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Zhenhua Liu
China University of Mining and Technology

Jingyan Huang
University of Chinese Academy of Sciences

Kun Guo
University of Chinese Academy of Sciences

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Climate Risks and the Connectedness between Clean and Dirty Energy Markets

Jingyan Huang [a], **Zhenhua Liu** [b], **Kun Guo** [c*]

[a] *Sino-Danish College, University of Chinese Academy of Sciences, Beijing, China*

[b] *School of Economics and Management, China University of Mining and Technology, Xuzhou, China.*

[c] *School of Economics and Management, University of Chinese Academy of Sciences, Beijing, China*

Abstract: Climate risks pose significant challenges and threats to complex energy market system. This paper illuminates the interactions between clean and dirty energy markets and further investigates their asymmetric responses to climate risks. The influence of climate risks extends beyond extreme values and has a substantial impact on the overall distribution of the connectedness between clean and dirty energy markets. As the physical risk intensifies, the connectedness within both clean and dirty energy markets increases. The abnormal transition risk will render energy market fluctuations more uncertain and accentuate the distinction between clean and dirty energy markets.

Keywords: clean energy; dirty energy; connectedness; climate risks

JEL: P45, Q43, Q54

1. Introduction

The burning of fossil fuels has caused global warming and environmental damage. To prevent the severe consequences of climate change, the world needs to shift to cleaner and renewable energy sources, the connectedness of which is complex. An increasing amount of research has been dedicated to examining the spillovers within clean and dirty energy markets (Farid et al., 2023; Umar et al., 2022b; Corbet et al., 2020; Foglia and Angelini, 2020). Majority of studies follows the connectedness approaches and multivariate generalised autoregressive conditional heteroskedasticity (GARCH) models, but few have delved deeper into the influence factors. The connectedness of clean and dirty energy markets is shaped by a multitude of external factors, each of which influence aspects such as availability, cost, environmental impact and societal acceptance (Chen et al., 2021; Khalfaoui et al., 2022; Ding et al., 2022). Climate risks are increasingly becoming a significant factor affecting the structure and connectedness of energy financial markets (Cifuentes-Faura et al., 2024; Lorente et al., 2023). However, the asymmetric impact of climate risks on spillover among energy markets has rarely been discussed in

[*] Corresponding author

E-mail addresses: guokun@ucas.ac.cn

previous literature.

This paper aims to fill this research gap by examining the interactions between clean and dirty energy markets and closely observe how this relationship shifts with climate risks. The main contributions of this paper are threefold. First, we propose a new framework to uncover the asymmetric impact of climate risks on energy markets, where the internal and external spillovers between clean and dirty energy markets are distinguished. Second, climate physical risk (CPR) and transition risk (CTR) are considered. The relationship between climate change and energy system attracts lot of attention. Extreme weather events increasing concerns about climate change can be illustrated as physical risk (Bergquist et al., 2019; Gong and Liao, 2024). However, previous study has generally focused on the public attention to climate change, which indirectly relates to the financial markets (Aliano et al., 2023; Ding et al., 2022). Therefore, professional climate physical attention is innovatively constructed. Third, we give special importance to the different situations of climate risks and market conditions. Quantile-on-quantile regression (QQR) is employed to investigate the asymmetric effects of climate risks on connectedness between clean and dirty energy markets.

The remainder of the paper is laid out as follows. The next section is an overview of the methodology and data. The empirical results are described in Section 3. Our conclusions and police implications are presented in Section 4.

2. Methodology and Data

2.1 Methodology

2.1.1 TVP-VAR-DY Connectedness Decomposition Approach

A time-varying parameter vector autoregression (TVP-VAR) that extended the Diebold and Yilmaz (2012) model (DY) is used (Antonakakis et al., 2020). Then, spillovers within and between markets is conducted to analyse the contributions of internal and external spillovers (Gabauer and Gupta, 2018). This TVP-VAR-DY connectedness decomposition approach is exceptionally well-suited for capturing the evolving dynamics and connectedness within energy markets in two groups: clean and dirty energy markets.

