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Asymmetric tail risk spillover and co-movement between climate risk and the international energy market

David Adeabah [a], Thu Phuong Pham [b,*]

[a] School of Accounting, Economics and Finance, Curtin University, Bentley, WA 6102, Australia
[b] School of Accounting, Economics and Finance, Curtin University, Australia & IPAG Business School, France

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ABSTRACT

We investigate the tail risk spillover, co-movement, and causal effect between climate risk and international energy markets using daily data from 2010 to 2022. Employing Bua et al.'s (2022) innovative measures of climate risk and various methodologies, we discover an asymmetric spillover of tail risk from climate to energy markets, emphasizing systemic tail risk contagion in extreme market conditions. Notably, climate risk primarily transmits downside tail risk in bearish states. The dynamic, negative, time-varying correlation between climate risk and energy markets is highlighted by wavelets analysis. Our study underscores that fluctuations in climate physical and transition risks can predict energy market tail risks, revealing tail risk dependence. The results also indicate a unidirectional causality from climate risks to the energy market.

1. Introduction

Climate change imposes two principal risks on the energy market: physical and transition risks. The former emerges from disruptions to supplies and operations, such as power plants, pipelines, and offshore drilling, due to environmental events, thereby augmenting the sector's vulnerability. On the other hand, transition risks are linked to the global progression towards a low-carbon economy and the implementation of climate change mitigation policies on energy firms. These changes introduce tail risks that may affect the profitability and valuation of traditional energy firms. Notably, transition and physical risks may respond differently to climate-related events, potentially moving in opposite directions and exerting varied influences on the markets. This distinction underscores the necessity to analyze each risk independently (NGFS, 2018). Despite extensive literature emphasizing the significant role of climate risk in risk assessment and management in the energy sectors (Guo et al., 2022; Guo et al., 2023; Hoque et al., 2023; Jin et al., 2023; Ren et al., 2023; Sarker et al., 2023; Vellachami et al., 2023; Zhang et al., 2023), the co-movement between these distinct climate risk components and international energy markets remains unexplored. Our study seeks to bridge this research gap.

In our study, we investigate the tail risk spillover, connectedness, and co-movement of the two categories of climate risk - physical and transition risks, with the international energy market. The importance of this research question stems from the crucial role of these co-movements in evaluating systemic risks, financial stability, investment decisions, and progress towards sustainability. Given the inherent interconnectedness of climate risk and the global energy market (Hoque et al., 2023; Zhang et al., 2023), these interactions can pose systemic risks to the broader financial system and economy. By elucidating the mechanisms of spillover, connectedness, and co-movement between these climate risk components and the global energy market, we can discern potential channels of shock propagation, which may amplify systemic risks.

The literature suggests divergent views on whether the influence between climate risk and energy market tail risk is unidirectional or bidirectional (see, e.g., Fahmy, 2022; Yu et al., 2015). On one side, efforts to mitigate climate risk often involve investment in cleaner and renewable energy infrastructure by existing and new energy actors. Energy markets' tail risk could cause a slowdown or even impede the transition efforts, leading to prolonged use of carbon-intensive energy and emission assets for energy firms (Gu et al., 2023; van Benthem et al., 2022). Consequently, tail risk in the energy market may pose significant threats to climate mitigation efforts through constraints on the supply of financial resources; we refer to the spillover effect from energy markets' tail risk to climate risk as the '*supply-leading*' view. Conversely, a '*demand-following*' effect suggests that climate risk influences energy

* Corresponding author.
E-mail addresses: david.adeabah@postgrad.curtin.edu.au (D. Adeabah), thuphuong.pham@curtin.edu.au (T.P. Pham).

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market tail risk through mechanisms like climate policy, technological innovation, and shifting consumer preferences, affecting investor behavior and altering the risk profiles of financial assets (Ardia et al., 2022; Bolton and Kacperczyk, 2021). Therefore, the directions of the relationship between climate risk and energy market tail risk may vary depending on market conditions and time horizons, highlighting the need for empirical research to elucidate this complex dynamic.

Our study utilizes daily data spanning from July 19, 2010, to March 31, 2022, on energy markets encapsulating coal, natural gas, crude oil (i.e., WTI, Brent, OPEC Oil, Crude Oil Oman, and Crude Oil Dubai) and refined petroleum markets (i.e., Gasoline, Heating Oil, and Propane). We employ the climate risk indices developed by Bua et al. (2022), which innovatively disaggregates climate risk into physical risk index (PRI) and transition risk index (TRI). This distinction addresses critical challenges identified by the Organization for Economic Co-operation and Development (OECD) in assessing transition risks, notably the absence of standardized metrics for evaluating firms' climate risk exposure and the complexities in measuring specific climate risks (OECD, 2021). The OECD highlights the necessity of differentiating between transition and physical risks due to their divergent impacts on markets. Bua et al. (2022) offer a solution using textual analysis of 2.5 million climate risk-related news articles published by Reuters to provide a quantifiable measure of climate risks. This methodology, validated by the OECD in 2021, ensures our climate risk index is recognized and pertinent for analyzing the nuanced effects of climate risks on energy markets. The PRI accounts for financial repercussions, such as monetary losses or higher costs due to chronic and acute physical climate disasters, while the TRI quantifies the financial implications of transitioning to a low-carbon economy. This transition is typically precipitated by changes in climate policy, technological advancements, and shifts in public preference.

Our empirical strategy is designed as follows: First, we estimate tail risk at both the 5 % and 95 % Value-at-Risk (VaR) using the asymmetric slope Conditional Autoregressive Value-at-Risk (CAViaR) approach developed by Engle and Manganelli (2004). This approach has two main strengths. It pioneered integrating climate-related tail risks into spillover analysis, extending beyond previous studies (e.g., Chatziantoniou et al., 2022b), which focused on the petroleum market but did not consider climate factors. Additionally, our method directly calculates VaR, offering a more direct measure than other methods that estimate VaR indirectly by determining the return distribution and extracting quantiles. Our model also uniquely handles asymmetric effects, a feature that is impossible with symmetric absolute value or traditional GARCH (1,1) methods. The flexibility of the Asymmetric Slope CAViaR model is notable, as it incorporates VaR calculations within an autoregressive process to effectively capture diverse market dynamics.

Second, significant climate events and energy policy changes notably impact energy markets (Shen et al., 2023; Yu et al., 2015). The extreme risk spillover is crucial in analyzing the risk interactions between climate and energy market risks. Our study employs quantile connectedness techniques, using the novel approach by Ando et al. (2022), to explore these interactions at extreme quantiles. This technique assesses the intensity and direction of shocks, revealing significant co-movements between variables (Chatziantoniou et al., 2021). While Gong et al. (2023) apply this method for analyzing tail risk contagion in international energy markets from a volatility perspective, Shen et al. (2018) critique the use of volatility as a risk measure due to its inadequate response to asymmetric gains and losses in the energy market. Our approach, which applies the QVAR model from a value-at-risk perspective, is, to our knowledge, the first to do so.

Third, we adopt a dynamic rolling window wavelet correlation (RWWC) method, allowing us to explore correlations across multiple dimensions in both time and frequency domains. This method aligns with findings that the inner interactive factors of carbon and energy markets vary over time (Yu et al., 2015; Yu et al., 2008). The multi-scale analysis provided by the RWWC approach offers a thorough assessment of the connections between climate risks and energy markets' tail risks, shedding light on the underlying factors of risk transmission. This methodology has proven highly effective in various finance studies examining different time intervals (Polanco-Martínez et al., 2018; Rehman, 2020).

Lastly, we explore the projected bi-directional relationships between climate risk and energy market tail risk. Utilizing Troster's (2018) quantile Granger causality test, we investigate the causal links between shifts in climate risk and changes in energy markets' tail risks.

We find the asymmetrical nature of downside tail risk in connectedness, indicating systemic tail risk contagion during extreme market conditions. We demonstrate that in bearish (and, inversely, in bullish) market conditions, climate-related risks primarily (and minimally) transmit downside tail risk to the energy markets. Additionally, our findings show that climate-related risks are involved in the least spillover of upside-tail risk to and from the energy markets, regardless of the market state.

The insights from our Rolling Window Wavelet Correlation (RWWC) analysis reveal considerable heterogeneity in correlation across time and frequency, with negative correlations predominantly appearing in the short term. This suggests the potential utility of climate risk as a short-term hedging tool for investments in the energy sector. However, the long-term correlation is notably unstable and subject to significant fluctuations.

Furthermore, our study employs Quantile Granger Causality tests to explore the causal relationships between climate risks and market dynamics. Variations associated with physical climate risks are shown to trigger fluctuations in the energy market's tail risk. We identify a clear Granger causality from changes in both physical and transition climate risks to both downside and upside tail risks at the lowest quantiles, highlighting a dependency on extreme tail risk scenarios. This indicates that substantial adverse shocks in climate risks can lead to severe tail risks within the energy market. Moreover, our evidence points to a unidirectional causality from climate risk to the energy market, further emphasizing the impact of climate-related factors.

The contributions of this study are twofold. First, our findings enhance our understanding of the investment risks posed by both physical and transition climate risks to the stability of the energy sector. Our results reveal that climate transition risk serves as the primary net risk transmitter of downside tail risk during bearish market conditions, reinforcing the assertion that the stability of the energy sector is particularly susceptible to climate transition risk. This finding has profound implications as increased climate transition risk could obstruct global efforts towards a low carbon transition, particularly as energy security becomes jeopardized, which extends the existing literature (Jin et al., 2023; Vellachami et al., 2023). Furthermore, we reveal that the causal relationship is unidirectional, originating from climate risk and impacting energy market tail risk.

Additionally, our study contributes to the literature that examines information contagion and systemic risk between climate risk and the energy market. We extend this literature on climate financial risk in the energy sector (Ding et al., 2022; Gong et al., 2023) by analyzing how the spillover effect of climate risks changes under extreme market states. This illuminates the pathways of tail risk contagion among the considered assets, providing a context within which a pass-through from climate risk to systemic risk in the energy market occurs. In this case, prolonged economic downturn or global uncertainty amplifies the role of climate risk in propagating systemic risks in the global energy market. This finding has implications for the long-term valuation of conventional energy assets.

Second, our study highlights the co-movement between climate risks and energy market tail risks (specifically, downside to downside tail risk and upside to upside tail risk relationship), thereby revealing potential diversification strategies using climate risk indices within traditional energy market portfolios. We offer this insight from both a temporal and frequency standpoint. While the dynamic cross-correlation over time is

crucial, the frequency perspective is equally vital to cater to different investors' varied investment time horizons. Thus, we contribute to a better understanding of the dynamics and cyclical characteristics of the interdependence between climate risk and energy markets (e.g., Gu et al., 2023; Jin et al., 2023; Vellachami et al., 2023) by providing insights into the timescales of the theoretical linkages between climate risk and energy markets' tail risk. We document that the risk posed by energy markets' tail risk on climate risk is short-lived. Meanwhile, the effect of climate risk on energy markets' tail risk would last for a more extended period.

The rest of the paper is structured as follows: Section 2 presents a related literature review. Section 3 describes the data samples and the methodology employed in the study. Section 4 presents the empirical results and discussions, and Section 5 concludes.

2. Related literature

This section surveys existing research on the dynamics between climate risk and energy markets, mainly focusing on the spillover effects and the methodologies employed in quantifying these relationships. Prior research has established a basic understanding of how energy markets interact and their associations with carbon markets, mainly using low-frequency indicators like the climate risk uncertainty index for climate transition risks (Sarker et al., 2023; Liu et al., 2023), carbon market volatility (Gong et al., 2021; Ji et al., 2018; Ma et al., 2023; Naeem and Arfaoui, 2023; Wu et al., 2022; Zheng et al., 2021; Zhu et al., 2020; Zhuang et al., 2014), and physical climate disasters (Jin et al., 2023). This approach overlooks the intricacies of high-frequency climate risks and their immediate impact on energy markets.

Regarding energy market risk, the prevalent focus has been on return volatility. However, Shen et al. (2018) challenge this approach, arguing that volatility fails to effectively capture the asymmetric transmission of gains and losses in the energy market. The majority of studies, rather than directly linking climate risk with energy market risk, concentrate on the relationship with carbon markets, leaving a significant gap in the literature (Gong et al., 2021; Karkowska and Urjasz, 2023; Lovcha and Perez-Laborda, 2020; Ma et al., 2023; Mensi et al., 2021). While Gu et al. (2023), Bouri et al. (2023a) and Jin et al. (2023) have begun to bridge this gap by exploring the relationship between climate risk and geopolitical risk within energy markets, their studies do not specifically tackle tail risk spillover effects, nor do they utilize high-frequency climate risk metrics.

Our study fills these critical gaps by (1) focusing on the asymmetric spillover effect between energy market tail risk and two distinct types of climate transition and physical risks and (2) employing high-frequency climate risk metrics. This approach distinguishes our work from prior research and offers new insights into the dynamics of climate risk spillover into energy markets.

Empirical evidence on spillover effects has been mixed, attributed to differences in sample selections, econometric approaches, and risk measures. Studies like those by Gong et al. (2021) and Ma et al. (2023) find asymmetric time-varying spillovers between carbon and fossil energy markets, whereas Wu et al. (2022) document net spillover effects from fossil energy to China's regional carbon emission trading market, highlighting heterogeneity within the carbon market itself (Zhu et al., 2020).

Concerning estimation techniques, most previous studies on risk spillover effects in the international energy market have primarily relied on time-varying parameter Vector autoregression (VAR) models. However, (Shen et al., 2023; Yu et al., 2015) highlight the impact of significant climate events and policy changes on energy markets, underscoring the importance of considering extreme risk spillovers. Our study innovatively uses quantile connectedness techniques to examine the spillover between climate risk and the tail risk of energy markets, focusing on extreme quantiles. This innovative approach, utilizing Ando et al. (2022) standard quantile VAR connectedness model alongside the quantile time-frequency model proposed by Chatziantoniou et al. (2022a), enables us to be the first, to our knowledge, to apply this approach from a value-at-risk perspective, capturing spillover effects across different quantiles and time scales. The quantile time-frequency approach is consistent with evidence in the literature that the inner interactive factors of carbon and energy markets exhibit variation across time scales (Yu et al., 2015; Yu et al., 2008). In such a situation, an appropriate multi-scale analysis is helpful for comprehensively assessing the linkages between climate risks and energy markets' tail risks. Furthermore, we employ the rolling window wavelet correlation technique proposed by Polanco-Martínez et al. (2018) to assess the co-movement between climate risk and international energy markets and explore the bi-directional relationship between climate risk and energy market tail risk through the quantile Granger causality test (Troster, 2018).

By addressing these gaps, our research contributes to climate risk literature and the study of tail risk in energy markets. We offer new insights into the timescales of the linkages between climate risk and energy markets' tail risk, hence enhancing understanding of the dynamics and cyclical characteristics of their interdependence (e.g., Gu et al., 2023; Jin et al., 2023; Vellachami et al., 2023). Our findings reveal that while energy markets' tail risks pose a short-lived risk to climate risk, the influence of climate risk on energy markets' tail risk persists longer. Additionally, we extend the literature on climate financial risk in the energy sector (Ding et al., 2022; Gong et al., 2023) by analyzing how the spillover effect of climate risks changes under extreme market states, thereby providing a context within which a pass-through from climate risk to systemic risk in the energy market occurs. In this case, prolonged economic downturn or global uncertainty amplifies the role of climate risk in propagating systemic risks in the global energy market. This finding has implications for the long-term valuation of conventional energy assets.

3. Methodology and data

3.1. Methods

This paper uses several robust estimation techniques to examine the effect and dynamic correlation between climate risk on the international energy market: (1) quantile connectedness approach in both time (Ando et al., 2022; Chatziantoniou et al., 2021) and frequency domains (Chatziantoniou et al., 2022a) and (2) a rolling window wavelet correlation approach (Polanco-Martínez et al., 2018). We also examine the robustness of our results using a quantile Granger causality test based on Troster (2018).

3.1.1. Tail risk estimation with the CAViaR model

We apply the CAViaR methodology to quantify the tail risk intrinsic to the climate risk index and international energy markets. Specifically, we use the asymmetric slope CAViaR model from Engle and Manganelli (2004) for direct Value-at-Risk (VaR) calculation. This method incorporates the asymmetric effects that are overlooked by symmetric absolute value and indirect GARCH (1,1) methods. Unlike other methodologies, such as CoVAR, which indirectly estimates VaR from return distribution, the asymmetric slope CAViaR model enables more direct and flexible estimation. This flexibility stems from its unique ability to incorporate the VaR of a specific quantile into an autoregressive process. The mathematical formulation is as follows:

$$f_{\alpha,t}(\beta) = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^{+}_{t-1} + \beta_3 x^{-}_{t-1}. \quad (1)$$

In this model, $f_{\alpha,t}$ represents the VaR at the α level, specifically at 5 % and 95 %, on day t. The model constant is denoted by β_0. The weight of lagged VaR is signified by β_1. $f_{\alpha,t-1}(\beta)$ indicates lagged VaR. β_2 and β_3 are the impacts of positive and negative returns on the VaR, respectively.

Table 1
Summary statistics.

Panel A: Downside Tail Risk

	PRI	TRI	Brent	Coal	CO.Dubai	CO.Oman	Gasoline	Heating.Oil	Natural.Gas	OPEC.Oil	Propane	WTI
Mean	0.015	0.003	−0.001	−0.001	−0.002	−0.001	−0.002	−0.002	−0.001	−0.001	−0.001	−0.001
Variance	274.360***	161.067***	0.090***	1.362***	0.099***	0.103***	0.117***	0.043***	0.059***	0.044***	0.091***	0.175***
Skewness	−0.291***	−0.487***	−4.030***	−4.211***	−5.248***	−7.580***	−4.492***	−4.021***	−1.666***	−7.468***	−2.453***	−4.868***
Ex.Kurtosis	1.120***	3.638***	56.338***	80.542***	75.627***	159.850***	56.159***	38.113***	7.165***	148.965***	12.026***	59.651***
JB	198.416***	1767.227***	403,510.919***	817,015.845***	726,267.044***	3,211,972.583***	402,977.251***	189,025.240***	7778.420***	2,792,377.020***	21,017.612***	455,113.237***
ERS	−11.253***	−4.764***	−22.330***	−33.728***	−21.507***	−13.976***	−16.301***	−18.274***	−20.351***	−16.049***	−18.476***	−24.406***
Q(20)	1273.396***	1121.808***	85.089***	219.043***	23.284***	45.473***	114.301***	38.800***	17.393**	83.399***	38.093***	52.828***
Q2(20)	681.149***	606.712***	1001.496***	663.381***	30.958***	28.733***	832.934***	91.715***	340.209***	228.434***	257.551***	626.374***

Correlation matrix

	PRI	TRI	Brent	Coal	CO.Dubai	CO.Oman	Gasoline	Heating.Oil	Natural.Gas	OPEC.Oil	Propane	WTI
PRI	1.000***											
TRI	0.200***	1.000***										
Brent	−0.001	0.015	1.000***									
Coal	−0.01	−0.001	0.011	1.000***								
CO.Dubai	−0.015	−0.02	0.368***	−0.001	1.000***							
CO.Oman	−0.001	0.012	0.326***	0.002	0.504***	1.000***						
Gasoline	−0.011	0.008	0.230***	0.001	0.329***	0.270***	1.000***					
Heating.Oil	0	0.009	0.289***	0.001	0.424***	0.357***	0.364***	1.000***				
Natural.Gas	0.001	0.021	0.024**	0.004	0.002	0.034***	0.045***	0.047***	1.000***			
OPEC.Oil	0	0.011	0.278***	0.026**	0.174***	0.218***	0.125***	0.154***	0.021	1.000***		
Propane	−0.007	0.008	0.142***	0.002	0.171***	0.147***	0.168***	0.171***	0.050***	0.107***	1.000***	
WTI	−0.014	−0.012	0.339***	0	0.501***	0.444***	0.315***	0.400***	0.043***	0.152***	0.174***	1.000***

Panel B: Upside Tail Risk

	PRI	TRI	Brent	Coal	CO.Dubai	CO.Oman	Gasoline	Heating.Oil	Natural.Gas	OPEC.Oil	Propane	WTI
Mean	0.015	0.003	0.002	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.001
Variance	274.360***	161.067***	0.177***	0.205***	0.049***	0.110***	0.197***	0.099***	0.053***	0.110***	0.367***	0.202***
Skewness	−0.291***	−0.487***	3.664***	8.162***	5.490***	7.235***	3.357***	2.271***	1.816***	8.268***	2.743***	4.803***
Ex.Kurtosis	1.120***	3.638***	52.299***	146.498***	78.640***	150.883***	39.594***	14.625***	8.027***	167.679***	15.805***	58.128***
JB	198.416***	1767.227***	347,451.741***	2,706,961.338***	785,465.002***	2,862,298.043***	200,922.612***	29,219.640***	9670.990***	3,536,890.629***	34,869.893***	432,446.432***
ERS	−11.253***	−4.764***	−24.064***	−28.922***	−21.490***	−17.357***	−16.682***	−7.937***	−23.236***	−24.677***	−27.353***	−26.418***
Q(20)	1273.396***	1121.808***	70.163***	155.006***	27.296***	59.637***	109.063***	46.763***	13.984	95.838***	42.913***	54.384***
Q2(20)	681.149***	606.712***	1093.345***	90.121***	31.584***	28.855***	1077.464***	531.188***	303.148***	223.200***	212.650***	579.011***

Correlation matrix

	PRI	TRI	Brent	Coal	CO.Dubai	CO.Oman	Gasoline	Heating.Oil	Natural.Gas	OPEC.Oil	Propane	WTI
PRI	1.000***											
TRI	0.200***	1.000***										
Brent	−0.005	−0.016	1.000***									
Coal	0.011	−0.007	0.033***	1.000***								
CO.Dubai	0.014	0.018	0.374***	0.014	1.000***							
CO.Oman	−0.005	−0.017	0.376***	0.016	0.519***	1.000***						
Gasoline	0.013	−0.008	0.181***	0.016	0.293***	0.224***	1.000***					
Heating.Oil	0.002	−0.002	0.152***	0.025**	0.310***	0.216***	0.336***	1.000***				
Natural.Gas	0	−0.022	0.016	0.014	0.002	0.030**	0.044***	0.044***	1.000***			
OPEC.Oil	−0.005	−0.01	0.361***	0.047***	0.209***	0.301***	0.119***	0.108***	0.019	1.000***		
Propane	0.007	−0.008	0.168***	0.01	0.190***	0.195***	0.169***	0.163***	0.051***	0.123***	1.000***	
WTI	0.013	0.011	0.351***	0.014	0.507***	0.460***	0.284***	0.286***	0.039***	0.194***	0.212***	1.000***

Note: This table presents the summary statistics of the downside and upside tail risk series at the 5 % and 95 % VaR using the CAViaR approach. Skewness: the D'Agostino (1970) test; Kurtosis: the Anscombe and Glynn (1983) test; JB: the Jarque and Bera (1980) normality test; and ERS: the Elliott et al. (1996) unit-root test.; ***,**,* denote significance at the 1 %, 5 % and 10 % significance levels. PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal.

