensuring stationarity prior to performing econometric analyses, we perform unit root tests on the data series. Excepting natural gas, which is integrated of order 1, all the volatility series are stationary at levels.

5.3. TVP-VAR analysis

As our starting point, we analyse the volatility spillovers among fossil fuels and clean energy stocks using the TVP-VAR of Antonakakis et al. [15]. The next section focuses on static connectedness and is then followed by a section on the dynamic spillovers among fossil fuels and clean energy stocks between December 2000 and August 2023.

5.3.1. Average connectedness

To uncover the nature of connectedness among fossil fuels and clean energy stocks, we begin with the average spillovers among them. Table 2 shows that the static Total Connectedness Index (TCI) is 74.4 %. This shows that the network of variables can explain the greater part of their volatility evolutions. Despite this high total connectedness, we can observe that clean energy stocks have a relatively weaker connectedness with the fossil fuels. By this we mean that the volatility connectedness among fossil fuels, specifically petroleum (crude oil, diesel etc.), is stronger. As shown in Table 2, the forecast error variance contribution of clean energy stocks to others is 40.4 %. while the spillovers it receives sum up to 64 %. This is markedly lower than those among petroleum. Certainly, WTI crude oil, Brent crude oil, NY gasoline, GC gasoline, diesel, heating oil, and jet fuel transmit spillovers well above 80 %. Similarly, all the petroleum fuels (incl. propane) receive spillovers above 76 %. However, there are some exceptions. For example, propane only transmits 49.7 % to the system. Interestingly, despite its sizable contribution to the U.S. primary energy mix, natural gas's share of forecast error variance to other variables is only 1.4 % while it receives 34.9 %. This clearly demonstrates the dominance of the petroleum market. Expectedly, we observe that clean energy stocks, propane, and natural gas are net receivers. Indeed, clean energy stocks and propane are dominated (that is, they receive more than they transmit) by 7 and 8 other assets/commodities, respectively. Worse yet, natural gas is dominated by all the other assets/commodities.

The observation that the clean energy stock market is a net-receiver of shocks from almost all the fossil fuels may be an indication that despite the present push towards renewable energy, the entrenched place of dirty energy sources ensures that they may not be dislodged soon. That is, the events in the fossil fuel market still dominate those in

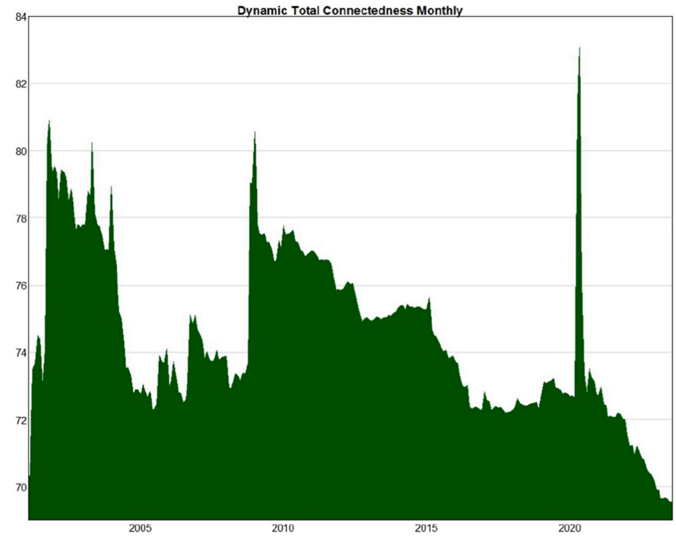

Fig. 5. Dynamic total connectedness
Note: The shaded area represents joint connectedness. The results are generated by a TVP-VAR model and a 10-step ahead forecast.
Source: Authors' computation.

the clean energy market. Moreover, the lower degree of connectedness between this asset class and its non-green alternatives in comparison to the spillovers among the fossil fuels provides evidence that these markets are not yet fully in competition. We may conclude that there is only a partial connection because of the deep roots of non-green energy commodities and the lack of ubiquitous green alternatives to compete with some fossil fuels.

5.3.2. Dynamic connectedness

We now appeal to dynamic analysis to assess intermarket connectedness across time. From Fig. 5, we see that total connectedness reached its greatest extent during the COVID-19 pandemic. This corroborates Tiwari et al. [4]'s finding that connectedness among green financial markets was greatest during this period. Although the rise in connectedness did not last long, it occurred during a period of chaos in commodity markets caused by swift quarantine measures put in place in response to the pandemic. Beyond this, we see two other prominent jumps in connectedness. The more recent of these two, the global financial crisis, is also followed by a period of relatively strong spillovers among energy commodities and clean energy stocks. The other period, which coincides with the 9/11 terrorist attacks and the Iraq war, shows a formidable level of connectedness.