$y_{i,t}$ is defined as the daily return of market *i,* considering the total vector for *k* markets $y_t = (y_{1,t}, \dots, y_{k,t})'$; hence, the TVP-VAR(p) model with y_t series satisfied is constructed:

$$y_t = \beta_t z_{t-1} + \epsilon_t \qquad \epsilon_t | \Omega_{t-1} \sim N(0, \Sigma_t) \tag{1}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + \xi_t \quad \xi_t | \Omega_{t-1} \sim N(0, \Xi_t) \tag{2}$$

$$z_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \dots \\ y_{t-p} \end{pmatrix} \qquad A_t^{'} = \begin{pmatrix} A_{1t} \\ A_{2t} \\ \dots \\ A_{pt} \end{pmatrix}$$

where Ω_{t-1} represents all known information up to period *t-1*. The model is then transformed into the VMA model:

$$y_t = \sum_{j=0}^{\infty} L' W_t^j L \epsilon_{t-j} \tag{3}$$

$$y_t = \sum_{j=0}^{\infty} A_{jt} \epsilon_{t-j} \tag{4}$$

with $L = [I_N, \dots, 0_p]'$ and $W = [\beta_t; I_{N(p-1)}, 0_{N(p-1)\times N}]$. The differences between a *J-step* ahead forecast once with variable *i* shocked and once without shocking variable *i*:

$$GIRF_t(J, \delta_{j,t}, F_{t-1}) = E(Y_{t+J} | \epsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(Y_{t+J} | F_{t-1}) \tag{5}$$

$$\psi_{j,t}^{g}(J) = \frac{A_{J,t} S_t \epsilon_{j,t}}{\sqrt{S_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{S_{jj,t}}} \quad \delta_{j,t} = \sqrt{S_{jj,t}} \tag{6}$$

$$\psi_{j,t}^{g}(J) = S_{jj,t}^{-\frac{1}{2}} A_{J,t} S_t \epsilon_{j,t} \tag{7}$$

where $\psi_{j,t}^{g}(J)$ denotes the GIRFs of variable *j* and *J* represents the forecast horizon, $\delta_{j,t}$ is the selection vector with one on the *jth* position and zero otherwise, and F_{t-1} is the information set until *t−1*. Then, the GFEVD is calculated as follows:

$$\tilde{\phi}_{ij,t}^{g}(J) = \frac{\sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}}{\sum_{j-1}^{k} \sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}} \tag{8}$$

with $\sum_{j=1}^{k} \tilde{\phi}_{ij,t}(J) = 1$ and $\sum_{i,j=1}^{k} \tilde{\phi}_{ij,t}^{g}(J) = k$.

The total connectedness index (TCI) illustrates the overall risk spillover within the network of risk spillovers constructed by all markets:

$$TCI_t^g(J) = \frac{\sum_{i,j=1,i\neq j}^{k} \tilde{\phi}_{ij,t}^{g}(J)}{\sum_{i,j=1}^{k} \tilde{\phi}_{ij,t}^{g}(J)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{k} \tilde{\phi}_{ij,t}^{g}(J)}{k} * 100 \tag{9}$$

Next, *total directional connectedness to others* (TO), *total directional connectedness from others* (FROM), *net total directional connectedness* (NET), and *net pairwise directional connectedness* (NPDC) are defined as follows:

$$TO_{i\to j,t}^{g}(J) = \frac{\sum_{j=1,i\neq j}^{k} \tilde{\phi}_{ji,t}^{g}(J)}{\sum_{j=1}^{k} \tilde{\phi}_{ji,t}^{g}(J)} * 100 \tag{10}$$