3.1.2. Static quantile connectedness approach

Following Ando et al. (2022) and Chatziantoniou et al. (2021), we apply the quantile connectedness approach to investigate the tail risk spillover mechanism between the climate risk index and international energy markets. We chose this method for its superior capabilities over the mean-based VAR models developed by Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014). The traditional models don't account for influences across the conditional distribution and, thus, are unable to capture the implications of exceptional occurrences over various quantiles effectively. Contrarily, our method offers a more comprehensive view. It enables us to assess the magnitude of a shock, whether it is positive (representing a high quantile) or negative (indicating a low quantile), and evaluate the presence of significant co-movement among variables, as indicated by Chatziantoniou et al. (2021). Our investigation initiates with the computation of the quantile vector autoregression QVAR(p) to measure connectedness as follows:

$$y_t = \mu(\tau) + \sum_{j=1}^{p} \Phi_j(\tau) y_{t-j} + u_t(\tau) \tag{2}$$

where y_t and y_{t-j} are vectors of $k \times 1$ design matrix of the variables in the first difference, τ ranges from 0.05 to 0.95 and represents the conditional distribution of the variables. The QVAR model is implemented with a lag length of p. $\mu(\tau)$ is a $k \times 1$ vector of conditional mean, while $\Phi_j(\tau)$ refers to a $k \times k$ design matrix of the QVAR coefficient. The component $u_t(\tau)$ symbolizes the $k \times 1$vector of residual error, with a $k \times k$ design matrix of variance-covariance, $\Sigma(\tau)$. By invoking Wold's theorem, we transform $QVAR(p)$ into its $QVMA(\infty)$ representation, as follows:

$$y_t = \mu(\tau) + \sum_{j=1}^{p} \Phi_j(\tau)\, y_{t-1} + u_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} \psi_i(\tau)\, u_{t-1} \tag{3}$$

To estimate the shock effect of variable j on variable i, we adopt H-step forward Generalized Forecast Error Variance Decomposition (GFEVD) following Pesaran and Shin (1998) and Koop et al. (1996):

$$\psi_{ij}^{g}(H) = \frac{\sum(\tau)_{ij}^{-1} \sum_{h=0}^{H-1} \left(e_i' \psi_h(\tau) \sum(\tau) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \psi_h(\tau) \sum(\tau) \psi_h(\tau)' e_j\right)} \tag{4}$$

$$\widetilde{\psi}_{ij}^{g}(H) = \frac{\psi_{ij}^{g}(H)}{\sum_{j=1}^{k} \phi_{ij}^{g}(H)} \tag{5}$$

The tail risk spillover to others (TO), spillover from others (FROM), net directional spillover (NET), and adjusted total connectedness index (TCI) are estimated using the following equations:

$$TO = C_{i \to j}^{g}(H) = \sum_{i,j=1, i \neq j}^{k} \widetilde{\psi}_{ji}^{g}(H) \tag{6}$$

$$FROM = C_{i \leftarrow j}^{g}(H) = \sum_{i,j=1, i \neq j}^{k} \widetilde{\psi}_{ij}^{g}(H) \tag{7}$$

$$NET = C_{i}^{g}(H) = C_{i \to j}^{g}(H) - C_{i \leftarrow j}^{g}(H) \tag{8}$$

$$TCI(H) = \frac{\sum_{i,j=1, i \neq j}^{k} \widetilde{\psi}_{ij}^{g}(H)}{k-1} \tag{9}$$

3.1.3. Rolling window wavelet correlation (RWWC)

Following the Rolling Window Wavelet Correlation (RWWC) approach proposed by Polanco-Martínez et al. (2018), we compute the Maximal overlap discrete wavelet transform (MODWT) wavelet correlation. This allows us to examine the impact of the climate risk index on international petroleum market tail risk at varying periods and across diverse investment horizons. The equitable wavelet correlation for scale λ_j between two time series X and Y is presented as follows:

$$\widetilde{\rho}_{XY} = \frac{cov(\widetilde{W}_{Y,jt}, \widetilde{W}_{Y,jt})}{\sqrt{var\{\widetilde{W}_{X,jt}\} var\{\widetilde{W}_{X,jt}\}}} = \frac{\widetilde{\gamma}_{XY}(\lambda_j)}{\widetilde{\sigma}_{X}^{2}(\lambda_j) \widetilde{\sigma}_{Y}^{2}(\lambda_j)} \tag{10}$$

In the preceding expression, $\widetilde{\gamma}_{XY}(\lambda_j)$ signifies the equitable approximator of wavelet covariance between market coefficient $\widetilde{W}_{Y,jt}$ and $\widetilde{W}_{Y,jt}$, whereas $\widetilde{\sigma}_{X}^{2}(\lambda_j)$ and $\widetilde{\sigma}_{Y}^{2}(\lambda_j)$ are the unbiased estimators of wavelet variances X and Y, respectively, associated with the scale λ_j. The definition of MODWT is given as follows:

$$\widetilde{\sigma}_{X}^{2}(\lambda_j) = \frac{1}{\widetilde{N}_j} \sum_{t=L_{j-1}}^{N-1} \widetilde{W}_{j,t}^{2} \tag{11}$$

where $\widetilde{W}_{j,t}^{2}$ signifies j th scale of MODWT coefficient for $X, L_j = (2j-1)(L-1)+1$ signifies length of scale λ_j. Following Daubechies (1992), we construct a confidence interval of $100(1-2p)\%$ for wavelet coherence. The formula for the $100(1-2p)\%$ confidence interval is as follows: by $tanh\{h[\widetilde{\rho}_{XY}(\lambda_j)] \varnothing^{-1}(i-p)/\sqrt{N_j - 3}\}$. In this expression, $\varnothing^{-1}(p)$ represents $100p\%$ points for the standard normal distribution and $h(\widetilde{\rho}_{XY}) = tanh^{-1}(\widetilde{\rho}_{XY})$ denotes the Fisher Z-transformation (Daubechies, 1992; Gençay et al., 2001). In our analysis, we set two decomposition levels (j=2) and a 22-day rolling window per month, moving one data point at a time and centering around a specific time.

3.2. Data, sample, and descriptive statistics

Our research analyzes daily data from July 19, 2010, to March 31, 2022, drawn from five crude oil markets and three refined petroleum markets. Additionally, we include data on natural gas and coal due to their association with high carbon emissions. The crude oil markets under study include WTI, Brent, OPEC Oil, Crude Oil Oman, and Crude Oil Dubai, while the refined petroleum products considered are Gasoline, Heating Oil, and Propane. We extracted all daily data for these selected energy markets from Datastream.

The daily data for climate-related risk – physical risk index (PRI) and transition risk index (TRI) – are downloaded from Bua et al. (2022). Bua et al. (2022) developed these indices by analyzing approximately 2.5 million climate risk-related news articles published by Reuters. The PRI measures potential monetary losses or increased costs stemming from both chronic and sudden physical climate disasters. On the other hand, the TRI gauges the financial implications of transitioning to a low-carbon economy. This transition is often triggered by changes in climate policy, technological advancements, or shifts in public preference. Recent studies have highlighted the significant predictive power of these indices in assessing climate risk (Cepni et al., 2023; Cepni et al., 2022; Goodell et al., 2023; Karmakar et al., 2023).

Table 1 presents the descriptive statistics on climate and energy market tail risks. Panel A shows the downside tail risk statistics, and Panel B reports on the upside tail risk statistics. We measure the upside risk (95 % CAViaR) and downside tail risk (5 % CAViaR) by employing the method established by Engle and Manganelli (2004).

Panel A reveals that the mean downside tail risk changes for all energy markets are negative. Conversely, the mean downside tail risk changes for climate-related risks – such as PRI and TRI – are positive. Moreover, all series display characteristics of left skewness, leptokurtosis, and non-normal distribution at the 1 % significance level. Importantly, all series are stationary at the 1 % significance level, indicating that all necessary test statistics for the quantile VAR model estimation have been met, as suggested by Stock's (1996) unit root test statistics. We also find that all unconditional correlations between the energy markets are positive. Interestingly, the unconditional correlation between TRI and energy markets is mostly positive, except for Coal, Crude Oil Dubai, and WTI. Similarly, the unconditional correlation between PRI and crude oil is negative, while its correlation with Natural

Table 2
Static connectedness results of downside-tail risk.

PANEL A: 50TH QUANTILE (NORNAL MARKET STATE)

	PRI	TRI	Brent	Coal	CO.Dubai	CO.Oman	Gasoline	Heating.Oil	Natural.Gas	OPEC.Oil	Propane	WTI	FROM others
PRI	77.41	9.88	0.97	2.22	1.39	0.83	1.47	1.23	1.09	0.8	1.35	1.36	22.59
TRI	10.62	79.14	0.91	1.68	1.2	1.01	0.92	1.01	0.59	1	0.86	1.06	20.86
Brent	0.21	0.28	36.7	0.44	11.78	12.85	5.78	8.54	0.42	8.82	2.99	11.2	63.3
Coal	0.92	0.72	0.83	91.95	0.72	0.55	0.66	0.76	0.76	0.92	0.42	0.8	8.05
CO.Dubai	0.43	0.23	9.83	0.25	30.46	16.57	8.23	11.21	0.32	4.84	2.77	14.87	69.54
CO.Oman	0.19	0.19	11.02	0.21	16.93	30.03	7.14	10.39	0.39	6.13	2.81	14.57	69.97
Gasoline	0.57	0.31	6.61	0.34	10.98	9.59	43.51	11.32	0.76	2.79	3.31	9.9	56.49
Heating.Oil	0.29	0.24	7.96	0.4	12.83	11.78	9.75	35.62	0.61	3.66	3.09	13.77	64.38
Natural.Gas	0.91	0.83	1.47	1.34	1.48	1.67	1.63	1.86	83.38	1.53	2.28	1.62	16.62
OPEC.Oil	0.36	0.35	10.61	0.58	12.05	12.6	5.89	8.58	0.7	35.43	3.21	9.62	64.57
Propane	0.61	0.45	4.83	0.44	5.06	5.11	4.59	5.19	1.2	3.35	63.37	5.8	36.63
WTI	0.31	0.19	9.67	0.3	15.28	14.8	7.81	12.45	0.47	3.86	3.25	31.61	68.39
TO others	15.42	13.67	64.71	8.21	89.69	87.37	53.86	72.53	7.32	37.7	26.32	84.57	561.38
NET	−7.16	−7.2	1.41	0.17	20.15	17.4	−2.63	8.15	−9.3	−26.87	−10.3	16.18	TCI = 46.78

PANEL B: 5TH QUANTILE (BEARISH MARKET STATE)

	PRI	TRI	Brent	Coal	CO.Dubai	CO.Oman	Gasoline	Heating.Oil	Natural.Gas	OPEC.Oil	Propane	WTI	FROM others
PRI	10.16	8.14	8.99	6.91	8.13	8.55	8.19	8.36	8.3	7.41	8.18	8.66	89.84
TRI	8.29	9.97	8.6	7.01	8.24	8.51	8.34	8.49	8.29	7.4	8.17	8.68	90.03
Brent	7.3	7.16	10.21	6.56	8.68	9.05	8.51	9.38	7.89	7.95	8.31	9.01	89.79
Coal	7.42	7.19	8.8	9.72	8.19	8.57	8.49	8.72	8.09	7.71	8.31	8.79	90.28
CO.Dubai	7.17	7.09	9.06	6.8	9.48	9.05	8.79	9.05	8.02	7.82	8.4	9.26	90.52
CO.Oman	7.37	7.1	9.35	6.73	8.77	9.64	8.56	9.16	8.01	7.84	8.27	9.18	90.36
Gasoline	7.17	7.04	9.21	6.83	8.58	8.94	9.72	9.13	7.97	7.79	8.42	9.2	90.28
Heating.Oil	7.16	6.99	8.97	6.72	8.72	8.85	8.66	10.46	7.87	7.89	8.37	9.33	89.54
Natural.Gas	7.45	7.21	9.03	6.94	8.38	8.67	8.47	8.88	9.78	7.74	8.48	8.97	90.22
OPEC.Oil	7.27	7.04	9.29	6.66	8.74	9.12	8.59	9.5	7.82	8.58	8.29	9.11	91.42
Propane	7.21	7.2	8.9	6.97	8.44	8.67	8.39	8.94	8.15	7.89	10.34	8.88	89.66
WTI	7.35	7.15	9.22	6.72	8.71	9.05	8.57	9.34	8.05	7.75	8.26	9.84	90.16
TO others	81.16	79.32	99.44	74.84	93.59	97.02	93.57	98.94	88.47	85.19	91.45	99.09	1082.09
NET	−8.67	−10.71	9.65	−15.44	3.07	6.66	3.3	9.4	−1.75	−6.23	1.79	8.93	TCI = 90.17

PANEL C: 95TH QUANTILE (BULLISH MARKET STATE)

	PRI	TRI	Brent	Coal	CO.Dubai	CO.Oman	Gasoline	Heating.Oil	Natural.Gas	OPEC.Oil	Propane	WTI	FROM others
PRI	19.85	11.67	6.41	7.09	6.45	5.61	7.15	6.7	8.1	7.19	7.24	6.54	80.15
TRI	12.2	19.73	6.47	7.06	6.39	5.72	7.32	6.78	7.8	7.29	6.91	6.34	80.27
Brent	5.8	5.69	17.21	4.5	9.83	9.77	7.63	8.85	5.12	9.45	6.45	9.7	82.79
Coal	8.54	8.3	6.36	22.22	6.57	5.87	6.8	7.01	7.63	7.45	6.73	6.54	77.78
CO.Dubai	5.37	5.37	9.11	4.26	15.92	11.33	8.74	10.02	4.76	7.67	6.37	11.08	84.08
CO.Oman	4.95	5.02	9.47	3.97	11.83	16.72	8.2	9.76	4.7	8.12	6.1	11.16	83.28
Gasoline	6.13	6.45	7.72	4.85	9.49	8.54	17.3	10.01	6.13	7.01	7.06	9.31	82.7
Heating.Oil	5.73	5.63	8.4	4.65	10.3	9.57	9.44	16.31	5.45	7.19	6.61	10.71	83.69
Natural.Gas	8.62	8.59	6.28	6.8	6.32	5.98	7.36	7.18	20.94	7.4	7.59	6.93	79.06
OPEC.Oil	6.73	6.75	9.75	5.67	8.54	8.67	7.22	7.87	6.2	17.49	7.03	8.08	82.51
Propane	7.28	7.11	7.33	5.43	7.72	7.09	7.81	7.89	7.06	7.63	19.68	7.99	80.32
WTI	5.52	5.38	8.99	4.32	11.09	10.67	8.64	10.49	5.22	7.22	6.57	15.88	84.12
TO others	76.88	75.95	86.29	58.6	94.51	88.82	86.32	92.56	68.18	83.62	74.66	94.38	980.78
NET	−3.27	−4.32	3.5	−19.19	10.43	5.54	3.61	8.87	−10.89	1.12	−5.66	10.26	TCI = 81.73

Notes: This table reports the directional spillover in percentage (%). Results are based on a GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 1 (BIC). The second-last row (TO others) in Table 2 reports the contribution of each variable to other variables. The last column of Table 2 (under "FROM others") reports the downside tail risk spillover that each variable experiences from the entire system. The row labeled "NET" classifies assets as either net risk receivers or transmitters based on their negative or positive values. PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. TCI = Total Connectedness Index

Gas is negative, and 0 for Heating Oil and OPEC Oil.

Panel B reveals that all mean upside-tail risk changes for the energy markets are positive, in contrast to the negative upside-tail risk changes for climate-related risks. Like Panel A, this series also shows a tendency for right-skewness, leptokurtosis, and a non-normal distribution at the 1 % significance level. Once again, the requirements for estimating the quantile VAR model have been satisfied and align with the unit root test statistics proposed by Stock's (1996). We also observe a consistent positive correlation among the energy markets for the upside tail changes, mirroring the trend of downside tail risk changes. In the case of PRI, we note a negative unconditional correlation with crude oil but a positive one with refined petroleum products. Additionally, except for Crude Oil Dubai and WTI, TRI negatively correlates with all series.

4. Empirical results and discussion

4.1. Quantile connectedness results

4.1.1. Static downside and upside-tail risk connectedness results

Table 2 provides a detailed analysis of the static downside tail risk

connectedness between climate risk and energy markets. The results show risk spillovers across different market states: the middle (50th quantile), left tail (5th quantile), and right tail (95th quantile) of the distribution. The rolling-window QVAR model is based on 200 trading days with a lag length of order 1 (BIC) and 20 steps ahead of forecast horizons. Following Urom et al. (2020), we define the extreme 5th and 95th quantiles as bear and bull market states, respectively, while the 50th quantile represents the normal market state. Specifically, the values in Table 2, Panel A, capture the connectedness in the mid-quantile; Panels B and C detail the connectedness at the extreme 5th and 95th quantiles, respectively.

The results show that the climate risk indices contribute the most to their own variance share spillovers across mid-quantile, left-tail, and right-tail states. Transition risk (TRI) records the highest own variance share at 79.14 % in the mid-quantile, with Heating Oil and Coal leading in the left and right tails at 10.46 % and 22.22 %, respectively. This highlights the unique response mechanisms of each asset to varying market conditions. The Total Connectedness Index (TCI) shows a low downside tail risk connectedness under normal conditions (46.78 %), which increases significantly during bear (90.17 %) and bull (81.73 %) markets, suggesting pronounced systemic downside tail risk contagion during extreme states. Prior research shows asymmetry in volatility spillover between the carbon and energy markets (Gong et al., 2021; Ma et al., 2023). Our findings build upon and extend this concept by illustrating that the spillover effect between the energy market's downside tail risk and climate risk also exhibits asymmetric characteristics.

Table 2 also indicates that the directional spillovers between climate-related risks and energy markets' downside tail risks are minimal during normal market conditions. Specifically, as shown in Panel A, the impacts of climate physical and transition risks on the energy markets' downside tail risks are less than 1 %, while the effects from energy market tail risks on climate risks are generally less than 2 %, with the notable exception of the coal market. However, the magnitude of these spillovers intensifies significantly during extreme market conditions. Specifically, during bearish states, the spillover effects from climate physical and transition risks escalate dramatically, reaching peak impacts of 7.45 % and 7.21 %, respectively. Similarly, the impact of energy market tail risks on climate risks reaches a peak of 8.99 % from Brent. In the bullish market, the spillover effect from climate risks peaks substantially, reaching 8.62 % and 8.54 % for the Coal and Natural Gas markets' tail risks, respectively.

Conversely, climate physical risk exerts the lowest impact on Crude Oil Oman, with a recorded effect of only 4.95 %. Notably, there is a significant reduction in the magnitude of the spillover effect from climate risks to energy markets when transitioning from bearish to bullish market states. Similarly, the spillover effect of energy markets' tail risks on climate risks also diminishes, except for Natural Gas, where the impact remains consistently high across both extreme market states. This observation underscores the variable influence of different energy sectors on climate risks, highlighting specific vulnerabilities and resilience in response to market conditions.