To better understand the transmitter/receiver roles of each of the variables in our network, we look to Figs. 6 and 7. We find that the relatively lower spillovers transmitted by clean energy stocks and propane we found in the static analysis in section 5.3.1 are uniformly observed across the entire sample period. Similarly, natural gas's 1.4 % average spillovers transmitted translate into virtually no spillovers from this energy commodity across the entire period. Conversely, the spillovers natural gas receives are more concentrated in periods that are closest to the 9/11 terrorist attacks and the war in Iraq, with a comparatively small spike during the COVID-19 pandemic. Adding context to Table 2, Figs. 6 and 7 further demonstrate the dominance of petroleum over the whole period. Consistent with what we observed in Fig. 2, WTI and Brent crude oil have had very similar spillover evolutions across the period. There is however a divergence after the COVID-19 pandemic as we see in Fig. 8. That is, while Brent crude oil maintains its net transmitter role, WTI crude oil takes the role of net receiver around March 2020. It is also apparent that while clean energy stocks, propane and natural gas are consistent net receivers of spillovers, diesel's role varies. In the earlier (later) half of the sample period, diesel is a

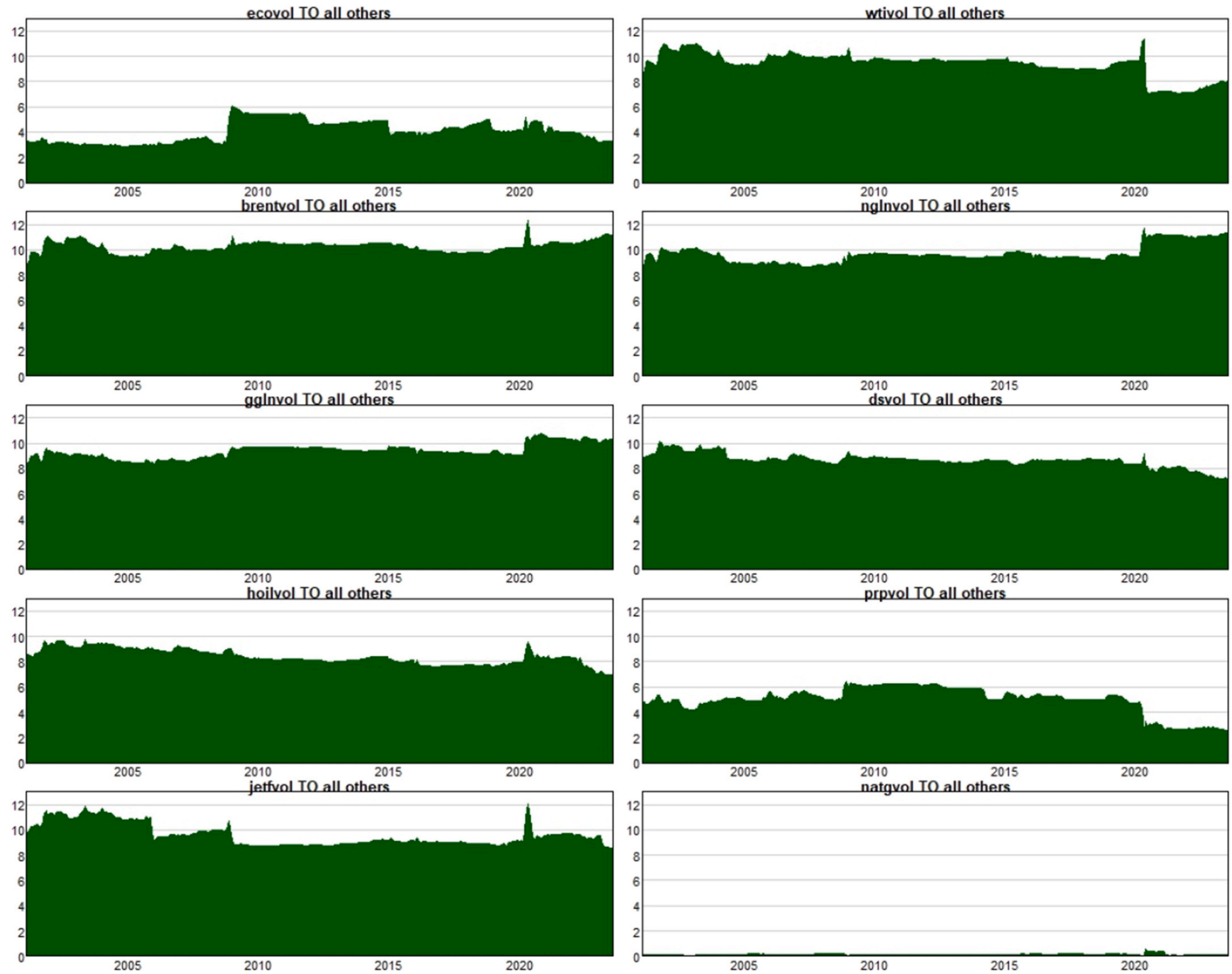

Fig. 6. Spillovers TO others
Note: Green shaded area represents spillovers TO other variables. Based on a 10-step ahead forecast.
Source: Authors' computation.

net transmitter (receiver) of spillovers. Lastly, from the pairwise connectedness in Fig. 9, we see that clean energy stocks are net transmitters to propane and natural gas. This is consistent with the results presented in Table 2, where clean energy stocks are dominated by 7 other variables.

The results in Table 2 as well as Figs. 6 and 7 contrast with those of Qi et al. [5] as they observed greater spillovers to and from the clean energy stock market in relation to fossil fuels. However, it is important to note that their study was focused on the Chinese economy and their variables differ somewhat from ours. Specifically, we use a composite clean energy stock index whereas they disaggregated the sector into photovoltaic, wind and nuclear. Moreover, the fossil fuels that were considered in their study, except for coal, are less extensive than the present study.

In contrast to Fig. 9 where we observe that the ECO index (clean energy stocks) is a net receiver of volatility spillovers from WTI crude during the GFC, Ferrer et al. [2] found that the ECO index was a net transmitter during this period. However, we submit that this seeming contradiction may be on account that the present study uses WTI spot prices whereas Ferrer et al. [2] used WTI futures prices. Similarly, using fossil fuel futures prices, Umar et al. [9] concluded that there was weak volatility connectedness among these commodities and clean energy stocks. This is contrary to section 5.3.1 and Fig. 5, where we find that the network explains the greater part of the volatility evolutions among these markets.