$$FROM_{i\leftarrow j,t}^{g}(J) = \frac{\sum_{j=1,i\neq j}^{k} \tilde{\phi}_{ij,t}^{g}(J)}{\sum_{j=1}^{k} \tilde{\phi}_{ij,t}^{g}(J)} * 100 \tag{11}$$

$$NET_{i,t}^{g}(J) = TO_{i\to j,t}^{g}(J) - FROM_{i\leftarrow j,t}^{g}(J) \tag{12}$$

$$NPDC_{ij}(J) = \frac{\left(\tilde{\phi}_{ji,t}^{g}(J) - \tilde{\phi}_{ij,t}^{g}(J)\right)}{T} * 100 \tag{13}$$

To discern the degree of spillover within clean and dirty energy markets, as well as to ascertain the extent of spillover from one to the other, calculations of both internal and external spillovers are undertaken. $C_{ij,t}$ represents the aggregated impact group j has on group i, where n and k represent two non-overlapping index sets. In this paper, i and j denote clean and dirty energy groups, while n and k denote the number of variables in each market group.

$$TO_{ij} = \sum_{n=1}^{m} C_{ij,nk} \tag{14}$$

$$FROM_{ij} = \sum_{n=1}^{m} C_{ji,nk} \tag{15}$$

$$NET_{ij} = TO_{ij} - FROM_{ij} \tag{16}$$

$$NI_{ij} = \sum_{n=1}^{m} \sum_{k=1}^{m} C_{ij,nk} - \sum_{n=1}^{m} \sum_{k=1}^{m} C_{ji,nk} \tag{17}$$

2.1.2 Quantile-on-Quantile Regression

QQR extends the conventional quantile regression model by integrating non-parametric techniques (Sim and Zhou, 2015; Zhou et al., 2023). A nuanced understanding of how extreme values and tail dependencies of climate risks influence the market interactions is provided by QQR. A model for the θ-quantile of spillovers as a function of climate risks (CR) is postulated as follows:

$$Spillovers_t = \beta^{\theta} CR_t + \alpha^{\theta} Spillovers_{t-1} + v_t^{\theta} \tag{18}$$

where v_t^{θ} denotes an error term that has a zero θ-quantile. Then a first-order Taylor expansion can be employed to provide an approximation of $\beta^{\theta} CR_t$:

$$\beta^{\theta} CR_t \approx \beta^{\theta} CR^{\tau} + \beta^{\theta'} CR^{\tau}(CR_t - CR^{\tau}) \tag{19}$$

Define $\beta^{\theta} CR^{\tau}$ and $\beta^{\theta'} CR^{\tau}$ as $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$:

$$\beta^{\theta} CR_t \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(CR_t - CR^{\tau}) \tag{20}$$

$$Spillovers_t = \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(CR_t - CR^{\tau}) + \alpha(\theta) Spillovers_{t-1} + v_t^{\theta} \tag{21}$$

where $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$ are the coefficients to be estimated. β_0 and β_1 are associated with θ and τ, capturing the impact of τ quantiles of CR on θ quantiles of the connectedness index.

2.2 Data

Three representative markets from clean and dirty energy markets are selected respectively, and a description of the variables collected from *investing.com* from January 4, 2012, to November 29, 2023, is show in **Table 1**. The return of each market i for time t is defined as $r_i(t) = lnP_i(t) - lnP_i(t-1)$, where $P_i(t)$ is the price of market i.