Overall, these results suggest that climate risk and downside tail risk in the international energy market contribute a small share of the forecast error variance of each other during normal and extreme market states, thereby suggesting a weak connectedness between them. Our findings corroborate the conclusion by Jin et al. (2023) that there is no significant risk spillover from the energy market to climate risk in the time domain. In another related study, Gu et al. (2023) evidenced that increased climate-related risk is associated with increased energy market risk. Our results demonstrate that climate risk does not significantly affect energy markets' downside tail risk in the time domain. This result highlights the importance of a multi-scale analysis to comprehensively understand the dynamics in the risk propagation mechanism between climate risk and energy markets' tail risks.

To understand the contribution of each variable to the system, we refer to the second-last row (TO) in Table 2. In normal market states, the highest downside tail risk spillover stems from Crude Oil Dubai (89.69 %), while the lowest comes from Coal and Natural Gas at 8.21 % and 7.32 %, respectively. In bear market states, Brent (99.44 %) and WTI (99.09 %) are the most prominent transmitters of downside tail risk in the system, whereas Coal (74.84 %) is the least transmitter. On the other hand, during bullish market states, Crude Oil Dubai (94.51 %) again contributes the most, while Coal (58.6 %) and Natural Gas (68.18 %) contribute the least to downside risk spillover in the system.

In the subsequent analysis, we delve into the downside tail risk spillover that each variable experiences from the entire system, as displayed in the last column of Table 2 (under "FROM"). During normal market conditions, Crude Oil Dubai (69.54 %), Crude Oil Oman (69.97 %), and WTI (68.39 %) are the primary recipients of downside tail risk spillover, while Coal (8.05 %) and Natural Gas (16.62 %) receive the least.

Similarly, in a bear market, the major recipients are OPEC Oil (91.42 %), Crude Oil Dubai (90.52 %), and Crude Oil Oman (90.36 %). In contrast, Heating Oil receives the least downside risk spillover. When the market is bullish, Crude Oil Dubai (84.08 %), WTI (84.12 %), and Heating Oil (83.69 %) again emerge as the primary recipients of downside risk spillover, while Coal and Natural Gas remain the least recipients.

The row labeled "NET" categorizes assets as either net risk receivers or transmitters, depending on whether their values are negative or positive, respectively. The net spillover analysis indicates that crude oil and refined petroleum markets predominantly transmit downside tail risk spillover across all market states. Conversely, OPEC oil emerges as the least significant net contributor to the energy market downside tail risk from the crude oil sector. This finding aligns with existing research on energy market volatility spillovers (Mensi et al., 2021). Natural gas acts as a net receiver of energy market tail risk in all market conditions, which diverges from the findings of Mensi et al. (2021) and Lovcha and Perez-Laborda (2020), who identify natural gas as a net contributor of risk spillover effects to other energy markets during extreme events. The analysis shows that climate risks are net receivers of tail risk spillover from the international energy market across all states in the time domain. The spillover effect is minimal but the result suggests that energy markets' tail risk is a potential source of the risk of the "waterbed effect" in efforts geared towards cleaner energy sources (Böhringer and Rosendahl, 2022). In summary, the primary sources of downside tail risk are crude oil (WTI, Crude Oil Dubai, and Crude Oil Oman) and refined petroleum products during normal and extreme market states, respectively.

Table 3 reports the results of the static upside-tail risk connectedness. We find that the directional spillover between climate-related risks and energy market upside tail risk is minimal during normal market states; specifically, the impact of climate-related risk on energy market tail risk is less than 1 %, except for the coal market, which receives a 1.05 % spillover effect from climate physical risk. Similarly, the spillover effect from the energy market's upside-tail risk to climate risk is also less than 2 %, except for climate physical risk, which receives a 2.03 % spillover from the coal market. These findings align with the patterns observed in the downside tail risks reported in Table 2. Additionally, the results indicate a consistent increase in the magnitude of the spillover effects from climate physical and transition risks to the upside-tail risk of the international energy market. However, the spillover effect from the energy market's upside-tail risk to climate risks is marginally greater than that from climate-related risks. This suggests a weak connectedness between climate risks (both physical and transition) and the international energy market under normal market conditions, which notably strengthens during extreme market states. This pattern underscores the variable influence of market states on the interplay between climate and energy market risks.

The analysis of the on-diagonal elements reveals that Coal and Natural Gas exhibit the highest own variance shocks, recorded at 89.8 % and 93.33 %, respectively, during the mid-quantile or normal market

Table 3
Static connectedness results of upside-tail risk.

PANEL A: 50TH QUANTILE (NORNAL MARKET STATE)													
	PRI	TRI	Brent	Coal	CO.Dubai	CO.Oman	Gasoline	Heating.Oil	Natural.Gas	OPEC.Oil	Propane	WTI	FROM others
PRI	77.75	9.68	1.01	2.03	1.42	0.82	1.41	1.44	1.1	0.66	1.32	1.37	22.25
TRI	10.43	78.82	1.04	1.62	1.35	1.12	0.83	1.32	0.61	0.8	1.06	1.02	21.18
Brent	0.21	0.23	36.23	0.66	12.99	13.71	4.27	3.13	0.34	12.44	3.84	11.96	63.77
Coal	1.05	0.77	1.19	**89.8**	1.13	0.95	0.78	0.95	0.77	1.17	0.39	1.06	10.2
CO.Dubai	0.32	0.2	10.9	0.4	31.26	17.56	7.06	5.82	0.3	6.76	3.64	15.77	68.74
CO.Oman	0.19	0.17	11.96	0.36	17.9	30.48	5.82	4.58	0.35	9.14	4.03	15.01	69.52
Gasoline	0.64	0.36	5.5	0.5	10.17	8.48	47.11	10.03	0.82	3.5	3.8	9.1	52.89
Heating.Oil	0.51	0.41	4.6	0.79	9.3	7.38	10.84	49.38	0.96	2.74	3.4	9.71	50.62
Natural.Gas	0.92	0.8	1.39	1.47	1.57	1.64	1.53	1.92	**83.33**	1.57	2.25	1.6	16.67
OPEC.Oil	0.23	0.27	13.97	0.67	13.4	16.15	4.44	3.33	0.44	31.53	3.7	11.87	68.47
Propane	0.54	0.35	5.53	0.42	6.13	6.63	4.32	3.63	1.1	3.72	60.74	6.89	39.26
WTI	0.3	0.18	10.59	0.53	16.37	15.38	6.82	6.38	0.46	5.89	4.31	32.77	67.23
TO others	15.33	13.42	67.69	9.44	91.74	89.8	48.1	42.53	7.25	48.4	31.74	85.36	550.81
NET	−6.91	−7.76	3.92	−0.76	23	20.28	−4.78	−8.09	−9.42	−20.07	−7.52	18.13	TCI = 45.90

PANEL B: 5TH QUANTILE (BEARISH MARKET STATE)													
	PRI	TRI	Brent	Coal	CO.Dubai	CO.Oman	Gasoline	Heating.Oil	Natural.Gas	OPEC.Oil	Propane	WTI	FROM others
PRI	19.62	12.08	5.77	6.74	6.09	5.75	7.63	7.92	7.84	6.51	7.55	6.5	80.38
TRI	10.94	19.54	6.18	6.97	6.27	5.78	7.21	7.95	7.71	6.81	7.74	6.88	80.46
Brent	5.45	5.9	17.47	4.36	9.96	10.12	7.33	7.07	4.94	10.47	7.03	9.91	82.53
Coal	8.28	8.44	6.02	23.67	5.96	5.77	7	7.54	7.15	6.9	6.84	6.44	76.33
CO.Dubai	5.3	5.32	9.39	3.94	16.39	11.84	8.49	8.37	4.52	8.03	6.93	11.49	83.61
CO.Oman	5.02	5.18	9.67	3.86	12.04	16.73	7.92	7.64	4.63	9.03	6.94	11.34	83.27
Gasoline	7.01	6.6	7.23	5.01	8.87	8.18	16.99	9.98	6.36	6.96	7.72	9.1	83.01
Heating.Oil	7	7.11	6.91	5.26	8.76	7.86	9.99	17.23	6.43	6.79	7.43	9.22	82.77
Natural.Gas	8.74	8.64	5.95	6.32	5.93	5.98	7.81	8.09	21.31	6.8	7.67	6.77	78.69
OPEC.Oil	6.2	6.55	10.55	5.03	8.7	9.66	7.2	7.15	5.67	17.55	7.08	8.65	82.45
Propane	7.35	7.36	7.42	5.05	7.8	7.68	8.18	8.02	6.81	7.37	18.59	8.37	81.41
WTI	5.62	5.8	9.11	4.14	11.23	10.9	8.5	8.62	5.1	7.68	7.29	16.03	83.97
TO others	76.9	78.97	84.19	56.68	91.6	89.52	87.26	88.35	67.17	83.35	80.21	94.67	978.88
NET	−3.48	−1.49	1.67	−19.65	7.99	6.25	4.25	5.58	−11.52	0.9	−1.2	10.7	TCI = 81.57

PANEL C: 95TH QUANTILE (BULLISH MARKET STATE)													
	PRI	TRI	Brent	Coal	CO.Dubai	CO.Oman	Gasoline	Heating.Oil	Natural.Gas	OPEC.Oil	Propane	WTI	FROM others
PRI	9.45	8.39	8.39	7.75	9.29	8.13	8.34	7.92	8.38	7.27	7.78	8.92	90.55
TRI	8.27	9.53	8.49	7.83	9.25	8.11	8.22	7.85	8.3	7.45	7.8	8.91	90.47
Brent	7.62	7.62	9.56	7.53	9.64	8.48	8.43	7.86	8.12	8	7.94	9.17	90.44
Coal	7.68	7.78	8.39	9.86	9.22	8.26	8.36	7.91	8.29	7.5	8	8.76	90.14
CO.Dubai	7.63	7.56	8.7	7.64	10.19	8.72	8.51	8.06	8.11	7.62	7.91	9.35	89.81
CO.Oman	7.56	7.51	8.83	7.65	9.71	9.19	8.51	7.91	8.01	7.77	7.97	9.38	90.81
Gasoline	7.62	7.7	8.52	7.76	9.57	8.48	9.44	8.08	8.09	7.67	7.93	9.15	90.56
Heating.Oil	7.58	7.64	8.59	7.73	9.35	8.42	8.61	9.16	8.2	7.67	7.97	9.07	90.84
Natural.Gas	7.8	7.71	8.49	7.9	9.25	8.27	8.47	7.95	9.71	7.59	7.89	8.98	90.29
OPEC.Oil	7.51	7.52	8.99	7.63	9.73	8.65	8.45	7.96	8	8.33	7.93	9.29	91.67
Propane	7.71	7.66	8.54	7.73	9.41	8.42	8.31	7.99	8.32	7.61	9.33	8.98	90.67
WTI	7.55	7.56	8.75	7.7	9.69	8.63	8.43	8	8.23	7.7	7.88	9.87	90.13
TO others	84.54	84.65	94.66	84.85	104.12	92.55	92.65	87.48	90.05	83.87	87.01	99.95	1086.38
NET	−6.01	−5.82	4.22	−5.29	14.31	1.74	2.09	−3.35	−0.24	−7.8	−3.67	9.82	TCI = 81.90

Notes: This table reports the directional spillover in percentage (%). Results are based on a GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 4 (BIC). The second-last row (TO others) in Table 3 reports the contribution of each variable to other variables. The last column of Table 2 (under "FROM others") reports the downside tail risk spillover that each variable experiences from the entire system. The "NET "row classifies assets as net risk receivers or transmitters based on their negative or positive values. PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural. Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. TCI = Total Connectedness Index.

state. In contrast, OPEC Oil displays the lowest own variance shock at 31.15 %. Under extreme market conditions, Natural Gas and Coal continue to experience the highest levels of their own variance shocks. This observation suggests that a significant proportion of the forecast error variance for these high carbon-emitting markets can be attributed to their internal shocks, irrespective of the market state.

In examining the "TO" row, it is apparent that Crude Oil Dubai, at 91.74 %, presents the highest upside-tail risk spillover to the rest of the network in a normal market state. On the other hand, the "FROM" column highlights Crude Oil Oman (69.52 %) as the primary recipient of upside-tail risk spillover from the rest of the network. WTI becomes the most significant upside-tail risk transmitter (94.67 %) and the primary recipient (83.97 %) in bearish conditions. In a bullish market, Crude Oil Dubai is the most substantial transmitter (104.12 %), whereas OPEC Oil emerges as the main recipient (91.67 %). Intriguingly, climate-related risks consistently demonstrate the least upside-tail risk spillover to and from petroleum products, regardless of market state.

The row labeled "NET" differentiates assets as either net upside-tail risk recipients or transmitters, contingent on whether the values are negative or positive. From this perspective, Crude Oil Dubai dominates

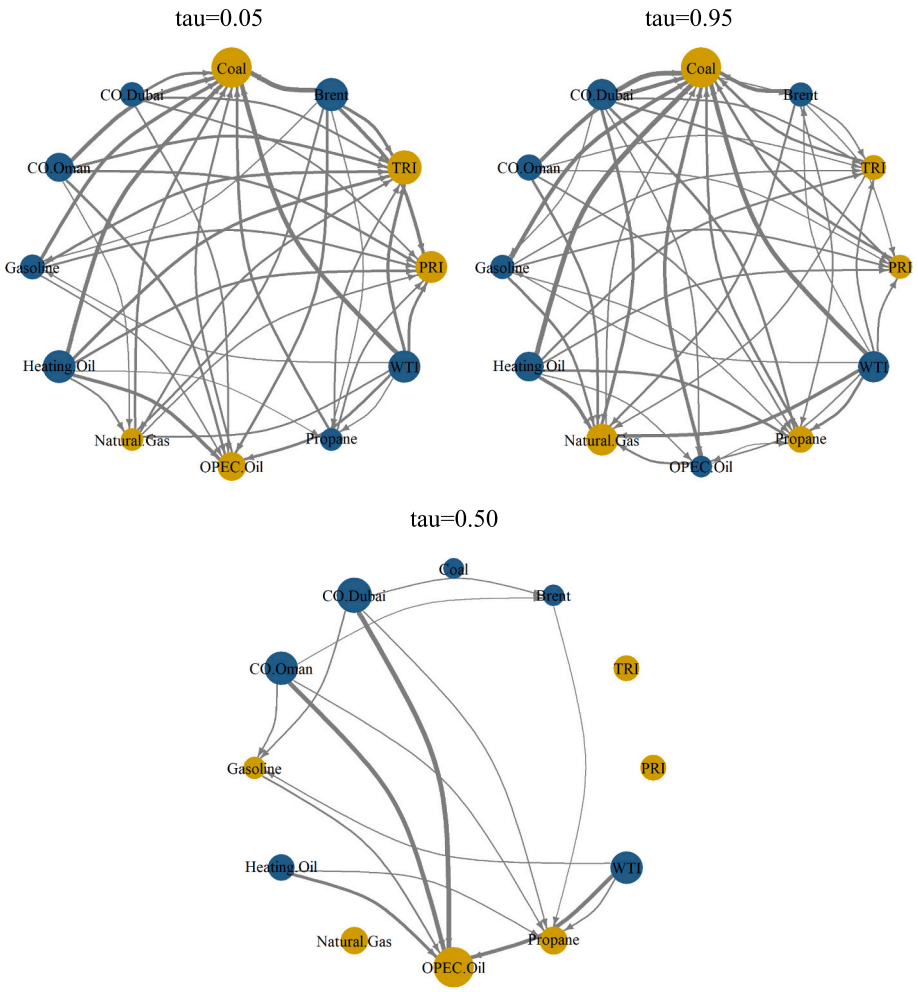


Fig. 1. Network transmission plot of downside tail risk.
Notes: Results are based on a GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 1 (BIC). PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. The blue nodes denote net transmitters of tail risk spillover, while the yellow nodes denote net receivers of tail risk spillover. The node's size represents the magnitude of the net spillover effect, either received or transmitted. The arrow shows the direction of the tail risk spillover in the network of variables. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the normal (23 %) and bullish markets (14.31 %), while WTI (10.7 %) dominates the bearish market state as the primary net upside risk transmitter. Contrastingly, climate-related risks consistently act as net recipients of upside risk spillover in all market states; however, the effect is minimal. Overall, crude oil surfaces as a net transmitter of upside risk in all market states. The role of refined petroleum products, however, oscillates depending on the market state. Interestingly, coal and natural gas serve as net recipients of upside-risk spillover in all market states. The total connectedness index reveals significant contagion between climate risk and international energy markets for upside-tail risk, especially in extreme market states.

4.1.2. Network transmission plot of the downside and upside tail risks

Figs. 1 and 2 illustrate network transmission plots of downside and upside tail risks, respectively. The results indicate that climate risk appears to be disassociated from the energy market in normal market states for both downside and upside-tail risks.

Fig. 1 shows that climate transition risk serves as the net recipient of downside tail risk from energy markets at the 5th distribution quantile. Similarly, climate physical risk emerges as the second largest recipient of downside tail risk from energy markets. Although climate-related risks act as receivers of downside tail risk, Coal serves as the network's net primary recipient of downside tail risk during normal market conditions. Interestingly, no downside tail risk spillover is apparent between Brent and WTI at the 5th quantile.

Furthermore, aside from a slight spillover connection between WTI, OPEC Oil, Crude Oil Dubai, and Brent, the crude oil and refined petroleum products markets are predominantly disconnected regarding downside tail risk at the 5th quantile of distribution. Notably, climate risk assumes the recipient's role for downside tail risk while all energy markets, except Propane, act as downside tail risk transmitters at the 95th distribution quantile. Meanwhile, coal and natural gas consistently act as net recipients.

Risk spillover between climate risk and energy markets seems more substantial than the spillover among the energy markets. The results also highlight that WTI detaches from Crude Oil Dubai, Crude Oil Oman, and Heating Oil. Similarly, Brent is isolated from OPEC Oil, Crude Oil Oman, Gasoline, and Heating Oil. These findings suggest potential diversification opportunities within the energy markets for downside tail risk during market upswings.

The findings in Fig. 2 reveal that in all market states, climate risk functions as a recipient of upside-tail risk. The connection in risk spillover is strong for both the 5th and 95th quantiles of the upside-tail risk distribution. The results for the 5th quantile of upside tail risk

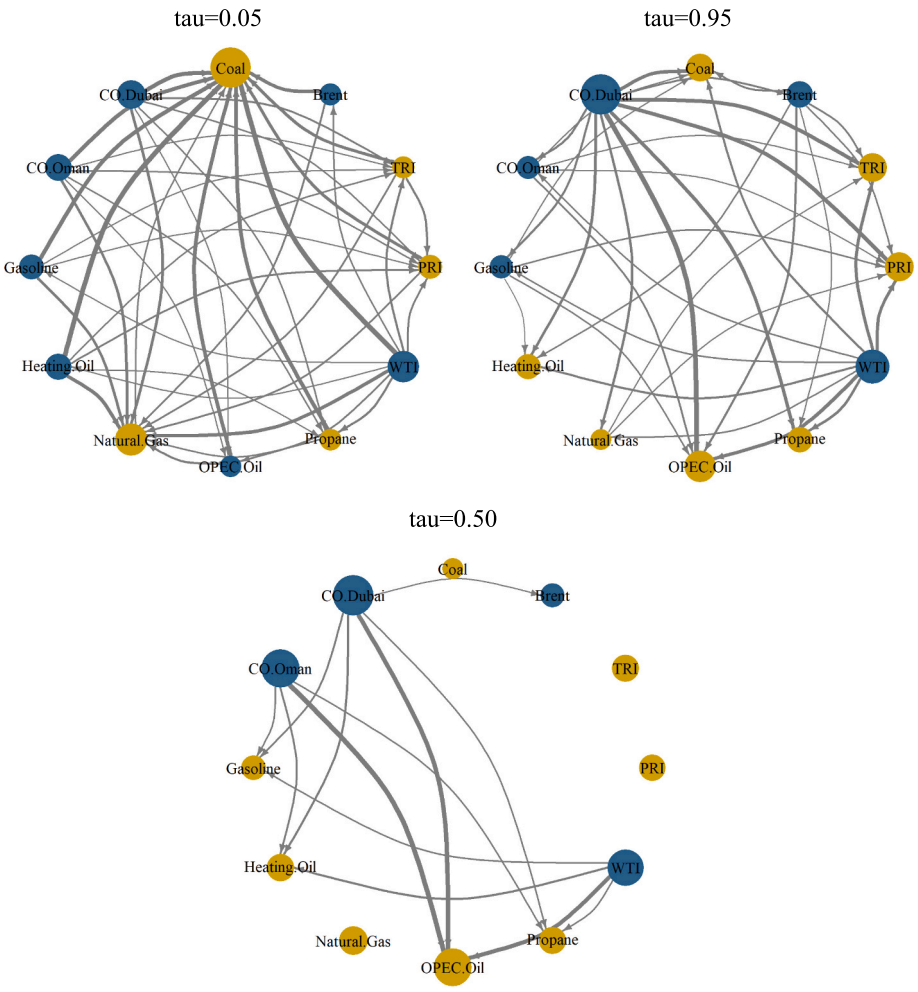


Fig. 2. Network transmission plot of upside-tail risk.
Notes: Results are based on a GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 1 (BIC). PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. The blue nodes denote net transmitters of tail risk spillover, while the yellow nodes denote net receivers of tail risk spillover. The node's size represents the magnitude of the net spillover effect, either received or transmitted. The arrow shows the direction of the tail risk spillover in the network of variables. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

distribution starkly contrast those of downside tail risk. Unlike downside tail risk, a correlation exists between WTI and Brent at the 5th quantile. No risk spillover is observed between climate risk and Propane at this quantile. However, consistent with downside tail risk results, Brent is found to be detached from the upside tail risk of OPEC Oil at the 5th quantile of the distribution.