5.4. The role of US climate policy uncertainty & geopolitical risk

In this section, we proceed to assess the impact of climate policy uncertainty and geopolitical risk on intermarket spillovers. Recalling that the concern of the present study has centered on the connection between fossil fuels and clean energy stocks, we focus on clean energy stock - fossil fuel intermarket spillovers. By this we mean the summation of the ECO "TO" spillovers and the ECO "FROM" spillovers. The series thus obtained is shown in Fig. 10.

In Fig. 10, we see that there are four notable peaks in volatility connectedness. These periods are highlighted in grey. The first coincides with the war in Iraq, the second with the onset of the global financial crisis, the third with the period before the commodity price crash around 2015/16 and the fourth with the COVID-19 pandemic. Interestingly, the peak around the Iraq war begins its ascent before the initiation of the conflict in March 2003. Certainly, the premature rise in connectedness is consistent with key moments preceding the conflict. Among these is the passing of a resolution permitting the use of military force against Iraq by the U.S. Congress in 2002. Although we still observe the same general

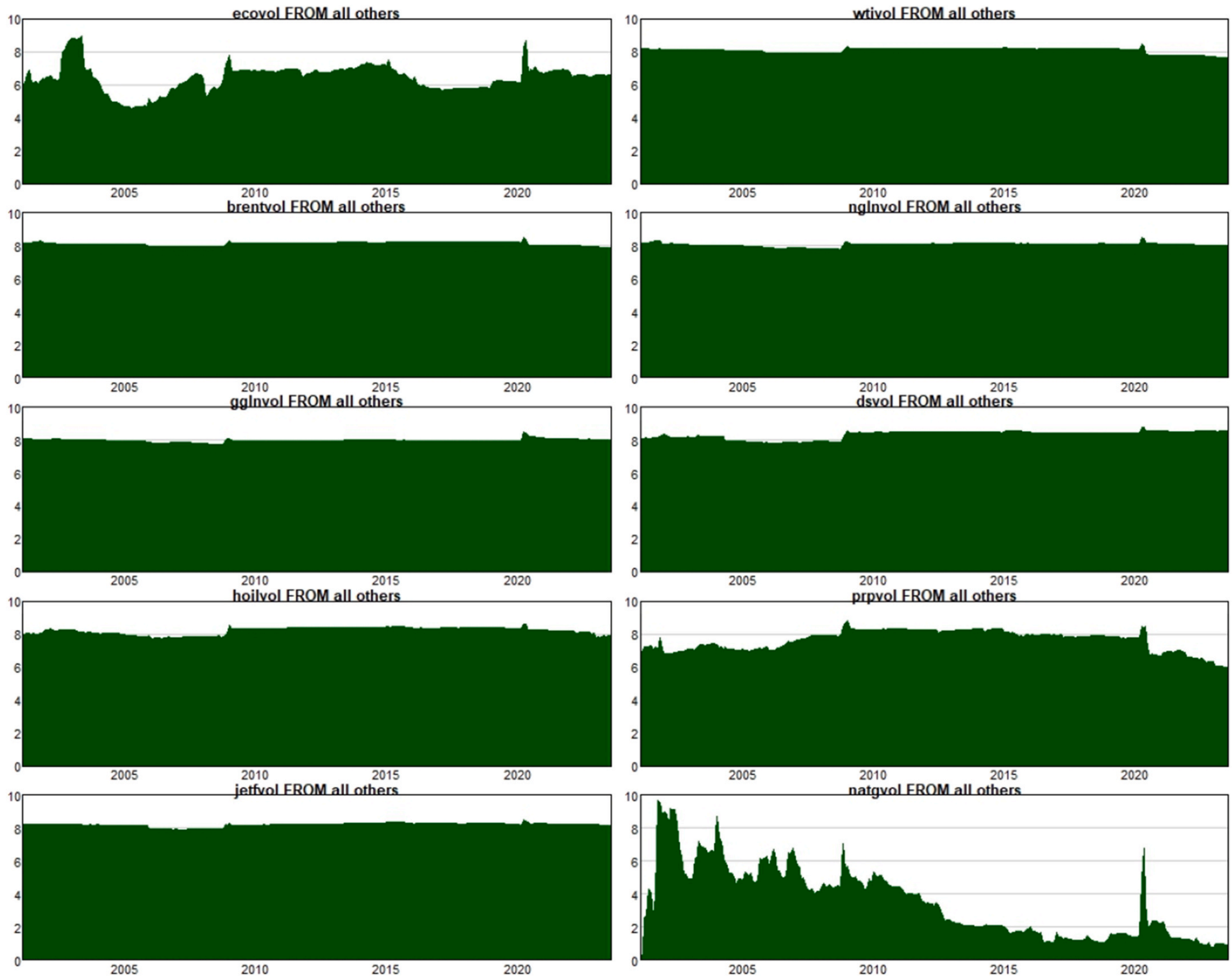

Fig. 7. Spillovers FROM others
Note: Green shaded area represents spillovers FROM other variables. Based on a 10-step ahead forecast.
Source: Authors' computation.

evolution for the clean energy stock - fossil fuel intermarket spillovers (CFIS) as we found for the total spillovers among all the variables, there are some differences. The most obvious is that the peak around the COVID-19 period is now much less prominent than the one observed during the GFC. This is not surprising given the way these intermarket spillovers have been calculated. The consequence of this is that the ECO index is given greater weight as the "TO" spillovers of the fossil fuels, at least those not directed at the ECO index, are not included. Before proceeding with further analyses, we assess the stationarity properties of the intermarket spillovers. The series is stationary after differencing.