Table 1 Description of variables

Classification	Variable	Description	Symbol
Clean energy markets	Biomass market	NASDAQ OMX Bio/Clean	BIO
	Solar market	NASDAQ OMX Solar	SOLAR
	Wind market	NASDAQ OMX Wind	WIND
	Geothermal market	NASDAQ OMX Geothermal	GEO
Dirty energy markets	Crude oil market	Bloomberg WTI Crude Oil subindex	OIL

	Natural gas market	Bloomberg Natural Gas Subindex	NGS
	Gas oil market	London Gas Oil	GOL
Climate risks	Financial attention to climate change	Google search index	CPR
	Climate Policy Uncertainty	Ma et al. (2024)	CTR

Figure 1 shows the descriptive statistics of the market variables. The average returns of BIO, OIL, NGS and GOL are negative, while those of other variables are positive. In terms of climate risks, professional attention to climate physical risk (CPR) is calculated by setting the Google Search Volume Index (GSVI) keywords 'climate change' and 'global warming' under the finance category following the principles from previous studies (Swamy et al., 2019; Zhang et al., 2021). The text-based climate policy uncertainty serves as a proxy for the climate transition risk (CTR) by quantifying the uncertainty associated with climate policy (Gavriilidis, 2021; Ma et al., 2024). **Figure** illustrates the trend of climate risks, demonstrating a fluctuating increase in global climate risks over the past decade.

Table 2 Summary of descriptive statistics.

	BIO	SOLAR	WIND	GEO	OIL	NGS	GOL
Min.	-0.181958	-0.193326	-0.132826	-0.133907	-0.340820	-0.191984	-0.408425
Median	0.000365	0.000863	0.000463	0.000721	0.001026	-0.000809	0.000000
Mean	-0.000016	0.000681	0.000420	0.000117	-0.000372	-0.001077	-0.000050
Max.	0.133931	0.120513	0.091540	0.182544	0.220483	0.166447	0.139988
Skewness	-0.829474	-0.424213	-0.340559	0.383537	-1.330730	-0.170675	-1.872894
Kurtosis	10.598635	5.910636	4.597765	12.274502	24.730939	3.247940	36.458806
Standard Deviation	0.019031	0.020730	0.017220	0.017041	0.025750	0.030356	0.023382
JB test	14342.653***	4445.008***	2693.704***	18849.595***	77092.217***	1330.383***	167367.588***
ADF test	-13.286***	-13.097***	-13.627***	-13.578***	-13.544***	-13.463***	-13.877***
LM(10) test	1002.394***	730.026***	125.386***	222.053***	526.789***	299.152***	166.179***

Notes: *, ** and *** represent significance at the confidence levels of 10%, 5% and 1%, respectively.

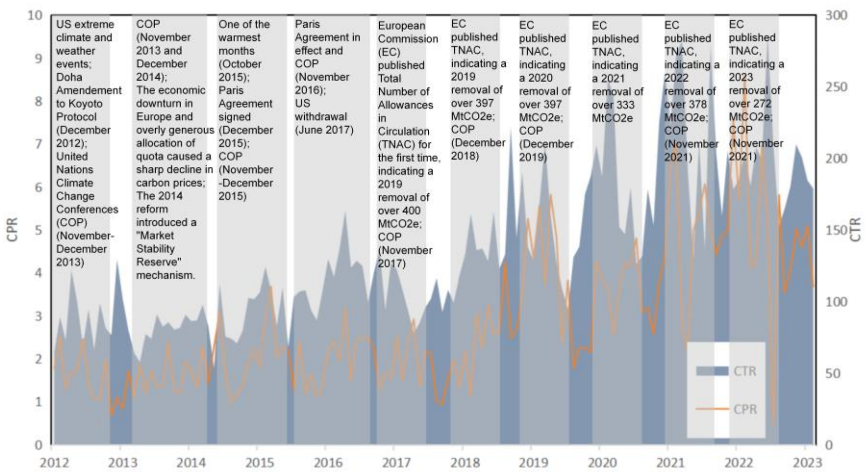

Figure 1 CPR and CTR trends averaged monthly.

3. Empirical Results

3.1 Connectedness Analyses

Table 3 reveals a total connectedness of 40.97%, an internal total connectedness of 25.28%, and an external total connectedness of 15.69%, indicating that most risk comes from the volatility spillover effects within the clean/dirty energy markets. Within the clean energy market, SOLAR has the strongest spillover effect, while OIL is dominant in dirty energy markets.