Moreover, WTI is disconnected from Crude Oil Dubai, Gasoline, Heating Oil, and Propane at the 95th quantile of the distribution of upside tail risk. The only risk spillover link that refined petroleum products have with crude oil at the 95th quantile involves OPEC Oil and Brent. Interestingly, no risk spillover connectedness is found within the refined petroleum market at the 95th quantile of upside-tail risk. These results suggest potential diversification opportunities within the energy markets for upside-tail risk during extreme market scenarios.

4.1.3. Dynamic downside and upside-tail risk connectedness results

The previous sections of this study have explored the static connectedness of both downside and upside-tail risk. We note that these analyses do not capture the time-varying nature of connectedness. Thus, this section explores the conditional distribution of spillovers across time.

Fig. 3 illustrates the dynamic and static Total Connectedness Index (TCI) results for downside tail risk across various quantiles. The static TCI results validate the asymmetry in connectedness, revealing that the TCI is higher across extreme quantiles. Equally, the dynamic TCI findings demonstrate that connectedness at extreme quantiles surpasses that at mid-quantiles. Moreover, the degree of connectedness appears to be significantly event-dependent (Massacci, 2017), exhibiting a noticeable surge in downside tail risk connectedness over time.

Similarly, Fig. 4's representation of upside-tail risk connectedness indicates a time-varying nature, suggesting that both upside and downside-tail risks are closely tied to specific events. This result suggests that climate awareness events may heighten the spillover of downside tail risk.

Our subsequent analysis delves into the time-varying net directional spillover transmissions across quantiles. Figs. 5 and 6 display the findings for downside and upside tail risks, respectively. Red signifies risk transmitters in these figures, while blue denotes net risk receivers across quantiles.

Our analysis indicates that Crude Oil Dubai, Crude Oil Oman, Heating Oil, and WTI persistently transmit downside tail risk over time and across quantiles. Contrarily, OPEC Oil and Propane emerge as primary receivers of downside tail risk spillover throughout time and across quantiles. Notably, climate-related risks - Physical Risk Index (PRI) and

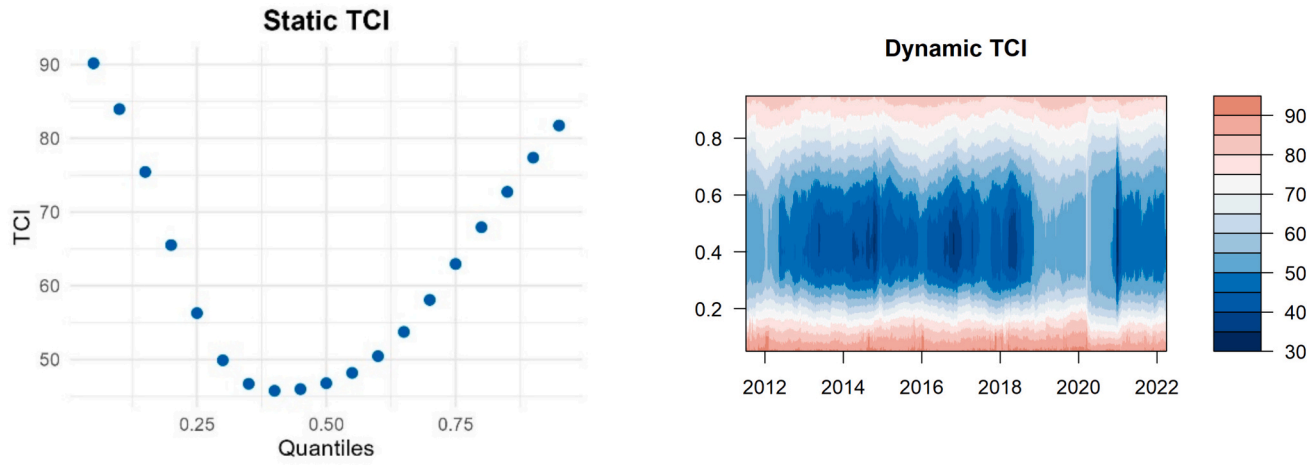


Fig. 3. Total return connectedness index across quantiles under downside tail risk.
Note: Results are based on GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 1 (BIC).

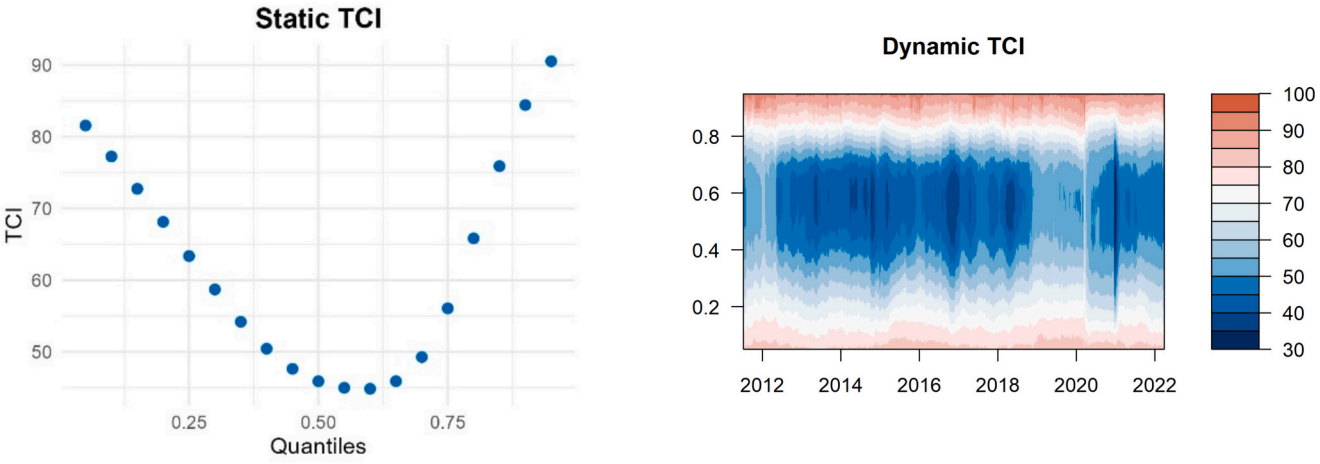


Fig. 4. Total return connectedness index across quantiles under upside-tail risk.
Note: Results are based on GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 1 (BIC).

Transition Risk Index (TRI) - are the minimal recipients of downside tail risk. However, echoing our earlier findings from Table 2, we note that climate risk is the most substantial receiver of downside tail risk during bearish market conditions.

The upside-tail risk results mirror the net risk transmission roles of Crude Oil Dubai, Crude Oil Oman, and WTI, suggesting that crude oil consistently acts as a net transmitter of both downside and upside-tail risks. Concurrently, we observe a surge in the risk spillover received by climate physical and transition risks within the system's upside-tail risk. The status of OPEC Oil and Propane as net receivers of downside tail risk persists for upside tail risk as well.

Notably, during the second wave of COVID-19, Brent maintained a steady position as a net risk transmitter for both downside and upside-tail risks. The same applies to Crude Oil Oman, which consistently acts as a net risk recipient for downside and upside tail risks.

Our study finds asymmetric connectedness over the sampled period, with more substantial connectedness at extreme quantiles than at the mid quantiles. Therefore, our research suggests that investors could potentially recalibrate their portfolios of conventional energy assets, particularly those vulnerable to climate risks, according to prevailing market conditions and the ebb and flow of climate change sentiment. Our findings emphasize the significance of incorporating extreme events in risk management and investment decision-making strategies, particularly in light of the shift towards low-carbon energy sources. Our findings extend those drawn by Ren et al. (2023) and Zhu et al. (2023), among others, who support the time-varying and heterogeneous impacts of climate-related risks within the energy market.

4.2. *Rolling window wavelet correlation (RWWC) results*

This section widens the lens on the interplay between climate risks and the international energy market, explicitly emphasizing cross-dependence. To delve into the impact of the climate risk index on international petroleum market tail risk across diverse periods and investment horizons, we employ the RWWC method, a strategy proposed by Polanco-Martínez et al. (2018).

The wavelet scales we use span from D1 to D4, representing investment time horizons ranging from short-term (daily, weekly) to long-term (monthly). Consistent with Nguyen et al. (2021), we define the timescales as 2 to 4 days for D1, 4 to 8 days for D2, 8 to 16 days for D3, and 16 to 32 days for D4. These wavelet scales are categorized into two broad classifications: short-lived reactions (corresponding to events in the scales of D1, D2, and D3) and long-lived reactions (reflected in D4). A colour bar illustrates the correlation coefficients, transitioning from red to blue to denote correlation values ranging from negative (low) to positive (high). Overall, we find a relatively minimal cross-dependence between climate risks and energy market tail risks, implying that the energy market tail risks, both downside and upside, exhibit relatively

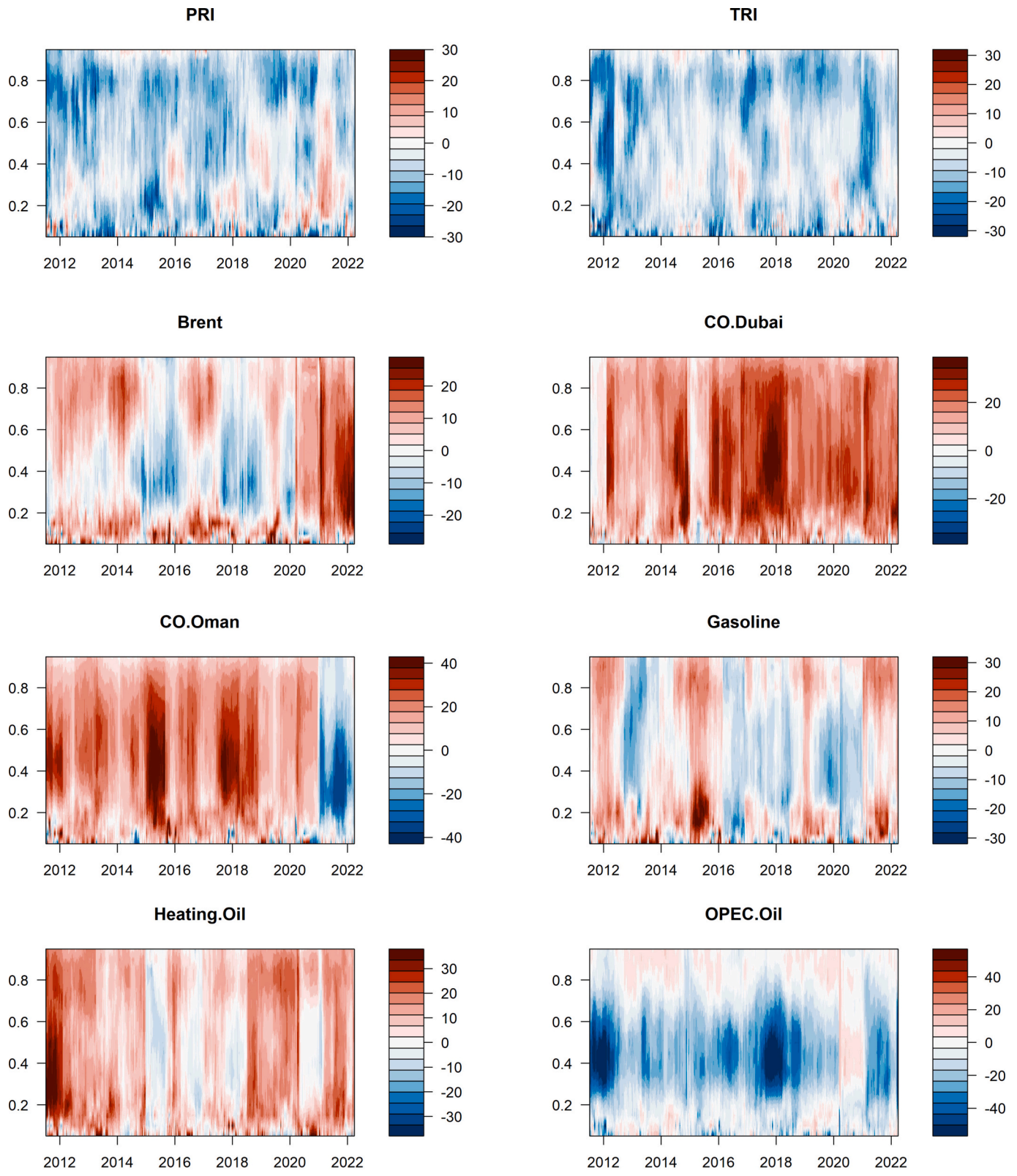


Fig. 5. Net directional return spillover across quantiles under downside tail risk.
Note: Results are based on GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 1 (BIC). This figure presents the net directional dynamic spillover index across time and quantile based on the median quantile. The colour bar illustrates the net risk spillover index, transitioning from blue to red to denote the spillover index ranging from negative (net receiver) to positive (net transmitter). PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

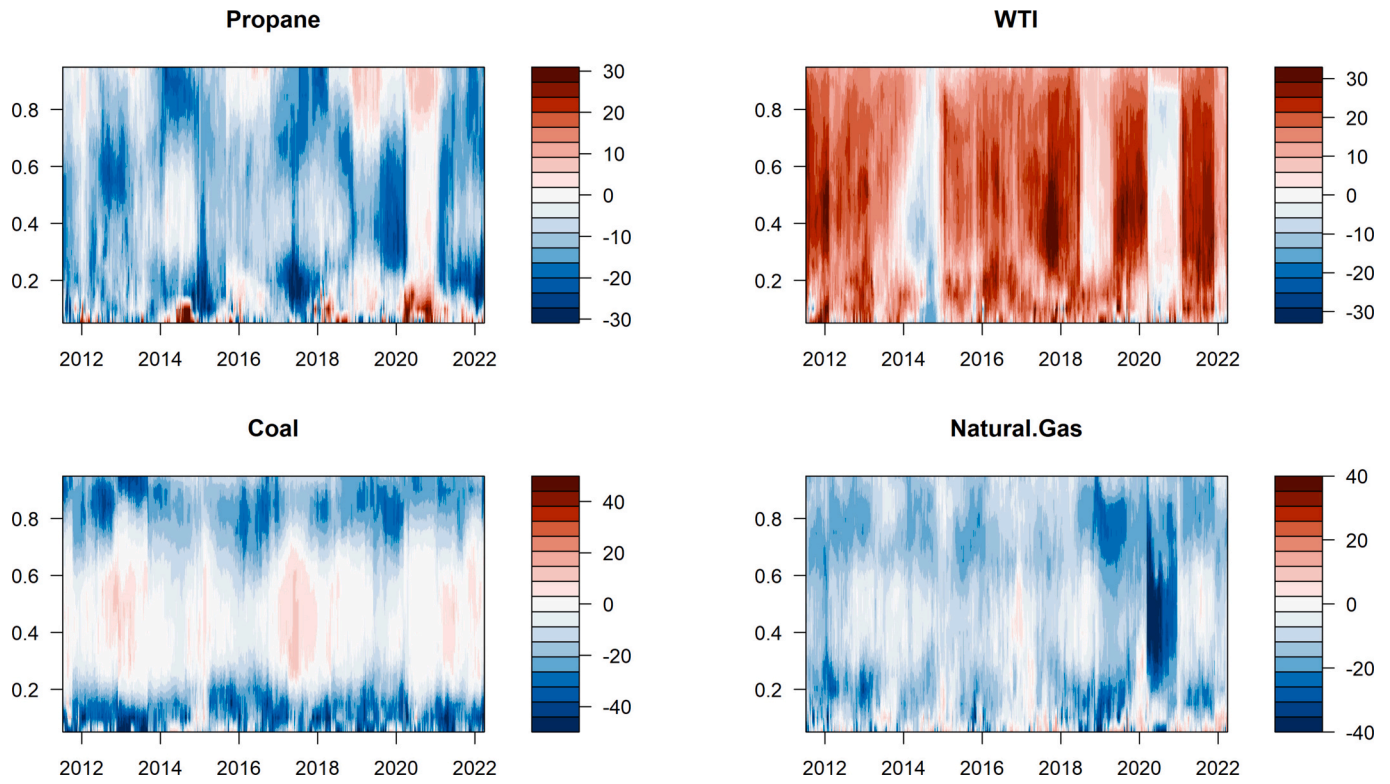


Fig. 5. (*continued*).

low sensitivity to climate risks. Notably, this is underscored by the traces of negative cross-dependence between the variables in both the short and long term.

Regarding downside tail risk, Fig. 7 visualizes the cross-dependence between climate risks and the energy market. Panel A represents the results for climate physical risk, while Panel B details the outcomes for climate transition risk. This figure demonstrates that the association between climate physical and transition risks is dynamic, varying over time, frequency, and markets. The colour bar illustrates the rolling window correlation coefficients spanning from −0.64 to 0.51. The weakest correlation is observed between the Physical Risk Index (PRI) and Gasoline, while the highest correlation appears between the Transition Risk Index (TRI) and Brent's downside tail risk. Consistent with the portfolio diversification theory, the cross-dependence between climate risk and the energy market for downside tail risk predominantly exhibits a negative trend in the long run. This suggests that the impacts of extreme economic events can be diversified in the traditional energy market portfolio by incorporating climate risk indices.

Interestingly, when the Paris Agreement was enforced in 2015, we noticed a temporary surge in positive correlation between the Physical Risk Index (PRI) and several commodities: Crude Oil Dubai, Crude Oil Oman, Heating Oil, and West Texas Intermediate (WTI). However, these strong correlations proved transitory and did not persist over a prolonged period.

The relationship between climate physical risk and the international energy market is heterogeneous. In the short term, low values tend to prevail, indicating the potential of using climate physical risk as a hedge in international energy market investments. Yet, in the long term, the correlation appears highly unstable, marked by significant fluctuations over time, with no dominance of either high or low values.

Regarding climate transition risk, we observe a similar pattern of unstable correlation concerning downside tail risk, with negative correlations seemingly outweighing the positive ones. Furthermore, these correlation coefficients do not show long-term persistence.

Our exploration of the relationship between climate risks and the international energy market continues with examining upside-tail risk. Fig. 8 displays this cross-dependence, with Panel A showing results for climate physical risk and Panel B for climate transition risk. The pairwise correlation between climate physical and transition risks is highly dynamic, varying across markets, time, and frequency. The colour bar depicts correlation coefficients ranging from −0.60 to 0.47. For climate physical risk (PRI), the weakest correlation is with Gasoline, while the strongest correlation is between climate transition risk (TRI) and Brent's downside tail risk.

A consistent theme across these findings is the instability of the correlations, which fluctuate and lack persistence. Notably, in 2015, when the Paris Agreement was enforced, a negative correlation for physical risk was observed, suggesting the Agreement may have influenced the relationship negatively.

Overall, these results indicate a generally weak relationship between climate risk indices and the energy market. Consequently, market participants could leverage this weak connection to devise innovative hedging strategies and diversification methods for upside-tail risk. This section underscores a distinctly heterogeneous and time-frequency-dependent relationship between climate risk and the energy market.

Our results align with those of Jin et al. (2023) and others, reinforcing the long-term correlation between climate risk and the energy market. Moreover, our study uncovers a high sensitivity in the tail risk spillover connectedness between climate risk and the energy market, which is particularly susceptible to market conditions.