As a precondition for analysing the effects of US CPU and GPR on these spillovers, we perform the BDS test of Broock et al. [23] to test for nonlinearity in the CFIS time-series data. If the null of linearity does not hold, linear models will be weak to produce reliable results. Certainly, as is evident in Table 3, the null of linearity in the series is rejected. We are therefore justified in appealing to the causality-in-quantiles technique.

From Fig. 11, we see that both US CPU and GPR have a significant impact across the quantiles of the intermarket spillovers. Specifically, except for the highest quantile, US CPU is particularly potent across the entire spectrum of quantiles. Meanwhile, GPR is significant across most quantiles except for the two highest quantiles. This is evidence that these phenomena have a non-trivial effect on clean energy stock and fossil fuel intermarket connectedness.

Although the causality-in-quantiles results showed us that US CPU and GPR had a significant causal impact on the clean energy stock - fossil fuel intermarket spillovers, we do not know much else. Therefore, we employ the Quantile-on-Quantile regression technique to better understand the nature of this causal impact. On account that we have made modifications to both the intermarket spillovers and the US CPU and GPR indices, care should be taken while interpreting the results in Fig. 12.

Immediately we see a very complex relationship between CFIS and US CPU as well as CFIS and GPR. Given that the intermarket spillovers have been differenced and the US CPU and GPR indices have been transformed into returns, the lower (upper) quantiles of both the dependent and independent variables are generally negative (positive) values. That is, the differenced CFIS series is to be taken as fluctuations in the intermarket spillovers among clean energy stocks and fossil fuels. Likewise, the US CPU and GPR values represent percentage changes in the series.

In Fig. 12 (a), we observe that when the intermarket spillovers are in their low quantiles and US CPU is in its higher quantiles, US CPU has a positive effect on the intermarket spillovers. This positive effect is also evident when the intermarket spillovers are in their highest quantiles

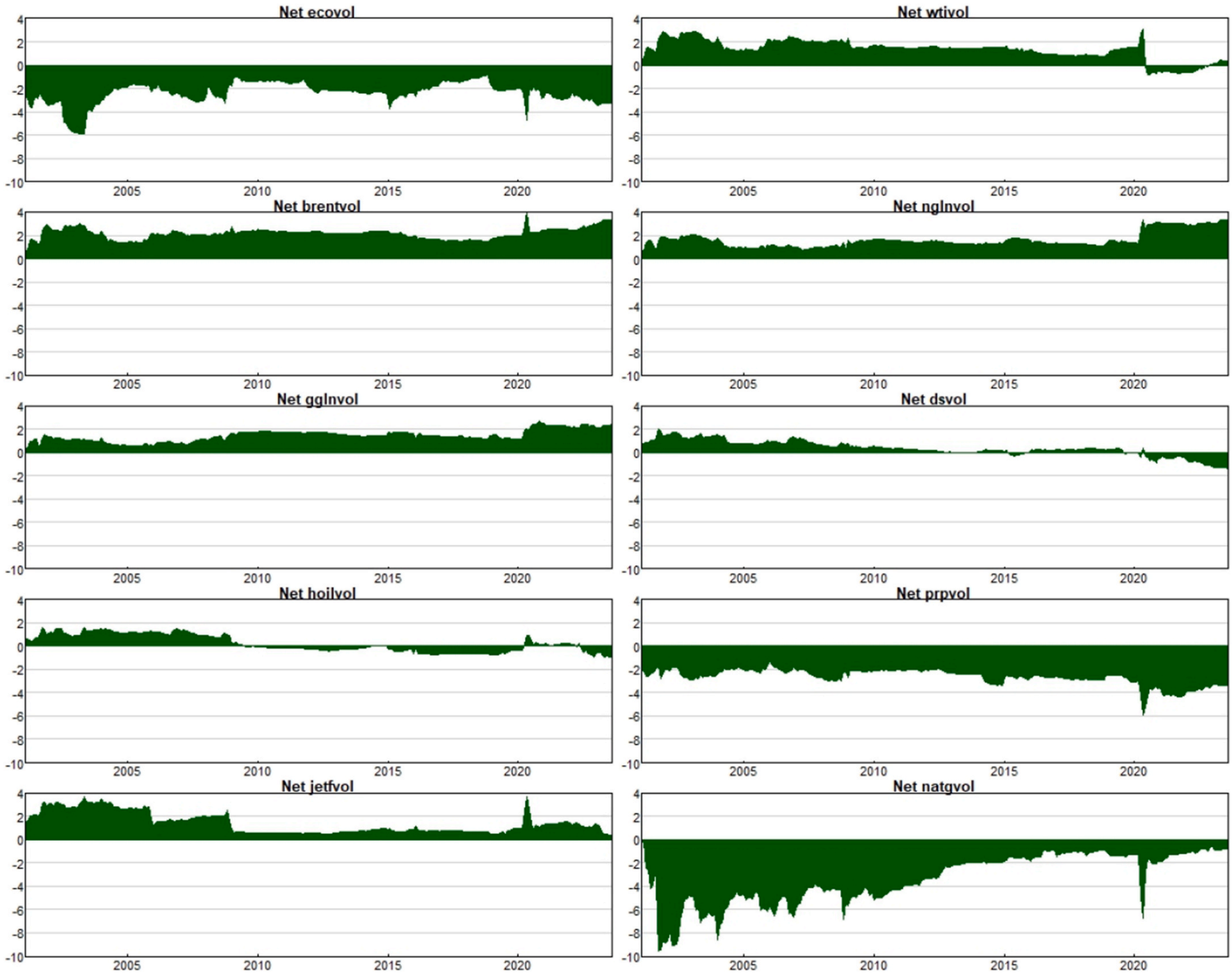

Fig. 8. Dynamic net connectedness
Note: Green shaded area represents net connectedness. Based on a 10-step ahead forecast.
Source: Authors' computation.