Table 3 Connectedness measures among clean and dirty energy markets.

	BIO	SOLAR	WIND	GEO	OIL	NGS	GOL	Internal FROM	External FROM	Overall FROM
BIO	55.56	11.48	7.28	7.26	9.14	2.92	6.36	26.02	18.43	44.44
SOLAR	12.14	55.28	10.77	8.45	6.17	2.70	4.49	31.37	13.35	44.72
WIND	8.60	12.87	59.37	7.41	4.84	2.47	4.45	28.88	11.75	40.63
GEO	8.76	9.46	6.88	62.69	5.20	2.77	4.24	25.10	12.22	37.31
OIL	8.58	5.53	3.66	4.03	51.78	2.49	23.94	26.42	21.80	48.22
NGS	3.82	3.76	3.59	3.04	5.14	76.00	4.66	9.80	14.21	24.00
GOL	6.49	4.64	3.60	3.32	26.58	2.79	52.57	29.38	18.06	47.43
Internal TO	29.50	33.81	24.93	23.12	31.72	5.28	28.60	176.96		
Internal NET	3.49	2.44	-3.95	-1.98	5.30	-4.52	-0.78			
External TO	18.89	13.93	10.85	10.39	25.35	10.86	19.54		109.81	
External NET	0.46	0.58	-0.90	-1.82	3.55	-3.35	1.48			
Overall TO	48.39	47.73	35.78	33.51	57.07	16.14	48.14			286.77
Overall NET	3.94	3.01	-4.85	-3.80	8.85	-7.86	0.70	Internal TCI	External TCI	Overall TCI
Inc.Own	103.94	103.01	95.15	96.20	108.85	92.14	100.70	25.28	15.69	40.97

Notes: Results are based on a TVP-VAR-DY with a lag length of order 8 (AIC) and a 10-step-ahead forecast.

The network is plotted in **Figure 2**, BIO, SOLAR and OIL act as net risk transmitters, while WIND, GEO and NGS function as net risk receivers. Notably, NGS receives net risk within the dirty energy connectedness network. OIL remains an important risk transmitter due to its strategic role in energy systems. Furthermore, the substitution of SOLAR and WIND as important clean energy sources has influenced natural gas, while renewable energy systems can serve as effective alternatives to natural gas (Ozdurak, 2021).

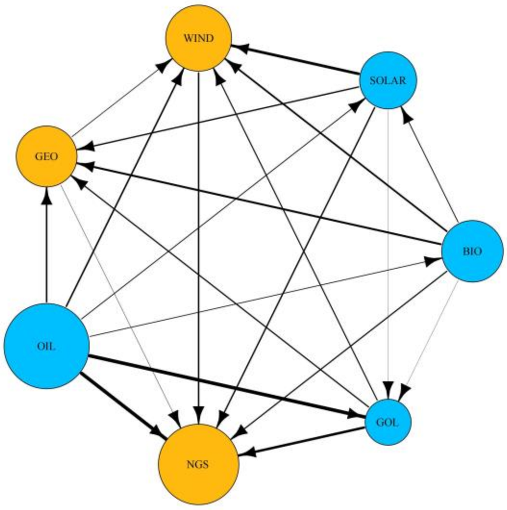

Figure 2 Network of net spillovers

As shown in **Figure 3**, the total connectedness index of clean and dirty energy markets fluctuated at around the 20%–70% range over the course of the entire sample period. The internal connectedness of clean energy markets is significantly greater than that of dirty energy markets, and exhibits higher volatility while being more sensitive to specific impact events, such as the COVID-19. The volatility of clean energy markets is attributed to their heavy reliance on technological advancements and government policies, which are susceptible to rapid alteration or disruption by external factors. In contrast, dirty energy markets, dependent on fossil fuels, exhibit greater stability due to established infrastructure and consistent consumption patterns; however, they are not impervious to external shocks. For instance, the COVID-19 pandemic precipitated a substantial decline in global oil demand as travel restrictions curtailed transportation needs. Nevertheless, this impact was relatively short-lived compared to the ongoing fluctuations observed in clean energy markets.