4.3. Robustness test results

4.3.1. Quantile frequency domain spillover index

We utilize the quantile time-frequency approach proposed by Chatziantoniou et al. (2022a) to estimate quantile frequency connectedness indices. This approach allows for identifying time-frequency dynamics within a conditional distribution framework, an essential feature given the varying interactions between climate and energy markets across different timescales. The QVAR frequency connectedness approach is

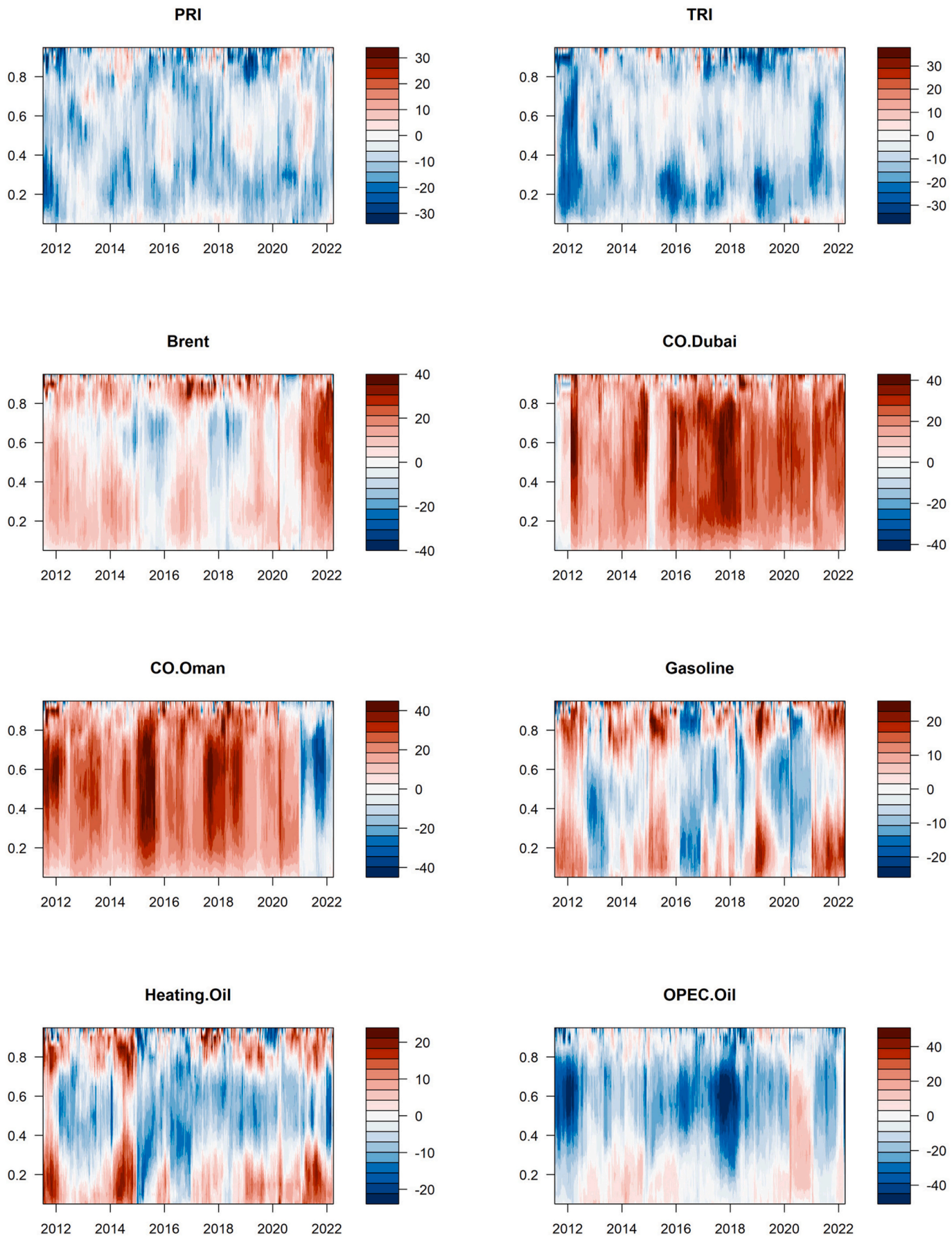

PRI
TRI
Brent
CO.Dubai
CO.Oman
Gasoline
Heating.Oil
OPEC.Oil
0.2
0.4
0.6
0.8
2012
2014
2016
2018
2020
2022

Fig. 6. Net directional return spillover across quantiles under upside-tail risk.
Note: Results are based on GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 1 (BIC). This figure presents the net directional dynamic spillover index across time and quantile based on the median quantile. The colour bar illustrates the net risk spillover index, transitioning from blue to red to denote the spillover index ranging from negative (net receiver) to positive (net transmitter). PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

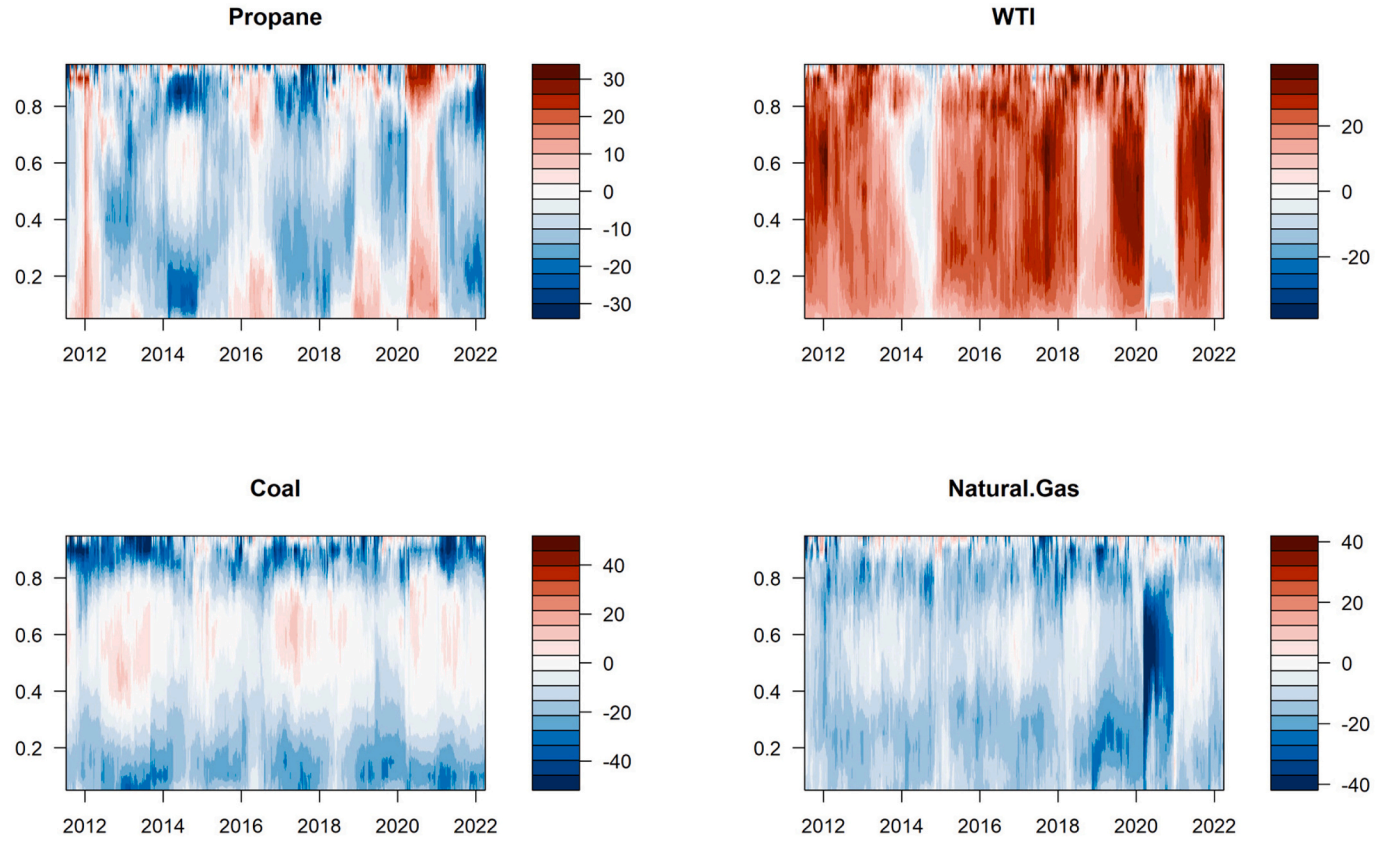


Fig. 6. (*continued*).

instrumental in testing the robustness of our RWWC results, thereby reinforcing our insights into the underlying mechanisms of risk propagation. Table 4 displays the results calculated based on the conditional mean at the 50th quantile. Panels A, B, and C of the table delineate the estimates of the spillover effect between climate risk and the energy market's downside tail risk across various time frames: short-term (1 to 5 days), intermediate-term (5 to 30 days), and long-term (over 30 days).

From Panel A of Table 4, we observe that the spillover effects of the Physical Risk Index (PRI) and Transition Risk Index (TRI) on energy market tail risk in the short term are 12.61 % and 12.06 %, respectively. In contrast, Panels B and C of Table 3 reveal that the spillover effects of climate-related risks on energy market tail risks are less than 2 % in the medium term and approximately 4 % in the long term. Climate risks are predominantly net receivers of spillovers from the energy markets' tail risks in the short term. However, the dynamics shift in the medium and long term, with climate risks increasingly acting as net transmitters of shocks to energy markets' tail risks.

Table 5 presents the results for the directional spillover effect during the bearish market state within the frequency domain, exhibiting a pattern consistent with the findings reported in Table 4 for the normal market state. In the short term, the spillover effect from climate-related risks to energy markets' tail risk is markedly high at 43.97 % for climate physical risks and 46.31 % for transition risks. Yet, these effects taper off in the medium term to 12.84 % and 12.65 %, respectively, and stabilize in the long term at 13.37 % and 12.68 %. The short-term spillover effect notably dominates the impact on energy markets' tail risk. This pattern of net spillover effects, where climate risks initially absorb but later transmit risk, underscores a complex, time-sensitive interplay of risk transmission.

Table 6 captures the directional spillover effect during the bullish market state. The results suggest that the influence of climate risk on energy markets' tail risk is significantly more pronounced in the short term compared to the medium and long term. Initially, climate risks act as net receivers of spillover from energy markets' tail risks. This role inversely shifts in the medium and long term as climate risks evolve into net transmitters of shocks. These observations underscore the transient nature of climate risk influence on energy markets, which does not persist over extended periods.

Overall, our analysis reveals that the role of climate risk as a net receiver, predominantly noted in the time-domain analysis across various market conditions, is primarily confined to the short term. Over the long term, however, climate risk emerges as a net transmitter of risk to energy markets' tail risk. This shift aligns with the forward-looking implications of climate change on financial assets. In a related vein, Jin et al. (2023) suggest that the energy market plays a significant role in transmitting volatility to climate risk in the short term. Our findings support this view, indicating that energy markets' tail risk influence on climate mitigation efforts is generally transient.

Ji et al. (2018) discuss a feedback effect from the carbon market to energy markets, though their findings open the question of whether this effect is enduring. Our research contributes new insights by delineating the frequency domain within which this feedback effect manifests. We

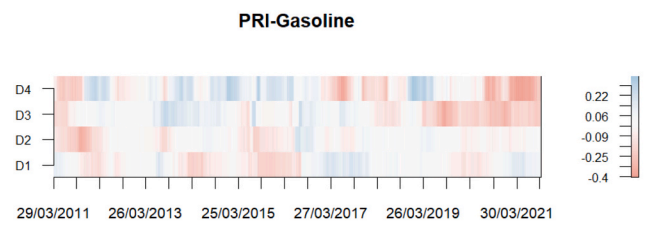
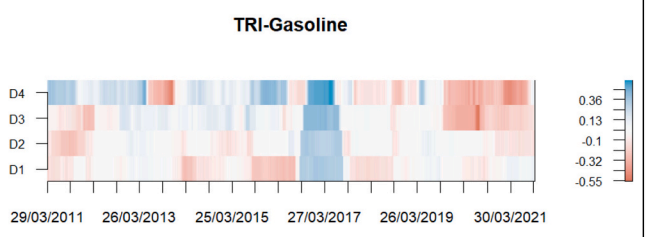
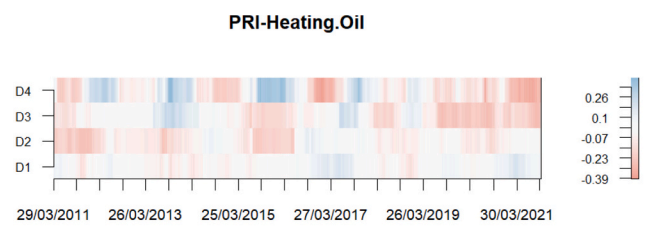
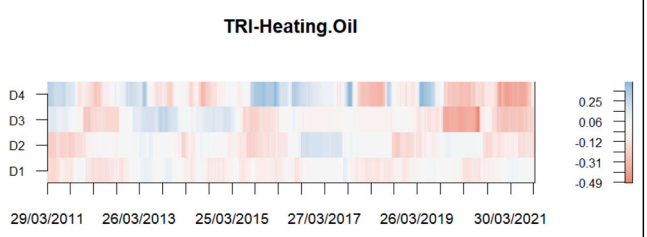
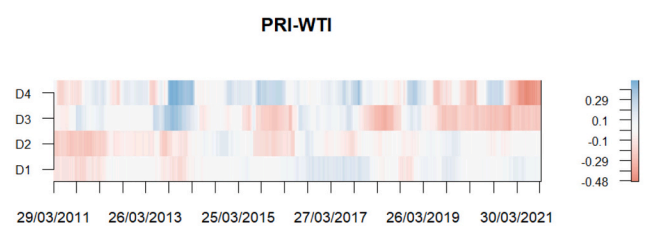
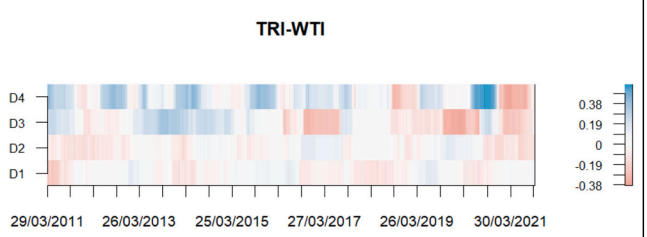
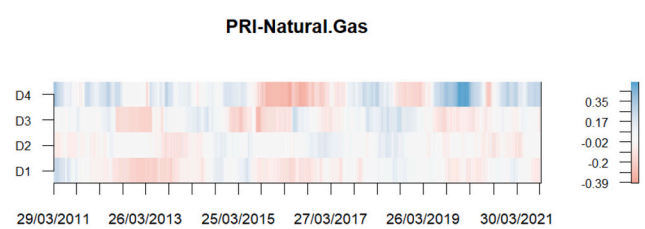
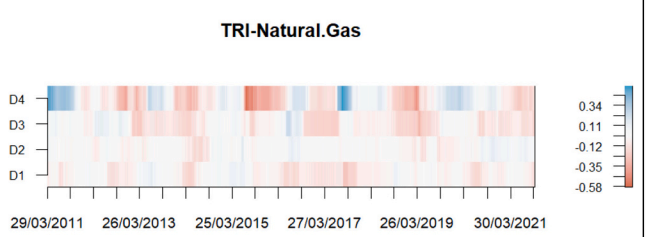
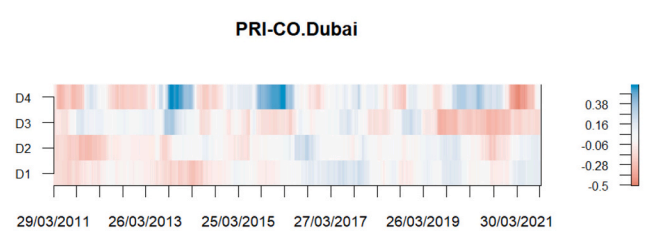
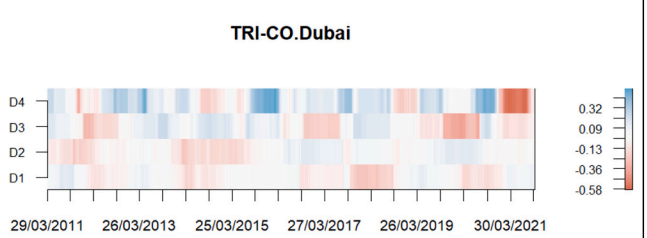
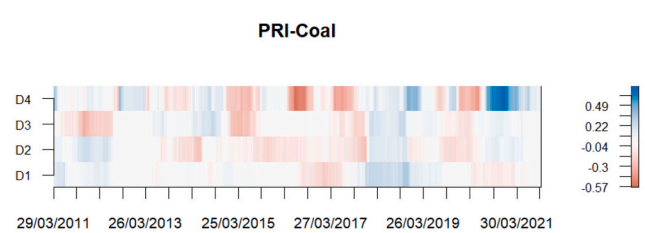
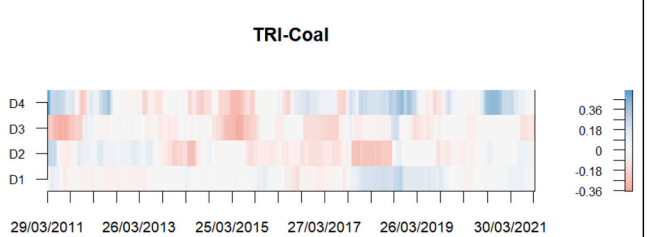
Panel A: Wavelet correlation between physical risk and energy market downside tail risk	Panel B: Wavelet correlation between transition risk and energy downside market tail risk
	
	
	
	
	
	

Fig. 7. Rolling wavelet window correlation results between climate risks and energy market downside tail risk.
Notes: The wavelet scales we use span from D1 to D4, representing investment time horizons ranging from short-term (daily, weekly) to long-term (monthly). We employ timescales of 2 to 4 days for D1, 4 to 8 days for D2, 8 to 16 days for D3, and 16 to 32 days for D4. The wavelet scales are categorized into two broad classifications: short-lived reactions (which correlate with events in the scales of D1, D2, and D3) and long-lived reactions (reflected in D4). A colour bar illustrates the correlation coefficients, transitioning from red to blue to denote correlation values ranging from negative (low) to positive (high). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

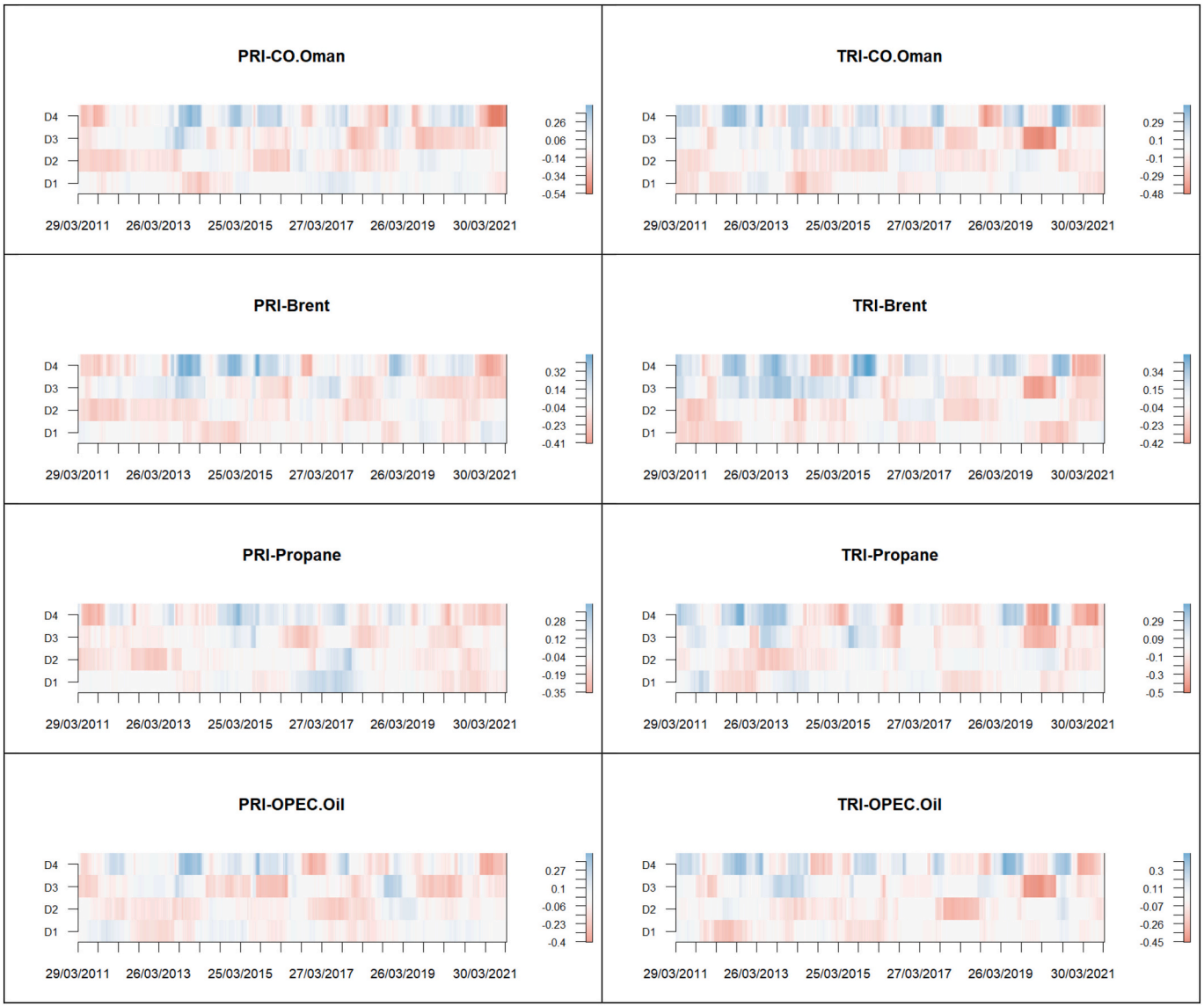


Fig. 7. (*continued*).

ascertain that the feedback effect from climate risk to energy markets' tail risk is evident in the medium and long terms, suggesting a more prolonged influence of climate risk on energy markets.