and US CPU is in its lowest quantiles. Conversely, we find a negative relationship when both the intermarket spillovers and US CPU are in the low or high quantiles. This means that when intermarket spillovers and US CPU are both experiencing negative or positive changes, US CPU will generally reduce the level of connectedness among clean energy stocks and fossil fuels. Meanwhile, when intermarket spillovers are already experiencing high positive changes, negative shifts in US CPU will increase these spillovers. So too, if this connectedness is already falling, high positive changes in US CPU will increase the intermarket spillovers.

Meanwhile, in Fig. 12 (b), we see a markedly different quantile association between intermarket spillovers and GPR. When intermarket spillovers are in their lowest quantiles and GPR is in its highest quantiles, GPR has a positive impact on intermarket spillovers. Moreover, a positive effect is also observed around the median quantiles of the intermarket spillovers when GPR is in its lower quantiles. Strikingly, we see a negative effect when both indices are in their lowest quantiles. Unlike the complex relationship we observe when intermarket spillovers are in the lower quantiles (0.05–0.5), there is a uniformly positive effect from GPR when intermarket spillovers are in their upper quantiles (0.5–0.95). However, it is worth noting that this impact is of much lower magnitude. These results entail that the association between intermarket spillovers and GPR depends on whether one or both is rising/falling.

Overall, it is evident from the preceding discussion that the effects of climate policy uncertainty and geopolitical risk on the clean energy stock - fossil fuel spillover nexus are not only significant, but they are also heterogeneous. That is, for the associations among these variables, it matters whether the magnitude of their movements is historically high or low. For example, we are likely to observe a special association between intermarket spillovers and US CPU during the global financial crisis, when the former was rising sharply and the latter's increase was relatively small, as compared to another period. Admittedly, there are other factors at work that affect the connectedness among fossil fuel markets and clean energy stocks (in terms of volatility spillovers) beyond what is under the purview of this study. Notwithstanding, from an analysis of Fig. 10, we conclude that disruptions in demand and supply of energy commodities have an especially potent effect on the connectedness among fossil fuels and clean energy stocks.

In light of these findings, it is apparent that investors (and speculators) in clean energy stock markets must not only anticipate possible contagion emanating from incumbent fossil fuels but must also account for the varying effects of climate policy uncertainty and geopolitical risk on their positions. That is, the strength of contagion from fossil fuels prices to clean energy stock prices changes depending on the state of