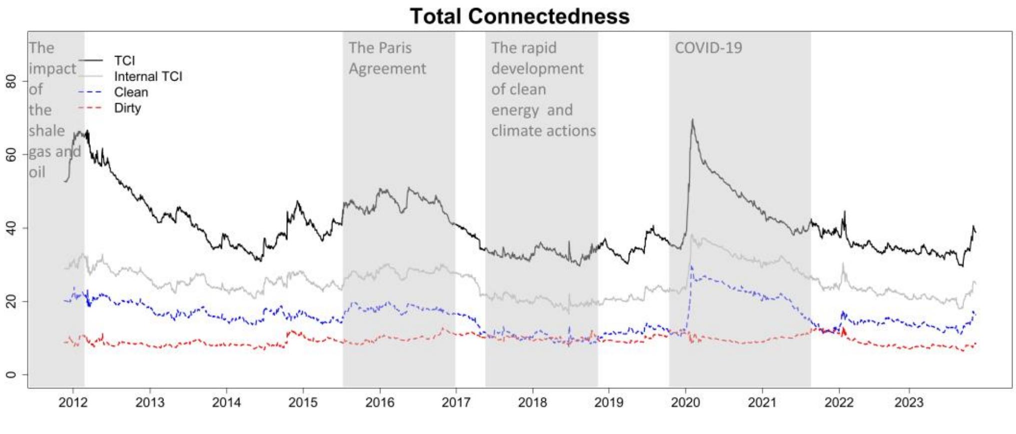

Figure 3 Dynamic total connectedness.

Figure 4 demonstrates the external net pairwise directional connectedness (NPDC). The interaction between clean and dirty energy indicates the dominance of NGS over BIO, SOLAR and GEO. OIL exhibits a dominant role in comparison to WIND. These interactions suggest that traditional fossil fuels, particularly NGS and OIL, continue to play a pivotal role in the energy market landscape. The dominance of NGS over clean energy sources underscores the ongoing reliance on natural gas as a transitional fuel in the global energy mix.