In the subsequent analysis, we delve into the time-varying directional spillover effect across different times and frequencies, with the findings presented in Fig. 9. In this figure, the total dynamic connectedness is depicted in black, long-term connectedness in blue, while short- and medium-term connectedness is marked by red and green lines, respectively. Our results indicate that long-term spillovers predominantly drive the total connectedness among energy market tail risks, suggesting a sustained downside tail risk spillover among energy markets. Extending the work of Ji et al. (2018), we clarify the temporal dimensions of the feedback effect, demonstrating that it occurs primarily in the medium to long term. Thus, while the immediate impact of climate risk on the energy market tail risk may be minimal, its effects are enduring. Additionally, our study highlights the asymmetric nature of the time-varying spillover between climate risk and energy markets' tail risk, as noted by Gong et al. (2021). This asymmetry underscores the complex interplay between these risks over varying temporal scales.

4.3.2. *Network plot of the downside tail risks and climate risks by frequency*

This section presents a detailed analysis of the network transmission plots between downside tail risks in the energy market and climate risks across different market states and time horizons, including short-term, intermediate-term, and long-term frequency bands.

Fig. 10 illustrates the network transmission plots during a normal market state (tau = 0.50). Fig. 10a shows that climate-related risks are the primary receivers of downside tail risk from the energy markets in the short term. Interestingly, tail risk spillover within the energy sector is decoupled in the short term, but the spillover effect is directed towards climate risk. In the intermediate-term and long-term (Fig. 10b and c),

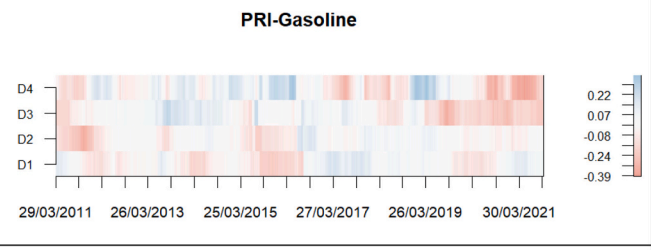
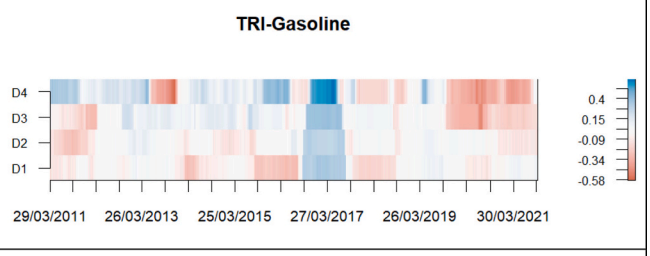
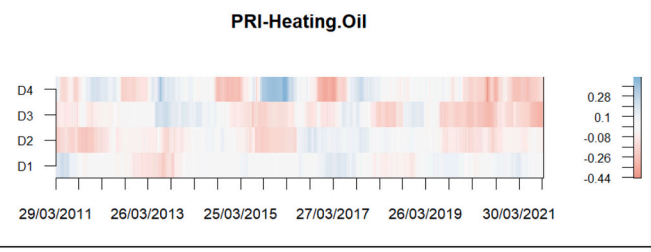
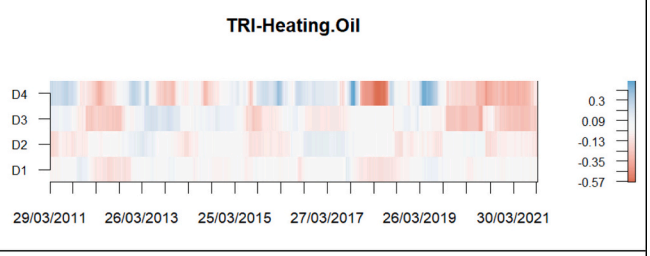
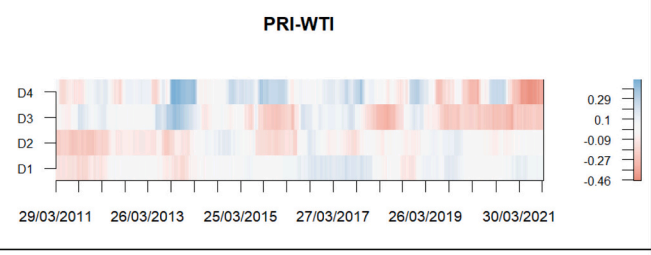
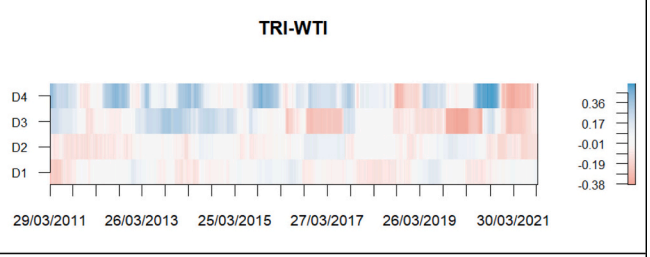
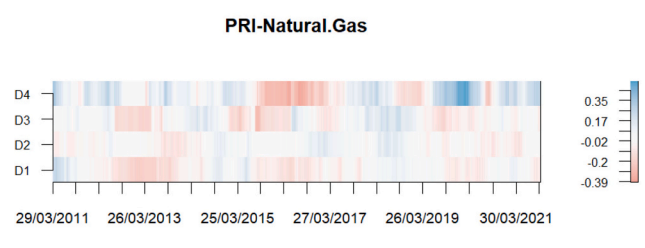
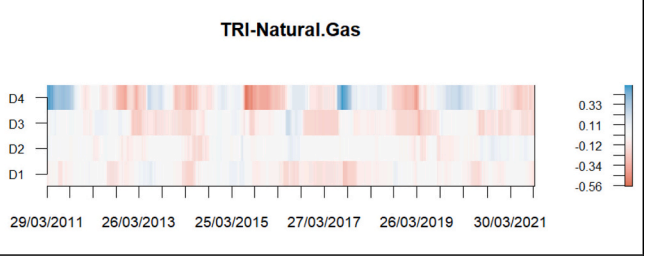
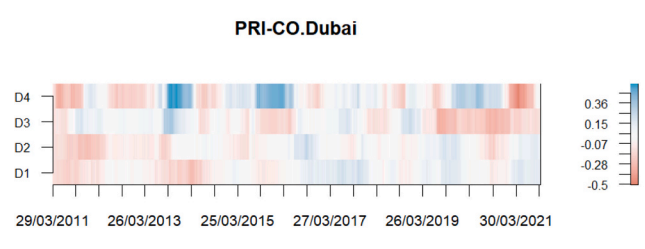
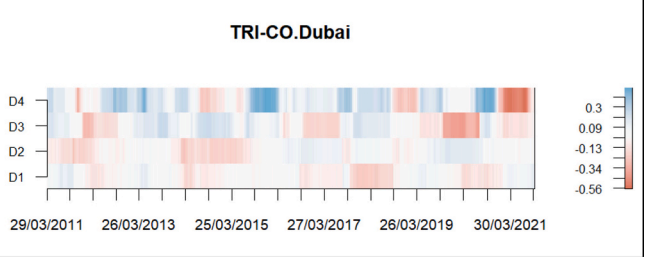
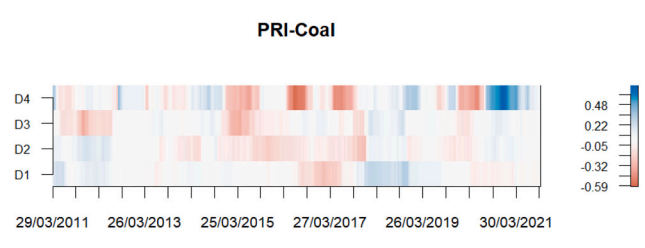
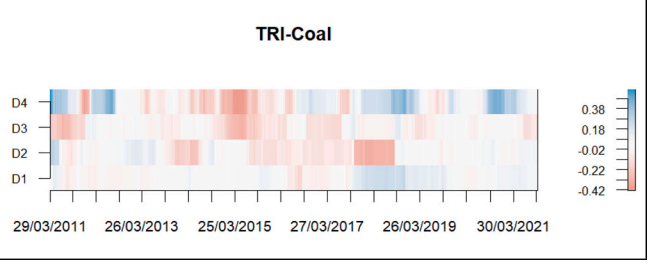
Panel A: Wavelet correlation between physical risk and energy market upside tail risk	Panel B: Wavelet correlation between transition risk and energy upside market tail risk
	
	
	
	
	
	

Fig. 8. Rolling wavelet window correlation results between climate risks and energy market upside tail risk.
Notes: The wavelet scales we use span from D1 to D4, representing investment time horizons ranging from short-term (daily, weekly) to long-term (monthly). We employ timescales of 2 to 4 days for D1, 4 to 8 days for D2, 8 to 16 days for D3, and 16 to 32 days for D4. The wavelet scales are categorized into two broad classifications: short-lived reactions (which correlate with events in the scales of D1, D2, and D3) and long-lived reactions (reflected in D4). A colour bar illustrates the correlation coefficients, transitioning from red to blue to denote correlation values ranging from negative (low) to positive (high). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

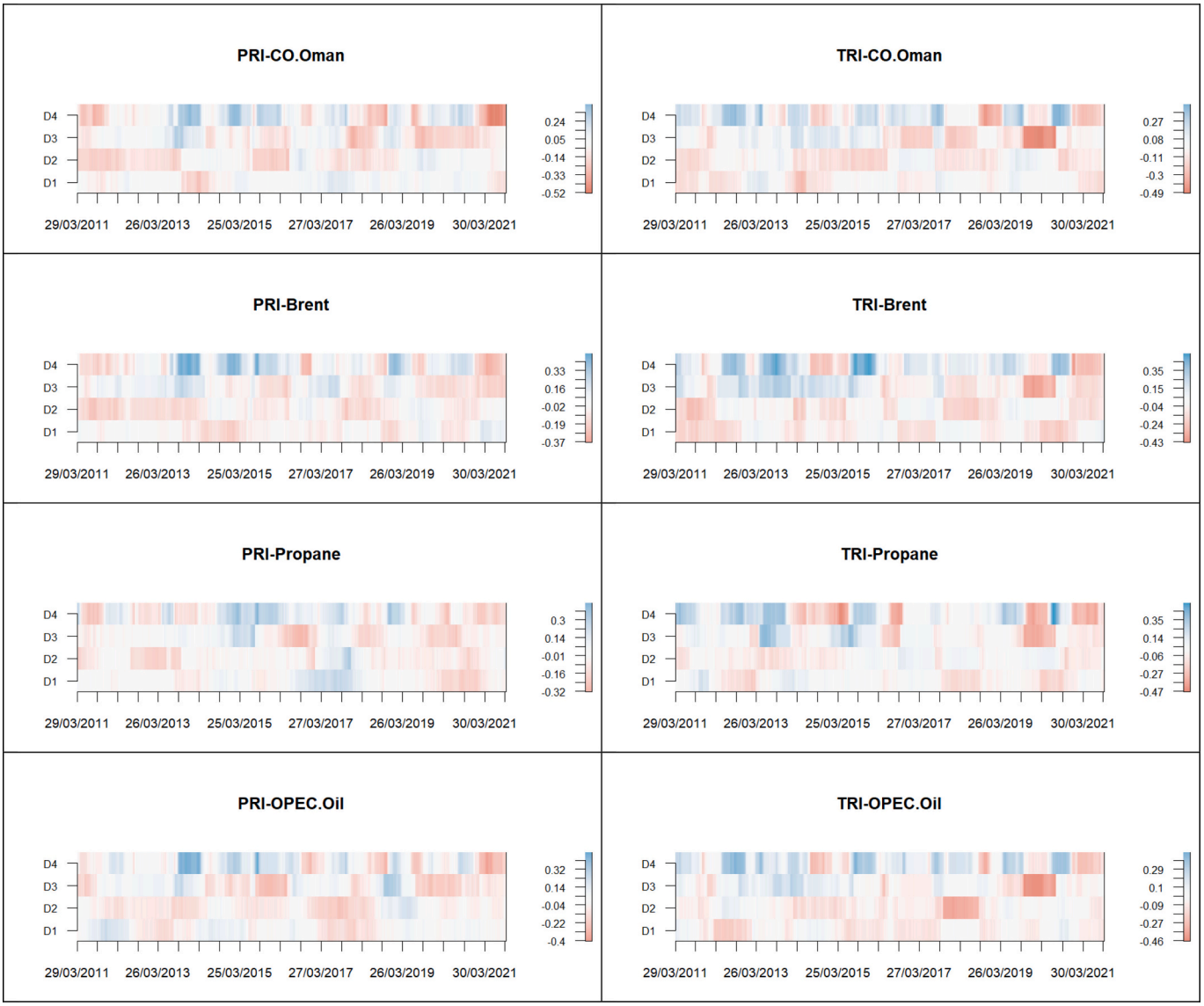


Fig. 8. (*continued*).

climate risk becomes a net risk transmitter to the energy markets. However, the impact remains insignificant as climate risk appears decoupled from the energy markets. This suggests that the effect of energy market tail risk on climate risk is short-lived, while the impact of climate risk on energy markets persists over the long term.

Fig. 11 presents the network transmission plots during a bearish market state (tau = 0.05). In the short term (Fig. 11a), climate-related risks are again the primary receivers of downside tail risk from the energy markets, with tail risk spillover within the energy sector being decoupled but directed towards climate risk. In the intermediate-term and long-term (Fig. 11b and c), climate risk emerges as a strong net risk transmitter to the energy markets' tail risk, indicating a long-term and persistent impact. This finding reinforces that the effect of energy market tail risk on climate risk is short-lived, while the influence of climate risk is more enduring.

Fig. 12 presents the network transmission plots during a bullish market state (tau = 0.95). Similar to the other market states, in the short term (Fig. 12a), climate-related risks are the primary receivers of downside tail risk from the energy markets, with a decoupled tail risk spillover within the energy sector directed towards climate risk. In the intermediate-term and long-term (Fig. 12b and c), climate risk is among the strongest net risk transmitters to the energy markets' tail risk. This result is consistent with the findings under the bearish market state, emphasizing the persistent and long-term impact of climate risk on energy markets.

These findings suggest that the threat posed by energy markets' tail risk to climate mitigation efforts is prominent in the short term during crisis events. However, in the medium to long term, there is a feedback effect from climate risk to energy markets' tail risk, with a long-lasting impact. Prolonged economic downturns or global uncertainty amplify the role of climate risk in propagating systemic risks in the global energy market.

Table 4
Quantile frequency connectedness results of downside tail risk based on conditional mean (tau = 0.50).

PANEL A: 1 TO 5 DAYS (SHORT TERM = HIGH FREQUENCY)

	PRI	TRI	WTI	Brent	OPEC.Oil	CO.Oman	CO.Dubai	Gasoline	Heating.Oil	Propane	Natural.Gas	Coal	FROM others
PRI	64.04	10.65	2.3	2.57	2.35	2.22	2.31	2.95	2.17	2.46	2.51	2.67	35.15
TRI	11.2	65.49	2.07	2.15	2.23	1.97	2.53	2.07	2.45	2.56	2.04	2.6	33.87
WTI	0.14	0.15	5.83	1.8	0.75	2.64	2.59	1.28	1.86	0.62	0.24	0.33	12.4
Brent	0.09	0.11	0.98	2.96	0.61	1.02	0.82	0.48	0.61	0.28	0.24	0.23	5.47
OPEC.Oil	0.08	0.08	0.52	0.42	1.15	0.64	0.56	0.34	0.42	0.2	0.26	0.22	3.74
CO.Oman	0.04	0.05	0.78	0.57	0.3	1.67	0.94	0.35	0.49	0.23	0.15	0.15	4.06
CO.Dubai	0.07	0.08	0.94	0.64	0.3	1.11	1.93	0.44	0.69	0.24	0.18	0.18	4.85
Gasoline	0.14	0.16	0.88	0.75	0.41	0.91	1.03	4.14	1.05	0.41	0.21	0.31	6.25
Heating.Oil	0.08	0.09	0.64	0.46	0.29	0.59	0.62	0.49	2.1	0.3	0.24	0.24	4.04
Propane	0.12	0.11	0.48	0.48	0.3	0.41	0.45	0.36	0.44	2.67	0.3	0.24	3.68
Natural.Gas	0.24	0.21	0.49	0.45	0.5	0.51	0.53	0.49	0.49	0.57	5.04	0.53	5.01
Coal	0.4	0.39	0.56	0.7	0.65	0.55	0.59	0.7	0.83	0.42	0.67	33.95	6.46
TO others	12.61	12.06	10.64	10.97	8.69	12.57	12.97	9.94	11.5	8.29	7.04	7.7	124.98
NET	−22.54	−21.81	−1.76	5.5	4.95	8.51	8.11	3.69	7.46	4.61	2.04	1.24	TCI = 10.42

PANEL B: 5 TO 30 DAYS (INTERMEDIATE/MEDIUM TERM)

	PRI	TRI	WTI	Brent	OPEC.Oil	CO.Oman	CO.Dubai	Gasoline	Heating.Oil	Propane	Natural.Gas	Coal	FROM others
PRI	0.25	0.04	0.03	0.02	0.02	0.02	0.02	0.03	0.02	0.02	0.01	0.02	0.25
TRI	0.04	0.21	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.19
WTI	0.1	0.11	6.29	2.46	1.06	3.48	3.13	1.53	2.44	0.73	0.51	0.8	16.34
Brent	0.09	0.12	1.84	4.05	1.21	1.94	1.75	0.92	1.35	0.52	0.55	0.73	11.02
OPEC.Oil	0.08	0.07	1.28	1.17	2.38	1.51	1.42	0.76	1.09	0.49	0.74	0.63	9.23
CO.Oman	0.05	0.06	1.73	1.26	0.79	2.9	1.87	0.81	1.12	0.51	0.4	0.47	9.06
CO.Dubai	0.06	0.07	1.81	1.28	0.65	2.06	3.16	0.89	1.51	0.46	0.5	0.55	9.84
Gasoline	0.14	0.16	1.9	1.78	1.05	2.05	2.33	6.25	1.86	0.69	0.57	0.91	13.45
Heating.Oil	0.1	0.09	1.23	1.19	0.65	1.28	1.29	0.97	3.46	0.63	0.65	0.81	8.89
Propane	0.12	0.11	1.25	1.07	0.8	1.08	1.08	0.85	1.06	4.18	0.53	0.72	8.66
Natural.Gas	0.13	0.13	1.02	1.09	1.06	1.16	1.27	0.97	0.92	0.98	5.75	1.03	9.77
Coal	0.19	0.2	0.97	1.14	0.79	0.71	0.8	0.9	1.02	0.37	0.62	24.08	7.72
TO others	1.1	1.16	13.08	12.47	8.1	15.3	14.97	8.64	12.41	5.41	5.1	6.67	104.43
NET	0.85	0.97	−3.26	1.46	−1.13	6.24	5.14	−4.81	3.52	−3.25	−4.68	−1.05	TCI = 8.7

PANEL C: ABOVE 30 DAYS (LONG TERM = LOW FREQUENCY)

	PRI	TRI	WTI	Brent	OPEC.Oil	CO.Oman	CO.Dubai	Gasoline	Heating.Oil	Propane	Natural.Gas	Coal	FROM others
PRI	0.11	0.02	0.02	0.02	0.01	0.03	0.02	0.02	0.02	0.02	0.01	0.02	0.2
TRI	0.02	0.09	0.02	0.02	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.15
WTI	0.2	0.24	14.38	6.44	3.78	9.74	9.09	4.63	5.09	2.67	1.25	1.62	44.76
Brent	0.26	0.43	8.86	17.54	7.77	10.39	11.22	5.44	5.97	4.16	1.54	2.94	58.97
OPEC.Oil	0.26	0.37	9.67	10.33	15.82	12.76	12.13	5.6	6.99	4.68	2.38	2.52	67.68
CO.Oman	0.25	0.3	12.66	9.14	6.18	19.84	12.72	7.51	6.72	3.62	1.44	1.92	62.47
CO.Dubai	0.26	0.35	12	8.72	6	13.19	18.73	7.6	7.12	3.1	1.53	1.63	61.5
Gasoline	0.44	0.38	7.78	6.02	4.73	8.49	8.44	21.02	5.6	3.17	1.18	2.66	48.89
Heating.Oil	0.34	0.37	9.58	8.75	6.09	10.26	11.73	6.48	18.96	3.15	2.26	3.54	62.55
Propane	0.57	0.94	4.61	4.46	5.28	6.54	5.78	4.66	4.29	37.3	3.58	2.8	43.51
Natural.Gas	0.51	0.55	4.19	4.96	4.96	5.84	4.26	2.53	3.11	3.86	36.65	3.03	37.78
Coal	0.17	0.2	0.87	1.04	0.94	1.1	1.24	0.96	1.17	0.86	0.87	18.39	9.41
TO others	3.29	4.14	70.25	59.9	45.76	78.34	76.63	45.42	46.08	29.31	16.05	22.68	497.86
NET	3.09	3.99	25.49	0.94	−21.93	15.87	15.14	−3.46	−16.47	−14.2	−21.73	13.28	TCI = 41.49

Notes: This table reports the directional spillover in percentage (%). Results are based on a GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 4 (BIC). The second-last row (TO others) in Table 4 reports the contribution of each variable to other variables. The last column of Table 3 (under "FROM others") reports the downside tail risk spillover that each variable experiences from the entire system. The "NET" row classifies assets as net risk receivers or transmitters based on their negative or positive values. PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural. Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. TCI = Total Connectedness Index.