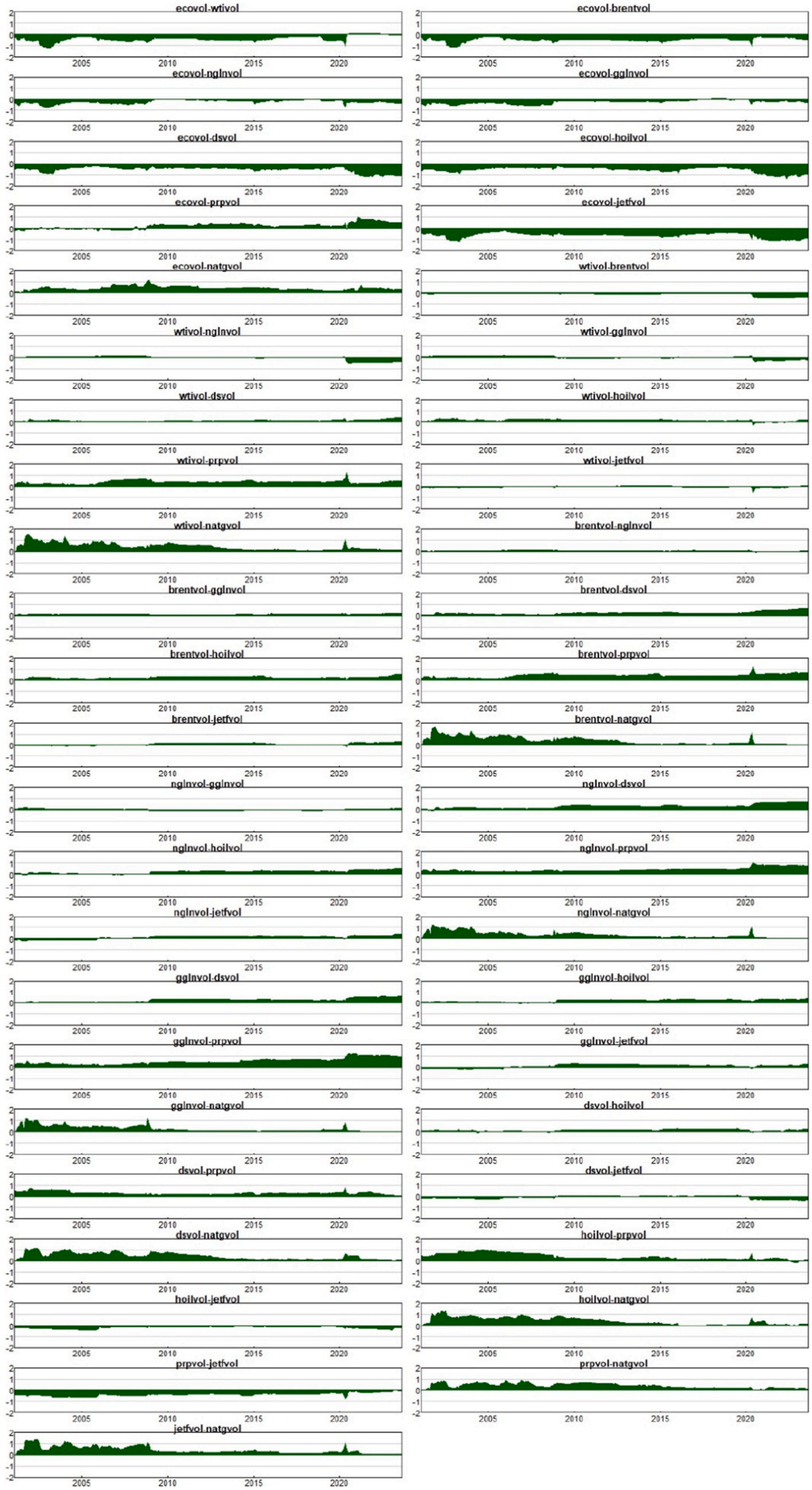

Fig. 9. Net pairwise connectedness
Note: Figure shows net pairwise spillovers from the net result of TO minus FROM spillovers. See Equation (6) in section 4.1. Based on a 10-step ahead forecast.
Source: Authors' computation.

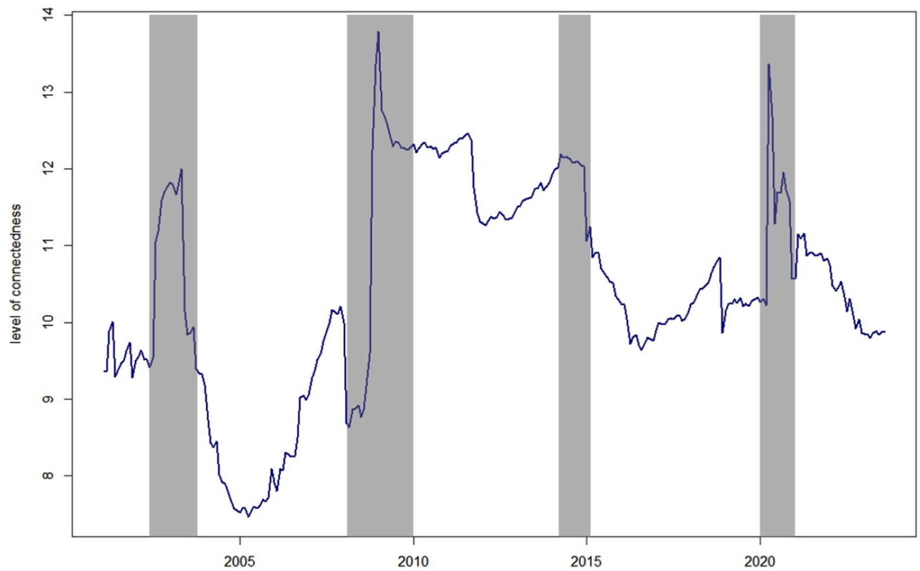

Fig. 10. Total spillovers between ECO index and fossil fuels
Note: The figure shows the summation of the ECO "TO" spillovers and ECO "FROM" spillovers. Based on a 10-step ahead forecast.
Source: Authors' computation.

Table 3
BDS test results.

Variable	2	3	4	5	6
CFIS	0.040***	0.078***	0.105***	0.118***	0.121***

Note: Table reports BDS statistics. *** represents significance at 1 %. Numbers 2 to 6 represent dimensions.
Source: Authors' computation.

climate policy uncertainty and geopolitical risk.

6. Conclusion

Driven by the observation that the energy sources underlying clean energy stocks are in competition with incumbent fossil fuels, the study sought to assess the volatility connectedness among these markets. Specifically, we employed the TVP-VAR methodology and arrived at some important findings. First, on average, clean energy stocks receive greater contributions in terms of forecast error variance from fossil fuels (WTI crude oil, Brent crude oil, etc.) than they transmit. Second, petroleum fuels exhibit the strongest intermarket spillovers. Third, natural gas differs greatly in its role as receiver/transmitter compared to the other fossil fuels. Its contribution of spillovers to the network is near negligible. Conversely, natural gas is vulnerable to spillovers from the other fossil fuels. However, these spillovers have diminished consistently since the early 2000s. Fourth, the study applied the causality-in-quantiles technique of Balcilar et al. [17] and found that US CPU and GPR had a significant impact on the spillovers between clean energy stocks and fossil fuels. Fifth, the study extended this causality analysis by appealing to the Quantile-on-Quantile regression technique of Sim and Zhou [20]. We found that the effects of US CPU and GPR were heterogeneous across the different states of the fossil fuel and clean energy stock intermarket spillovers.