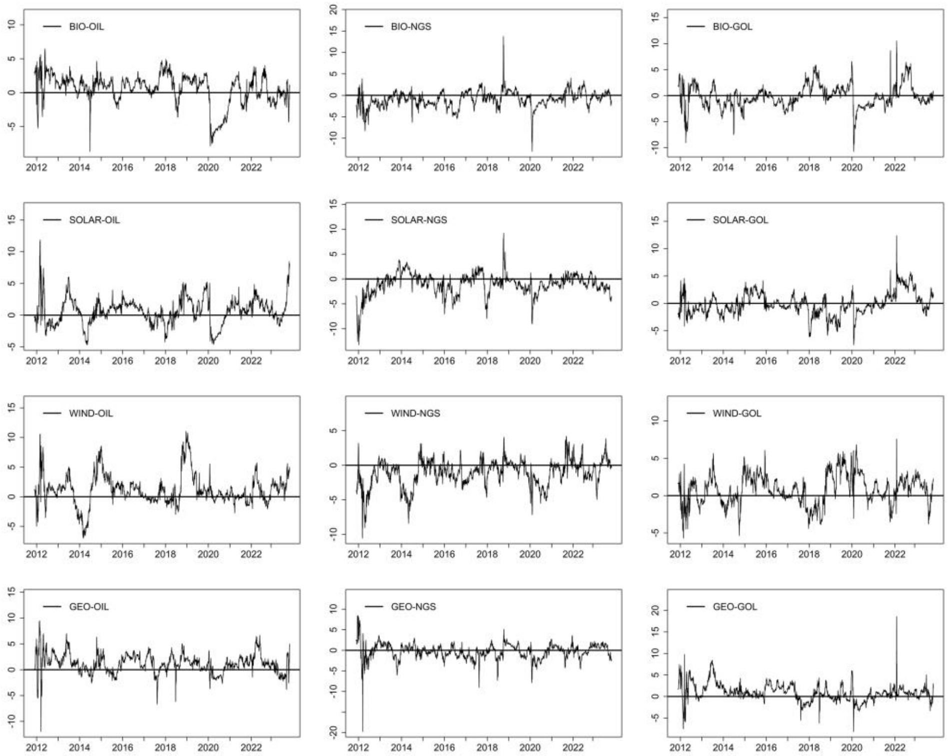

Figure 4 External net pairwise total directional connectedness.

3.2 The Impact of Climate Risks on the Connectedness

Figure 5 and **Figure 6** demonstrate the response coefficients between the climate physical and transition risks and the external connectedness, internal connectedness of clean energy market and dirty energy market respectively. The impact of CPR is significantly larger than that of CTR. As physical risks increase, connectedness in the energy market also rise. The impact of CPR on external connectedness is more pronounced than that on internal connectedness, given the considerable heterogeneity in the effects of climate physical risk on different types of clean and dirty energies. Specifically, the rise in physical risks indicates that energy infrastructure faces a higher probability of damage, which could lead to supply disruptions or increased costs, especially for fossil fuel infrastructure. It is noteworthy that when the physical risks increase significantly (at the upper quantiles of CPR), the interdependence between the clean and dirty energy markets may intensify. This interdependence can create a hedging mechanism to some extent. However, both clean and dirty energy markets still contend with their own specific risks. For instance, the awareness of physical risks by professional investors at normal quantiles may heighten the connectedness among the dirty energy markets.

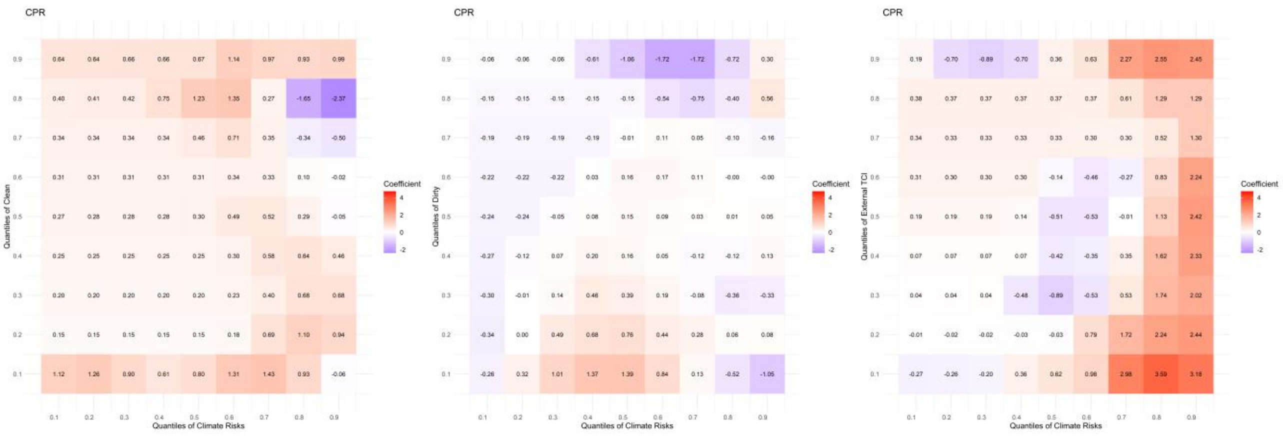

Figure 5 The impact of CPR on the connectedness under different markets conditions.

Notes: The coefficients represent the estimation of the slope $\beta_1(\theta,\tau)$ (Eq.21) which captures the impact of the τth quantile of CPR on the θth quantile of the connectedness and the colour represents the strengths of correlations.