4.3.3. Alternative length of window

In our baseline results, we consider 200 days (approximately 40 weeks) as the length of the window, similar to studies by Diebold and Yilmaz (2012), Barunk et al. (2015), and Antonakakis et al. (2016). Nonetheless, as a test of robustness, we repeat our baseline analysis for longer windows of 400 and 600 days, as in Lovcha and Perez-Laborda (2020). Table 7 reports the robustness results using alternative window lengths (i.e., for the 400-day and 600-day window) with 100 steps ahead of the forecast horizon. We find quantitatively similar results as presented in the baseline using a 200-day window length.

4.3.4. Different levels of downside tail risk

This section presents additional robustness test results based on different levels of downside tail risk metrics. We estimated downside tail risk at the 1 % VaR and repeated all the baseline analyses based on the QVAR frequency model with 20 steps ahead of the forecast horizon using a 250-day window length and a lag length of order 4 (BIC). We present the results in the online supplementary file accompanying this paper for brevity. The findings show that TCI in the long term dominates the short term; climate risk acts as the net receiver of tail risk spillover in the short term across all market states; however, there is a feedback effect from

Table 5
Quantile frequency connectedness results of downside tail risk based on lower quantile (tau = 0.05).

PANEL A: 1 TO 5 DAYS (SHORT TERM = HIGH FREQUENCY)

	PRI	TRI	WTI	Brent	OPEC.Oil	CO.Oman	CO.Dubai	Gasoline	Heating.Oil	Propane	Natural.Gas	Coal	FROM others
PRI	7.49	7.46	7.87	7.45	6.91	7.84	8.16	7.38	7.4	7.24	7.05	8.04	82.8
TRI	7.02	8.26	7.84	7.38	6.98	7.82	8.04	7.42	7.54	7.3	7.13	8.15	82.62
WTI	4.2	4.33	5.67	4.99	4.94	5.49	5.76	5.15	5.33	4.95	4.72	5.53	55.38
Brent	3.85	4.06	5.22	4.97	4.72	5.12	5.46	4.9	5.23	4.69	4.47	5.29	53.01
OPEC.Oil	3.17	3.41	4.51	3.94	4.18	4.31	4.69	4.19	4.59	4.05	3.75	4.38	44.97
CO.Oman	3.53	3.7	4.79	4.38	4.29	4.95	5.04	4.49	4.82	4.29	4.09	4.78	48.2
CO.Dubai	3.69	3.93	5.13	4.45	4.47	4.94	5.5	4.64	5.03	4.46	4.28	4.96	49.98
Gasoline	3.46	3.65	4.75	4.27	4.28	4.7	5	4.7	4.92	4.26	4.08	4.67	48.03
Heating.Oil	3.36	3.56	4.63	4.16	4.25	4.49	4.77	4.43	4.92	4.22	4	4.64	46.5
Propane	3.15	3.3	4.5	3.93	4.02	4.35	4.58	4.15	4.6	4.11	3.78	4.4	44.76
Natural.Gas	3.72	3.82	4.9	4.43	4.43	4.76	5.08	4.65	5	4.47	4.51	4.91	50.17
Coal	4.82	5.08	6.28	5.67	5.63	6.06	6.53	5.89	6.18	5.69	5.36	6.98	63.2
TO others	43.97	46.31	60.4	55.05	54.92	59.89	63.12	57.3	60.65	55.6	52.7	59.75	669.65
NET	−38.84	−36.31	5.02	2.04	9.95	11.68	13.14	9.27	14.15	10.84	2.53	−3.46	TCI = 55.8

PANEL B: 5 TO 30 DAYS (INTERMEDIATE/MEDIUM TERM)

	PRI	TRI	WTI	Brent	OPEC.Oil	CO.Oman	CO.Dubai	Gasoline	Heating.Oil	Propane	Natural.Gas	Coal	FROM others
PRI	0.33	0.33	0.57	0.48	0.5	0.55	0.66	0.43	0.59	0.49	0.43	0.48	5.51
TRI	0.28	0.3	0.53	0.45	0.46	0.52	0.6	0.42	0.54	0.46	0.39	0.42	5.06
WTI	1.12	1.12	1.96	1.69	1.79	1.85	1.9	1.78	1.92	1.72	1.68	1.69	18.26
Brent	1.22	1.17	1.92	1.83	1.88	1.83	1.94	1.84	1.96	1.8	1.82	1.84	19.21
OPEC.Oil	1.33	1.32	2.07	1.87	2.08	2.06	2.15	2.02	2.16	1.94	1.97	1.92	20.82
CO.Oman	1.3	1.28	2.04	1.92	1.96	2.07	2.02	1.94	2.08	1.9	1.88	1.92	20.24
CO.Dubai	1.25	1.22	1.94	1.8	1.87	1.89	2.01	1.89	2.02	1.8	1.88	1.84	19.4
Gasoline	1.35	1.32	2.14	1.93	2.05	2.07	2.15	2.16	2.2	1.92	2.01	1.95	21.09
Heating.Oil	1.39	1.37	2.16	1.97	2.11	2.11	2.16	2.11	2.21	2.05	2.08	2.07	21.58
Propane	1.38	1.38	2.29	2.01	2.19	2.16	2.25	2.17	2.33	2.12	2.12	2.06	22.34
Natural.Gas	1.23	1.2	1.99	1.81	1.93	1.91	2.08	2.05	2.1	1.83	1.89	1.79	19.94
Coal	0.98	0.94	1.61	1.43	1.5	1.49	1.63	1.44	1.63	1.44	1.41	1.56	15.5
TO others	12.84	12.65	19.26	17.35	18.25	18.45	19.52	18.08	19.53	17.37	17.67	17.99	208.96
NET	7.33	7.59	1.01	−1.86	−2.57	−1.79	0.11	−3.02	−2.05	−4.98	−2.28	2.49	TCI = 17.41

PANEL C: ABOVE 30 DAYS (LONG TERM = LOW FREQUENCY)

	PRI	TRI	WTI	Brent	OPEC.Oil	CO.Oman	CO.Dubai	Gasoline	Heating.Oil	Propane	Natural.Gas	Coal	FROM others
PRI	0.21	0.22	0.38	0.32	0.34	0.37	0.43	0.29	0.39	0.32	0.29	0.31	3.66
TRI	0.19	0.21	0.38	0.32	0.32	0.38	0.41	0.3	0.38	0.32	0.29	0.28	3.56
WTI	1.01	1.01	1.86	1.48	1.72	1.86	1.67	1.8	1.82	1.58	1.49	1.44	16.88
Brent	1.26	1.18	1.82	1.89	1.84	1.88	1.97	1.77	1.97	1.73	1.97	1.7	19.09
OPEC.Oil	1.65	1.53	2.55	2.4	2.75	2.64	2.67	2.31	2.67	2.24	2.4	2.16	25.2
CO.Oman	1.41	1.37	2.22	2.1	2.18	2.49	2.21	2.24	2.29	2.06	1.97	1.99	22.04
CO.Dubai	1.33	1.25	2.05	1.94	2.04	2.28	2.29	2.02	2.16	1.91	2.01	1.84	20.83
Gasoline	1.35	1.33	2.25	1.97	2.19	2.23	2.09	2.61	2.16	2.02	1.89	1.91	21.41
Heating.Oil	1.47	1.35	2.22	1.96	2.17	2.35	2.18	2.2	2.61	2.05	2.25	1.98	22.18
Propane	1.58	1.47	2.28	1.98	2.24	2.27	2.36	2.27	2.39	2.8	2.9	2.12	23.85
Natural.Gas	1.39	1.27	1.97	1.8	2.07	2.11	2.06	2.2	2.2	1.96	2.78	1.68	20.71
Coal	0.75	0.7	1.2	1.04	1.13	1.11	1.15	1.14	1.23	1.08	1.09	1.16	11.61
TO others	13.37	12.68	19.32	17.31	18.25	19.48	19.19	18.53	19.66	17.27	18.54	17.4	211
NET	9.72	9.12	2.44	−1.78	−6.95	−2.56	−1.64	−2.88	−2.52	−6.58	−2.16	5.79	TCI = 17.58

Notes: This table reports the directional spillover in percentage (%). Results are based on a GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 4 (BIC). The second-last row (TO others) in Table 5 reports the contribution of each variable to other variables. The last column of Table 4 (under "FROM others") reports the downside tail risk spillover that each variable experiences from the entire system. The "NET" row classifies assets as net risk receivers or transmitters based on their negative or positive values. PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural. Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. TCI = Total Connectedness Index.

climate risk to energy markets' tail risk in the medium- and long-term. These results are consistent with our baseline results and support the robustness of our findings.

4.3.5. *Troster's (2018) quantile causality test*

To explore the causal link between climate risk and international energy markets' tail risks, we implemented Troster's (2018) quantile causality test. Following Mighri et al. (2022), we defined market states using three quantile intervals: lower quantiles (0.05, 0.20) indicating bearish states, middle quantiles (0.40, 0.60) representing normal states, and upper quantiles (0.80, 0.95) for bullish states. The benchmark for a statistically significant Granger causality is at the 1 % significance level, which is in line with Troster (2018). The Granger causality test results from (to) climate physical risk to (from) energy markets' tail risks are presented in Tables 8 and 9, respectively. We find that the Granger causality exists from changes in physical risk to energy markets' tail risks, which are statistically significant at the extreme tails of the conditional distribution, τ=(0.05) or τ=(0.95). These results suggest that significant negative climate physical risks lead to elevated energy markets' tail risks.

Table 6
Quantile frequency connectedness results of downside tail risk based on upper quantile (tau = 0.95).

PANEL A: 1 TO 5 DAYS (SHORT TERM = HIGH FREQUENCY)

	PRI	TRI	WTI	Brent	OPEC.Oil	CO.Oman	CO.Dubai	Gasoline	Heating.Oil	Propane	Natural.Gas	Coal	FROM others
PRI	28.08	12.78	4.93	5.35	6.4	4.7	5.43	6.2	6.21	5.92	7.79	4.59	70.3
TRI	13.21	29.04	4.93	5.28	6.22	4.88	5.5	5.87	6.3	5.92	7.17	4.35	69.64
WTI	0.73	0.7	4.49	2.19	1.48	2.68	2.64	1.92	2.38	1.25	0.87	0.43	17.27
Brent	0.41	0.4	1.09	2.1	0.98	1.02	0.96	0.81	0.9	0.55	0.45	0.24	7.81
OPEC.Oil	0.28	0.28	0.43	0.51	1.1	0.44	0.45	0.43	0.42	0.29	0.29	0.18	3.99
CO.Oman	0.23	0.22	0.77	0.62	0.47	1.22	0.83	0.49	0.6	0.36	0.27	0.14	5
CO.Dubai	0.29	0.28	0.88	0.74	0.57	0.98	1.43	0.68	0.8	0.4	0.29	0.18	6.1
Gasoline	0.51	0.54	1.04	0.93	0.74	0.98	1.1	2.53	1.2	0.67	0.62	0.33	8.64
Heating.Oil	0.29	0.29	0.67	0.5	0.42	0.58	0.6	0.65	1.29	0.37	0.35	0.2	4.9
Propane	0.35	0.34	0.5	0.49	0.45	0.49	0.46	0.5	0.5	1.59	0.43	0.21	4.72
Natural.Gas	1	0.93	0.79	0.81	0.91	0.74	0.8	0.9	0.98	0.91	3.41	0.65	9.4
Coal	2.55	2.28	1.77	2.07	2.43	1.72	1.98	2.29	2.6	1.92	2.9	21.3	24.52
TO others	19.83	19.04	17.81	19.5	21.05	19.2	20.76	20.73	22.88	18.57	21.42	11.49	232.29
NET	−50.47	−50.6	0.54	11.68	17.07	14.2	14.67	12.09	17.98	13.85	12.02	−13.03	TCI = 19.36

PANEL B: 5 TO 30 DAYS (INTERMEDIATE/MEDIUM TERM)

	PRI	TRI	WTI	Brent	OPEC.Oil	CO.Oman	CO.Dubai	Gasoline	Heating.Oil	Propane	Natural.Gas	Coal	FROM others
PRI	0.16	0.08	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.06	0.04	0.59
TRI	0.07	0.15	0.05	0.05	0.06	0.04	0.05	0.05	0.06	0.04	0.06	0.04	0.57
WTI	0.85	0.82	5.37	2.79	1.85	3.38	3.07	2.48	2.95	1.51	1.13	0.65	21.48
Brent	0.71	0.67	1.89	3.47	1.69	1.82	1.77	1.52	1.63	1.01	0.9	0.53	14.15
OPEC.Oil	0.52	0.53	1.05	1.21	2.13	1.04	1.05	1.06	1.02	0.66	0.63	0.51	9.29
CO.Oman	0.4	0.37	1.47	1.24	0.89	2.15	1.56	0.99	1.19	0.71	0.53	0.31	9.67
CO.Dubai	0.53	0.5	1.63	1.49	1.08	1.82	2.43	1.32	1.59	0.79	0.6	0.42	11.77
Gasoline	0.89	0.92	1.94	1.83	1.53	1.88	2.06	4.26	2.16	1.23	1.09	0.83	16.36
Heating.Oil	0.46	0.44	1.13	1.03	0.8	1.04	1.12	1.24	2.02	0.64	0.69	0.46	9.06
Propane	0.55	0.53	0.96	0.93	0.82	0.88	0.83	0.9	0.89	2.6	0.71	0.47	8.46
Natural.Gas	1.1	1.13	1.2	1.3	1.5	1.13	1.23	1.54	1.42	1.43	4.6	1.15	14.13
Coal	1.51	1.38	1.45	1.65	1.57	1.32	1.52	1.65	1.82	1.32	2.01	12.38	17.19
TO others	7.57	7.38	12.83	13.58	11.86	14.4	14.3	12.81	14.77	9.39	8.41	5.42	132.72
NET	6.98	6.81	−8.65	−0.57	2.56	4.73	2.53	−3.55	5.71	0.94	−5.72	−11.77	TCI = 11.06

PANEL C: ABOVE 30 DAYS (LONG TERM = LOW FREQUENCY)

	PRI	TRI	WTI	Brent	OPEC.Oil	CO.Oman	CO.Dubai	Gasoline	Heating.Oil	Propane	Natural.Gas	Coal	FROM others
PRI	0.13	0.07	0.07	0.07	0.07	0.06	0.07	0.08	0.08	0.06	0.07	0.04	0.75
TRI	0.05	0.09	0.04	0.06	0.05	0.04	0.04	0.06	0.05	0.04	0.05	0.03	0.51
WTI	1.6	1.58	9.36	5.46	4.16	6.7	6.76	4.38	4.88	3.15	2	1.36	42.02
Brent	2.53	2.34	7.82	13.89	7.24	8.1	8.78	5.7	6.48	4.75	2.53	2.3	58.58
OPEC.Oil	3.27	3.25	8.13	9.42	13.47	9.44	9.62	6.34	7.71	5.82	4.16	2.85	70.02
CO.Oman	2.41	2.38	10.47	8.62	6.88	15.87	10.98	7.21	7.75	4.69	2.76	1.95	66.1
CO.Dubai	2.63	2.62	9.8	7.96	6.33	10.23	14.06	6.99	7.78	4.74	2.96	2.17	64.21
Gasoline	2.71	2.86	7.05	6.04	5.64	6.92	7.36	13.4	6.51	4.07	3.04	2.6	54.81
Heating.Oil	3.22	3.03	9.01	8.5	6.79	8.34	9.72	7.69	14.35	4.97	4.02	3.1	68.38
Propane	3.85	3.96	6.31	6.56	6.36	6.48	7.15	6.01	6.51	22.05	4.44	2.94	60.58
Natural.Gas	3.82	3.9	4.9	4.15	5.31	4.93	4.99	4.95	4.82	4.35	19.24	3.09	49.22
Coal	1.29	1.18	1.4	1.34	1.57	1.34	1.5	1.46	1.69	1.22	1.41	9.21	15.4
TO others	27.39	27.16	65	58.18	50.41	62.57	66.98	50.87	54.27	37.86	27.44	22.43	550.58
NET	26.64	26.65	22.97	−0.39	−19.61	−3.52	2.77	−3.93	−14.11	−22.72	−21.78	7.04	TCI = 45.88

Notes: This table reports the directional spillover in percentage (%). Results are based on a GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 4 (BIC). The second-last row (TO others) in Table 6 reports the contribution of each variable to other variables. The last column of Table 5 (under "FROM others") reports the downside tail risk spillover that each variable experiences from the entire system. The "NET" row classifies assets as net risk receivers or transmitters based on their negative or positive values. PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural. Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. TCI = Total Connectedness Index.

The negative impact (in the lower quantile) appears more potent than the positive one (in the upper quantile), indicating that energy markets are more susceptible to adverse shocks from climate physical risks. This finding aligns with earlier observations that the spillover from climate risk to energy markets' tail risks intensifies during extreme market states. Table 9 demonstrates a lack of Granger causality from energy market tail risks to climate physical risks, except for the Coal and Gasoline markets. These results confirm the minimal spillover effects between climate-related risks and the broader international energy markets. Consequently, our results highlight a predominantly unidirectional causality from climate physical risks to energy markets' tail risks, consistent across short-, medium-, and long-term analyses.

Next, we explore the causal relationship between climate transition risk and energy markets' tail risk, as detailed in Tables 10 and 11. We find a consistent pattern of Granger causality, where fluctuations in climate transition risk led to significant changes in energy markets' tail risk, particularly at the lower quantile and between the 60th and 75th quantiles. This pattern mirrors our earlier findings with climate physical risk, with the impact being more pronounced in bearish rather than bullish market states. Our result of energy markets' tail risks

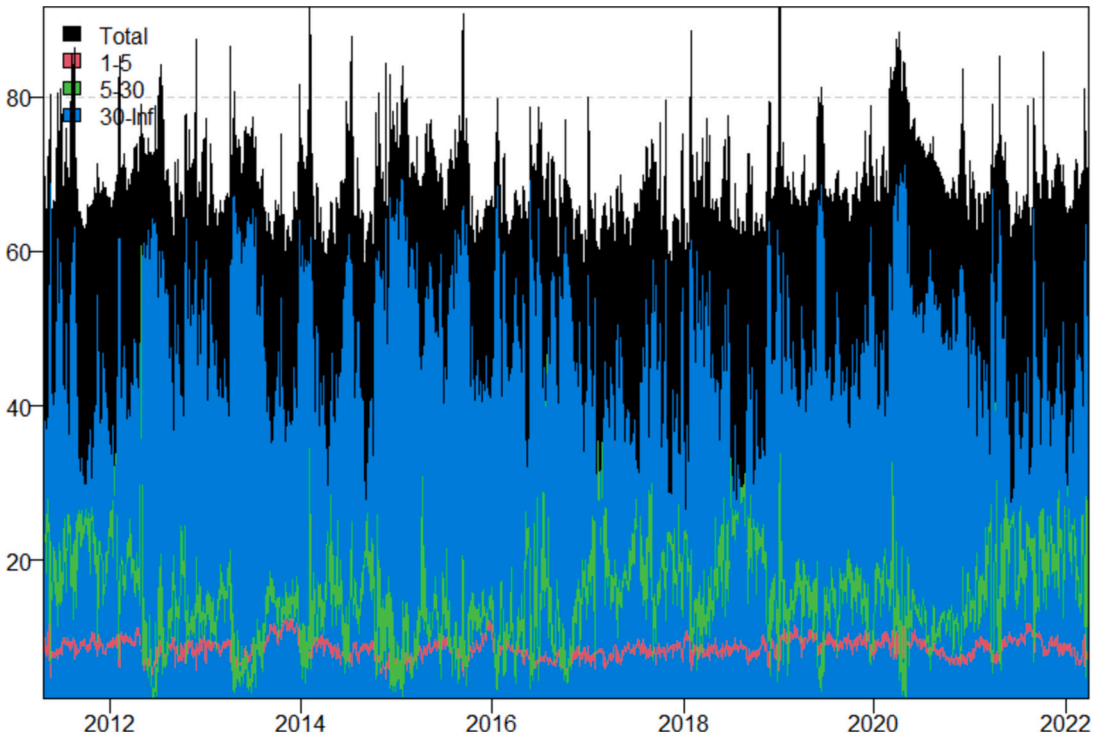


Fig. 9. Dynamic total connectedness index.
Note: Results are based on GFEVD with 100 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 1 (BIC). The black shaded area corresponds to the total averaged connected index under the normal market state. The blue shaded part represents the portion of the averaged total connectedness index which is classified as long-term. The red trend line showcases total connectedness in the short term, while the green trend line shows total connectedness in the medium term. The y-axis denotes the range of the total connectedness index between climate risk and energy market tail risk. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

predictability from climate risks is related to the study by Bouri et al. (2023b), which found energy assets and green bonds' returns and volatility predictability from climate risks.

Focusing on the extremes of the conditional distribution, $\tau = (0.05)$ and $\tau = (0.95)$, we observe that the impact of climate transition risk on energy markets' tail risk is notably significant at the 1 % level in the 5th quantile. However, this significance is not maintained across all energy markets at the 95th quantile. Moreover, Table 11 shows that significant Granger-causality effects are largely absent from most energy markets towards climate transition risk, except in the Coal and Gasoline, where significant causality spans from the 5th to 95th quantile, indicating a strong causal effect of the Coal and Gasoline market tail risk on climate transition risk.