The shift toward sustainable economies, and clean energy generation

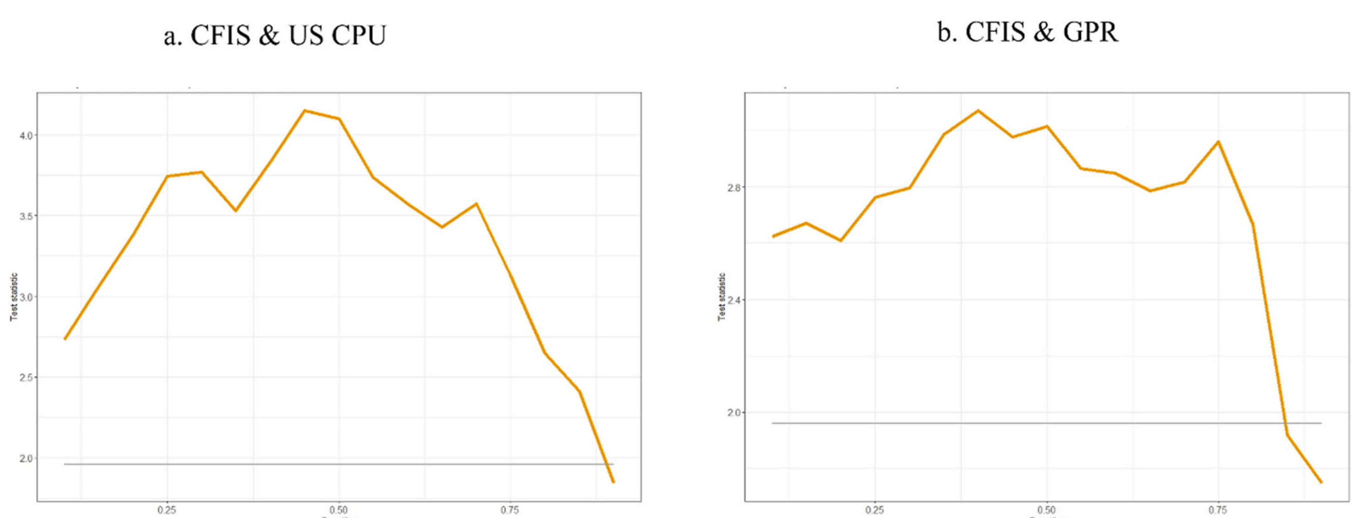

Fig. 11. Causality-in-quantiles
Note: The dependent variable is clean energy stock–fossil fuel intermarket spillovers (CFIS). US CPU/GPR is the independent variable. Bandwidth is selected using SJ.
Source: Authors' computation.

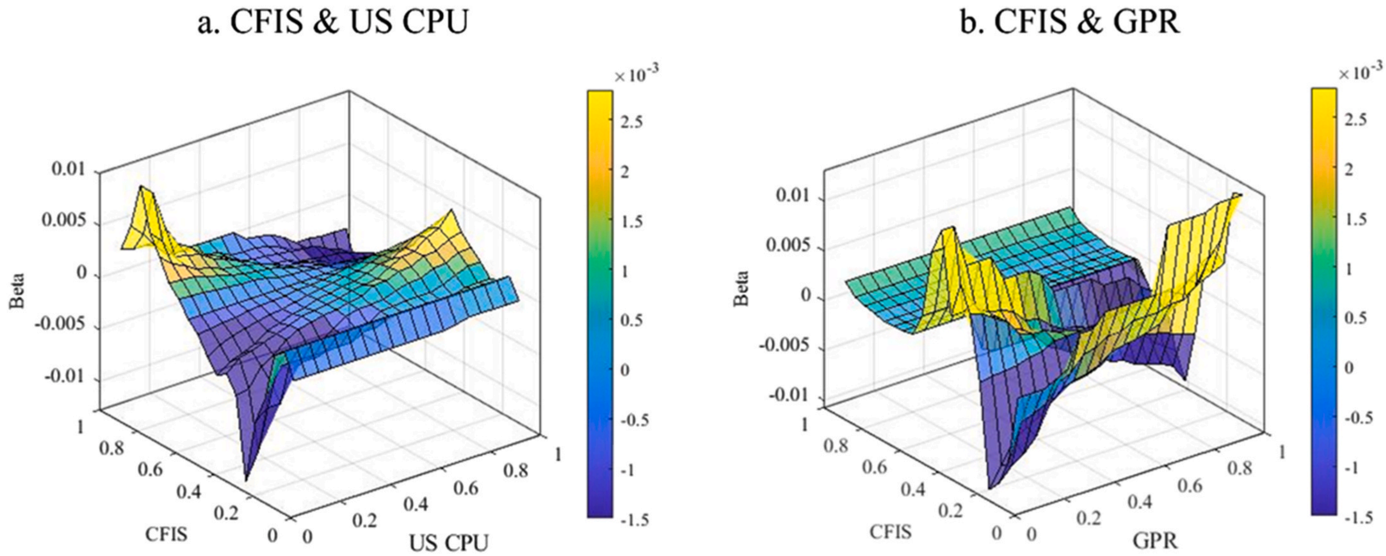

Fig. 12. Quantile-on-quantile regression
Note: Figure shows the relationship between two variables across each of their distributions. CFIS (intermarket spillovers) is the dependent variable. US CPU/GPR is the independent variable.
Source: Authors' computation.

in particular, is a great undertaking that requires the combined effort of the public and private sectors. For policymakers, the findings uncovered in this study provide more information about the links among green financial assets and fossil fuels. For investors and financial practitioners, the study gives an accounting of the extent of risks emanating from incumbent dirty energy sources under a dynamic framework.