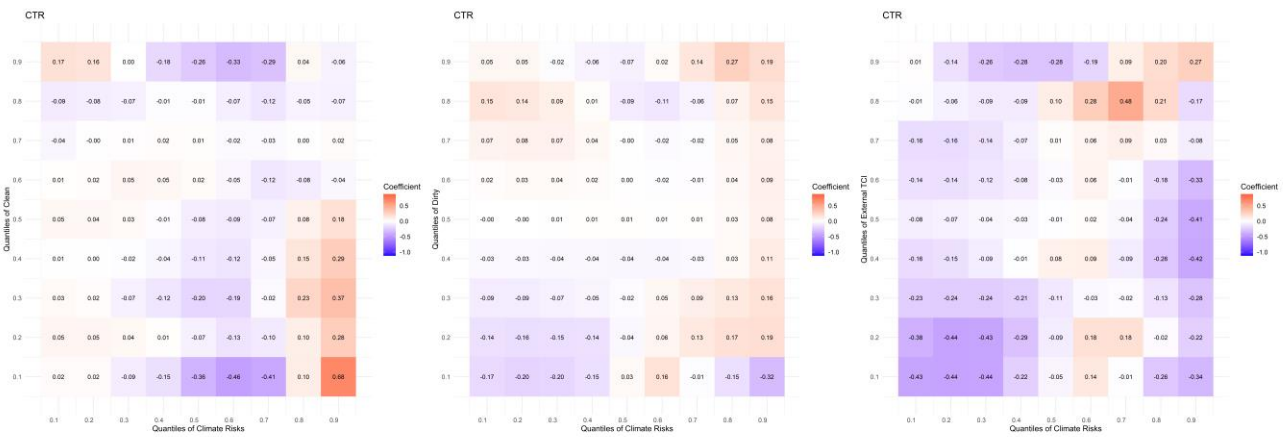

Figure 6 The impact of CTR on the connectedness under different markets conditions.

Notes: The coefficients represent the estimation of the slope $\beta_1(\theta,\tau)$ (Eq.21) which captures the impact of the τth quantile of CTR on the θth quantile of the connectedness and the colour represents the strengths of correlations.

As climate transition risks intensify, energy markets are likely to experience increased volatility in connectedness. It can be seen that the internal connectedness of clean/dirty energy markets is not significantly influenced by the CTR due to the fact that investors' assessments and expectations may vary considerably across different forms of energy under highly uncertain climate policies. With regard to external connectedness, the clean and dirty energy markets are less integrated and more independent at lower/higher climate transition risk due to significant discrepancies in market expectations among investors. However, at typical transition risk levels, the trajectory of energy transition gives rise to an uptick in investment substitution between the two markets, which is indicative of a positive impact.

4. Conclusions and Implications

This paper investigates the relationship between clean and dirty energy markets and how it evolves with changes in climate risks. The results reveal that most risks originate from volatility within the clean/dirty energy markets. SOLAR and OIL are identified as significant spillover contributors, implying that policy-makers should prioritize solar and wind power and promote energy independence. The asymmetric responses to different climate risks vary with energy portfolios and market conditions. Climate physical risk has a larger impact on energy markets than transition risk, which is more influential on external connectedness between clean and dirty energy markets.

As physical risks rise, investment risks in both clean and dirty energy markets increase. Intensified transition risks will further increase the uncertainty in the interdependence between clean and dirty energy markets. The study also indicates that while the tail risks associated with climate change are crucial, the broader spectrum of climate risks play a pivotal role in shaping the connectedness between clean and dirty energy markets. Our analysis attaches particular importance to market conditions and differences among different quantiles, contributing to the rare literature on cross-market connectedness study on clean and dirty energy markets. But this study has several limitations that could be addressed in future research. For example, we only focus on the global market, but there are geographical differences.

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