Although the study arrives at some important findings, it has some limitations. Foremost of these is our focus on the United States economy. Apart from using local U.S. fossil fuel prices, the study employs a U.S. based climate policy uncertainty index. Given that political and economic realities vary across developed and developing countries, the results obtained in this study may not be directly applicable to countries/regions like China, the European Union, Russia, and India.

CRediT authorship contribution statement

Ismail O. Fasanya: Writing – original draft, Software, Conceptualization, Writing – review & editing, Supervision, Methodology. **Darren T. Mubaiwa:** Writing – original draft, Data curation, Writing – review & editing, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

[1] United Nations. Framework convention on climate change. Report of the Conference of the Parties on its twenty-first session, held in Paris from 30 November to 13 December 2015. Geneva: United Nations; 2016.
[2] Ferrer R, Shahzad SJ, López R, Jareño F. Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. Energy Econ 2018;76:1–20. https://doi.org/10.1016/j.eneco.2018.09.022.
[3] Coskun M, Khan N, Saleem A, Hammoudeh S. Spillover connectedness nexus geopolitical oil price risk, clean energy stocks, global stock, and commodity markets. J Clean Prod 2023;429:139583. https://doi.org/10.1016/j.jclepro.2023.139583.
[4] Tiwari AK, Aikins Abakah EJ, Gabauer D, Dwumfour RA. Dynamic spillover effects among green bond, renewable energy stocks and carbon markets during COVID-19 pandemic: implications for hedging and investments strategies. Glob Finance J 2021;51:100692. https://doi.org/10.1016/j.gfj.2021.100692.
[5] Qi H, Ma L, Peng P, Chen H, Li K. Dynamic connectedness between clean energy stock markets and energy commodity markets during times of COVID-19: empirical evidence from China. Resour Policy 2022;79:103094. https://doi.org/10.1016/j.resourpol.2022.103094.
[6] Chen Y, Zhu X, Chen J. Spillovers and hedging effectiveness of non-ferrous metals and sub-sectoral clean energy stocks in time and frequency domain. Energy Econ 2022;111:106070. https://doi.org/10.1016/j.eneco.2022.106070.
[7] Deng J, Xu Z, Xing X. Dynamic spillovers between clean energy and non-ferrous metals markets in China: a network-based analysis during the COVID-19 pandemic. Resour Policy 2023;83:103575. https://doi.org/10.1016/j.resourpol.2023.103575.
[8] Ding Q, Huang J, Zhang H. Time-frequency spillovers among carbon, fossil energy and clean energy markets: the effects of attention to climate change. Int Rev Financ Anal 2022;83:102222. https://doi.org/10.1016/j.irfa.2022.102222.
[9] Umar M, Farid S, Naeem MA. Time-frequency connectedness among clean-energy stocks and fossil fuel markets: comparison between financial, oil and pandemic crisis. Energy 2021;240:122702. https://doi.org/10.1016/j.energy.2021.122702.
[10] U.S Energy Information Administration. U.S. energy facts explained – consumption and production. Retrieved from, https://www.eia.gov/energyexplained/us-energy-facts/; 2023.
[11] Miller JI, Ratti RA. Crude oil and stock markets: stability, instability, and bubbles. Energy Econ 2009;31(4):559–68. https://doi.org/10.1016/j.eneco.2009.01.009.
[12] Baruník J, Křehlík T. Measuring the frequency dynamics of financial connectedness and systemic risk. J Financ Econom 2018;16(2):271–96. https://doi.org/10.1093/jjfinec/nby001.
[13] Diebold FX, Yılmaz K. Better to give than to receive: predictive directional measurement of volatility spillovers. Int J Forecast 2012;28(1):57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006.
[14] Williams JB. The theory of investment value. Amsterdam: North-Holland; 1938.
[15] Antonakakis N, Chatziantoniou I, Gabauer D. Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. J Risk Financ Manag 2020;13:84. https://doi.org/10.3390/jrfm13040084.
[16] Diebold FX, Yılmaz K. On the network topology of variance decompositions: measuring the connectedness of financial firms. J Econom 2014;182(1):119–34. https://doi.org/10.1016/j.jeconom.2014.04.012.
[17] Balcilar M, Bekiros S, Gupta R. The role of news-based uncertainty indices in predicting oil markets: a hybrid nonparametric quantile causality method. Empir Econ 2016;53(3):879–89. https://doi.org/10.1007/s00181-016-1150-0.
[18] Jeong K, Härdle WK, Song S. A consistent nonparametric test for causality in Quantile. Econom Theory 2012;28(4):861–87. https://doi.org/10.1017/s0266466611000685.
[19] Nishiyama Y, Hitomi K, Kawasaki Y, Jeong K. A consistent nonparametric test for nonlinear causality—specification in time series regression. J Econom 2011;165(1):112–27. https://doi.org/10.1016/j.jeconom.2011.05.010.
[20] Sim N, Zhou H. Oil prices, US stock return, and the dependence between their quantiles. J Bank Finance 2015;55:1–8. https://doi.org/10.1016/j.jbankfin.2015.01.013.

[21] Gavriilidis K. Measuring climate policy uncertainty. SSRN Electron J 2021. https://doi.org/10.2139/ssrn.3847388.
[22] Caldara D, Iacoviello M. Measuring geopolitical risk. Am Econ Rev 2022;112(4):1194–225. https://doi.org/10.1257/aer.20191823.
[23] Broock WA, Scheinkman JA, Dechert WD, LeBaron B. A test for independence based on the correlation Dimension. Econom Rev 1996;15(3):197–235. https://doi.org/10.1080/07474939608800353.