This exception could be explained by the significant concentration of the coal and gasoline industries, which account for more than a third of global electricity generation (Preonas, 2023). In these sectors, unexpected events or extreme outcomes can significantly magnify the environmental impacts associated with fossil fuel consumption. This relationship is exacerbated by the "waterbed effect," where emission reductions in one region can result in increases elsewhere, thereby complicating efforts towards climate transition (see e.g., Böhringer and Rosendahl, 2022). Such dynamics worsen environmental outcomes and introduce additional costs that must be considered against the benefits of transitioning to cleaner energy sources.

5. Conclusion

In this study, we investigated the tail risk spillover, causal effect, and co-movements between climate risk and the international energy market using the Asymmetric Slope CAViaR methodology. We focused on the 5 % VaR downside and 95 % VaR upside tail risks, leveraging the climate risk measurement model by Bua et al. (2022), which separates climate risk into physical and transition components. Our analysis included a broad representation of the energy market through Brent, WTI, OPEC Oil, Crude Oil Oman, Crude Oil Dubai, Gasoline, Heating Oil, Propane, Natural Gas, and Coal, utilizing daily data from July 19, 2010, to March 31, 2022. We employed robust analytical techniques: the quantile connectedness approach, the rolling window wavelet correlation approach, and the quantile Granger causality approach.

The key findings of our study include the following: First, we established that tail risk between climate risks and energy markets exhibits asymmetrical connectedness. Specifically, climate risks in bearish markets primarily transmit downside tail risk, whereas, in bullish markets, the spillover from climate risks is minimal. Second, we revealed that the correlation between climate risk and energy markets' tail risks is both temporal and frequency-dependent. This correlation is predominantly negative in the short term, while the long-term correlation is characterized by significant instability. Finally, we demonstrated that variations in climate physical and transition risks can predict energy market tail risks, indicating a unidirectional causality from climate risks to the energy market.

These findings have significant implications for investors and policymakers. The asymmetric relationship between climate-related risks and the energy market highlights the potential for systemic tail risk contagion during periods of extreme market volatility. Stakeholders, particularly those in crude oil and refined petroleum products, should closely monitor sustainability dynamics to mitigate potential investment losses. Additionally, the climate risk index could serve as an effective short-term hedging tool for energy sector investments, aiding companies in protecting against downside tail risk. Our insights into the mechanisms of spillover, connectedness, and co-movement between climate risk and the energy market will help investors and policymakers manage systemic risks in the energy sector more effectively.

Future research should explore several directions to build on these

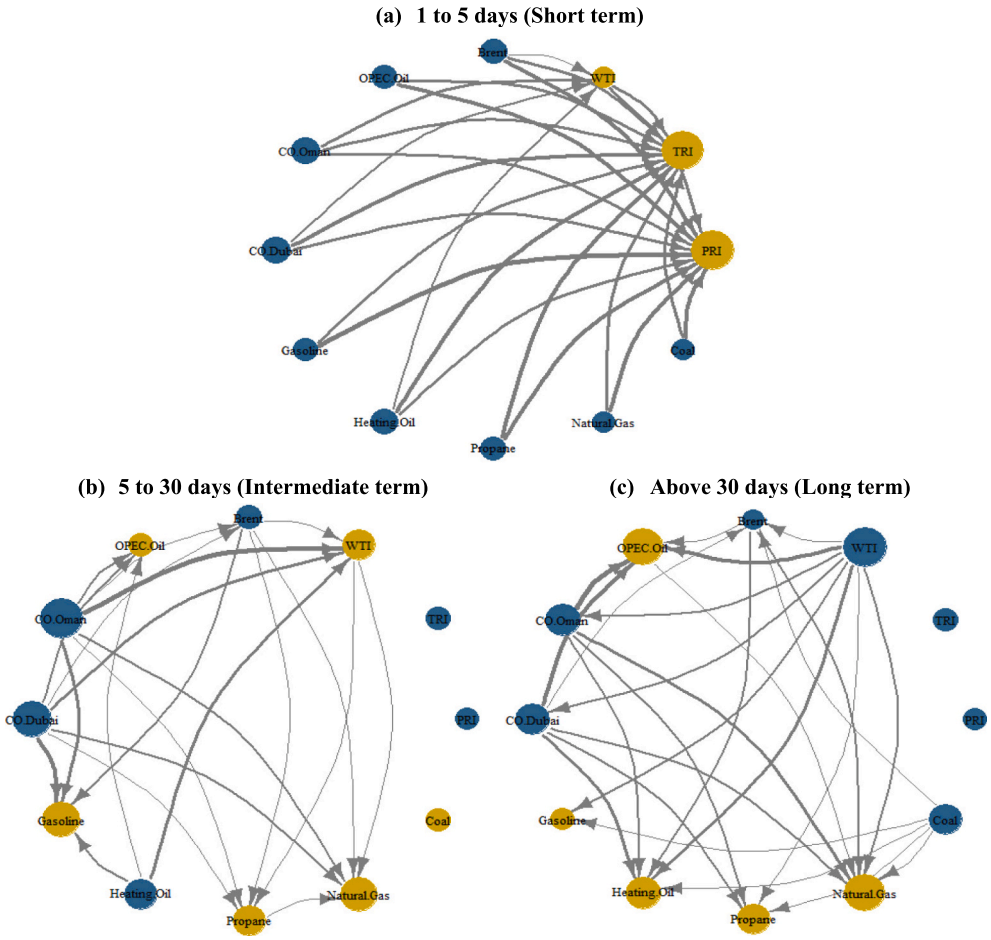


Fig. 10. Network plot of tail risk during the normal market state.
Notes: Results are based on a GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 1 (BIC). PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. The blue nodes denote net transmitters of tail risk spillover, while the yellow nodes denote net receivers of tail risk spillover. The node's size represents the magnitude of the net spillover effect, either received or transmitted. The arrow shows the direction of the tail risk spillover in the network of variables. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

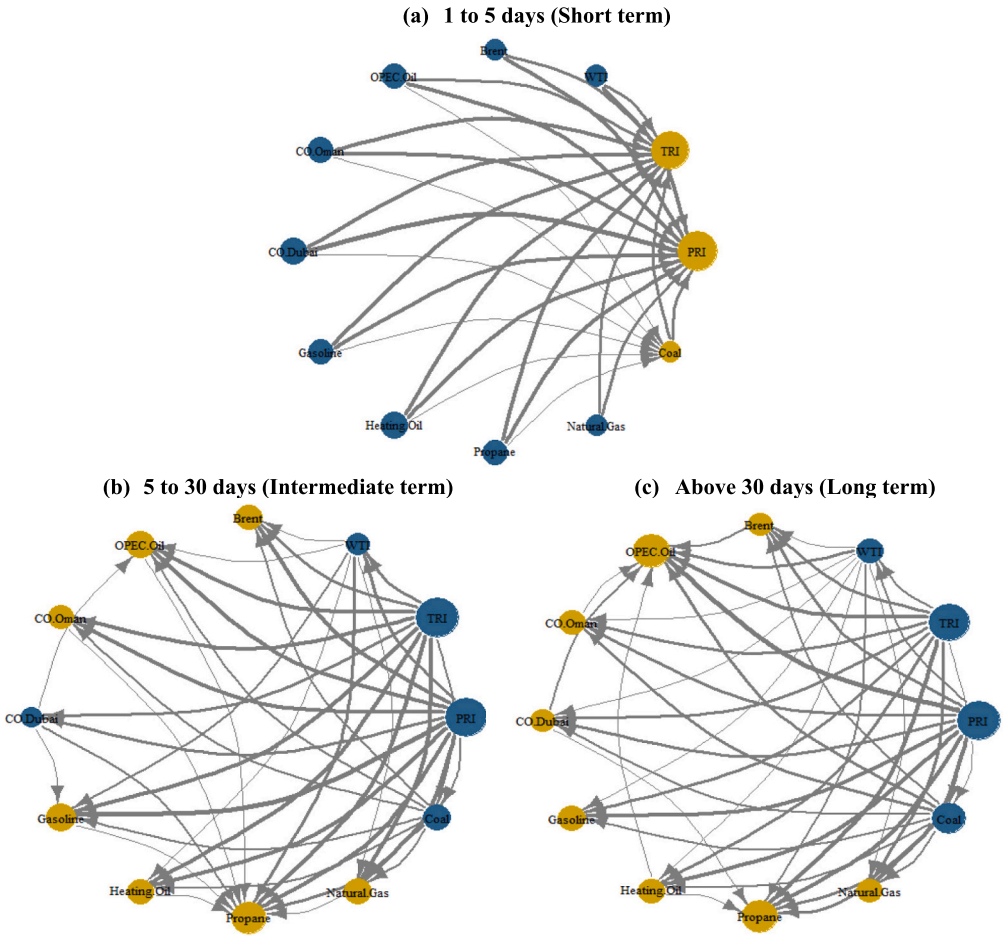


Fig. 11. Network transmission plot of tail risk during the bearish market state.
Notes: Results are based on a GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 1 (BIC). PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. The blue nodes denote net transmitters of tail risk spillover, while the yellow nodes denote net receivers of tail risk spillover. The node's size represents the magnitude of the net spillover effect, either received or transmitted. The arrow shows the direction of the tail risk spillover in the network of variables. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

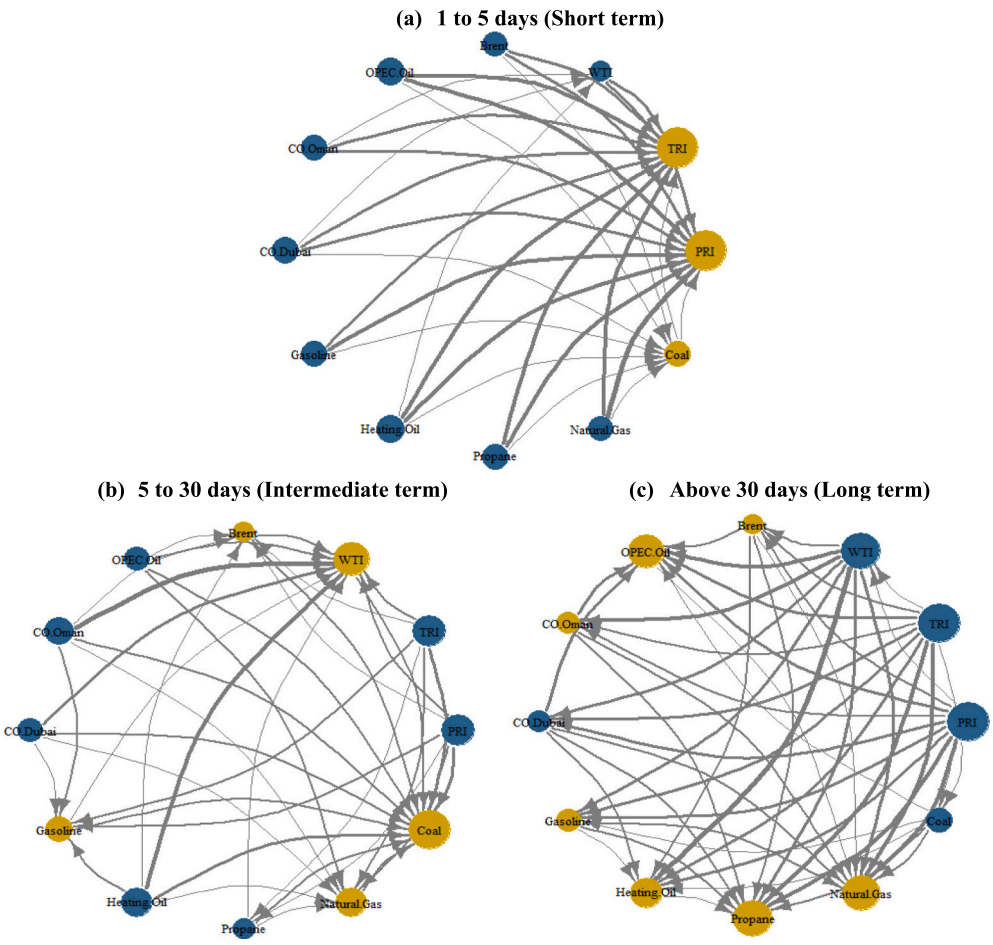


Fig. 12. Network transmission plot of tail risk during the bullish market state.
Notes: Results are based on a GFEVD with 20 steps in advance and a 200-day rolling-window QVAR model with a lag length of order 1 (BIC). PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. The blue nodes denote net transmitters of tail risk spillover, while the yellow nodes denote net receivers of tail risk spillover. The node's size represents the magnitude of the net spillover effect, either received or transmitted. The arrow shows the direction of the tail risk spillover in the network of variables. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 7
Robustness test results of downside tail risk using alternative lengths of window.

	Baseline (200-day window)			400-day window			600-day window		
	5th Quantile	50th Quantile	95th Quantile	5th Quantile	50th Quantile	95th Quantile	5th Quantile	50th Quantile	95th Quantile
PRI	−8.67	−7.16	−3.27	−25.6	−8.13	−10.55	−27.64	−6.11	−9.23
TRI	−10.71	−7.20	−4.32	−28.59	−7.27	−11.32	−28.86	−4.96	−9.03
Brent	9.65	1.41	3.50	17	21.39	12.37	12.85	27.04	12.45
Coal	−15.44	0.17	−19.19	−1.88	4.38	6.47	−2.18	−2.2	6.54
CO.Dubai	3.07	20.15	10.43	0.36	−15.79	4.46	5.06	−18.83	5.14
CO.Oman	6.66	17.40	5.54	11.35	43.77	13.4	17.3	47.48	11.03
Gasoline	3.30	−2.63	3.61	14.33	24.96	16.67	20.42	24.45	15.11
Heating.Oil	9.40	8.15	8.87	3.7	−5.65	3.72	2.15	−8.31	3.01
Natural.Gas	−1.75	−9.30	−10.89	1.27	−10.41	12.48	13.72	−11.21	12.74
OPEC.Oil	−6.23	−26.87	1.12	12.58	−22.51	−9.38	4.82	−21.87	−7.99
Propane	1.79	−10.30	−5.66	6.25	−27.78	−15.05	3.08	−26.59	−14.85
WTI	8.93	16.18	10.26	−10.78	3.04	−23.26	−20.72	1.12	−24.92
Total TCI	90.17	46.78	81.73	91.53	57.70	76.68	91.60	55.78	76.43

Notes: This table presents the NET spillover results (in %) of the baseline quantile VAR connectedness analysis based on a GFEVD with 100 steps in advance and both 400-and 600-day rolling-window QVAR models with a lag length of order 1 (BIC). PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. Total TCI = Total Connectedness Index.

Table 8
Granger causality test results from changes in climate physical risk to changes in energy market tail risk.

	ΔPRI→ΔBrent		ΔPRI→ΔCoal		ΔPRI→ΔCO.Dubai		ΔPRI→ΔCO.Oman		ΔPRI→ΔGasoline		ΔPRI→ΔHeating Oil		ΔPRI→ΔNatural Gas		ΔPRI→ΔOPEC Oil		ΔPRI→ΔPropane		ΔPRI→ΔWTI	
	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside
0.05	5.42***	5.27***	5.59***	5.65***	5.1***	4.84***	6.04***	5.42***	4.62***	4.83***	5.39***	5.47***	5.15***	4.93***	5.3***	5.81***	5.1***	5.22***	4.68***	4.57***
0.1	2.91***	3.46***	3.55***	3.54***	3.22***	2.94***	3.31***	3.19***	2.76***	2.8***	3.17***	3.01***	3.6***	3.36***	2.87***	3.53***	3.07***	3.28***	2.56***	2.5***
0.15	2.17**	2.74***	2.74***	3.14***	2.23**	2.28**	2.73***	2.37***	2.26**	2.44***	2.99***	2.63***	3.23***	2.95***	2.11**	2.81***	2.83***	2.92***	1.94**	1.8**
0.2	1.77**	2.42***	2.75***	3.16***	2.01**	2.21**	2.4***	2.2**	2.55***	2.5***	3.01***	2.86***	3.41***	3.15***	2.2**	2.89***	2.31**	2.82***	2.04**	1.81**
0.25	1.76**	2.82***	2.96***	3.2***	1.82**	2.15**	2.4***	2.42***	2.56***	2.49***	2.94***	2.95***	3.54***	3.44***	2.13**	3.25***	2.43***	2.65***	2.31**	2.03**
0.3	1.77**	3.12***	3***	3.21***	1.86**	2.25**	2.7***	2.54***	2.87***	2.68***	3.01***	2.9***	3.75***	3.7***	2.31**	3.24***	3.03***	3.08***	2.72***	2.42***
0.35	1.81**	2.83***	2.83***	3.47***	2.1**	2.35***	3.04***	2.68***	2.68***	2.51***	3.72***	3.45***	4.13***	4.42***	2.24**	3.33***	2.87***	3.04***	3.2***	2.85***
0.4	1.9**	2.76***	3.13***	3.89***	2.12**	2.69***	2.88***	2.77***	2.94***	2.57***	4.11***	3.81***	4***	4.38***	2.69***	3.73***	2.76***	3.19***	3.26***	3.05***
0.45	1.77**	2.73***	3.2***	3.54***	2.56***	3.31***	2.96***	2.68***	3.19***	2.96***	4.03***	3.77***	4.12***	4.4***	2.63***	3.48***	2.47***	3.03***	3.15***	2.99***
0.5	1.91**	2.48***	3.11***	3.42***	2.77***	3.59***	2.54***	2.46***	2.98***	2.87***	4.01***	3.42***	4.21***	4.54***	2.65***	3.45***	2.64***	3.3***	3***	2.95***
0.55	1.9**	2.67***	2.99***	3.48***	2.96***	3.72***	2.46***	2.81***	3.05***	2.89***	4.08***	3.48***	4.53***	4.46***	2.8***	3.28***	2.86***	3.01***	3.26***	3.14***
0.6	1.99**	2.93***	3.13***	3.51***	2.82***	3.47***	2.42***	2.37***	3.06***	2.68***	3.9***	3.31***	4.07***	3.95***	2.52***	3.54***	2.61***	3.02***	2.9***	2.87***
0.65	1.72**	3.02***	3.18***	3.48***	2.46***	3.13***	2.05**	1.96**	3.12***	2.87***	3.52***	3.36***	3.79***	3.66***	2.39***	3.09***	2.5***	2.78***	2.4***	2.61***
0.7	4.65***	5.49***	4.92***	5.5***	4.48***	4.99***	4.43***	4.45***	5.34***	5.36***	5.36***	5.08***	5.7***	5.69***	3.88***	4.55***	4.28***	4.7***	4.51***	4.57***
0.75	3.58***	4.45***	4***	4***	3.49***	3.78***	3.23***	3.4***	4.4***	4.26***	4.15***	3.68***	4.64***	4.74***	2.9***	3.84***	3.47***	3.3***	3.58***	3.36***
0.8	2.9***	3.57***	3.04***	3.09***	2.63***	2.71***	2.44***	2.53***	3.32***	3.22***	3.24***	3.02***	4.39***	4.6***	2.34***	2.79***	3.28***	3.12***	2.77***	2.48***
0.85	2.13**	2.58***	2.24**	2.64***	1.94**	2.01**	1.88**	1.8**	2.53***	2.52***	2.51***	2.54***	3.75***	3.75***	2.17**	2.61***	2.07**	2.17**	2.09**	1.89**
0.9	2**	2.28**	2.69***	2.52***	1.84**	1.91**	1.84**	1.81**	2.23**	2.46***	2.5***	2.34***	3.24***	3.41***	2.56***	2.54***	2.2**	2.28**	1.91**	1.81**
0.95	1.51*	1.76**	1.96**	1.99**	1.44*	1.45*	1.48*	1.4*	1.6*	1.73**	1.66**	1.43*	2.04**	2.01**	1.76**	1.97**	1.65**	1.7**	1.57*	1.65**

Note: Results are based on the estimation following the quantile Granger casualty test (Troster, 2018). ***, **, and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. τ = the range of quantiles from 0.05 to 0.95.

Table 9
Granger causality test results from changes in energy market tail risk to changes in climate physical risk.

	ΔBrent→ΔPRI		ΔCoal→ΔPRI		ΔCO.Dubai→ΔPRI		ΔCO.Oman→ΔPRI		ΔGasoline→ΔPRI		ΔHeating Oil→ΔPRI		ΔNatural Gas→ΔPRI		ΔOPEC Oil→ΔPRI		ΔPropane→ΔPRI		ΔWTI→ΔPRI	
	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside
0.05	0.91	0.68	3.79***	3.85***	0.28	0.67	0.89	0.96	1.57*	1.67**	1.53*	0.94	1.24	0.77	0.61	0.52	1.14	0.95	0.93	0.51
0.1	0.68	0.8	2.37***	2.51***	0.38	1.19	0.95	0.78	1.86**	2.17**	1.55*	0.75	1.3*	0.93	0.55	0.79	1.13	1.34*	1.03	1.01
0.15	0.74	0.82	2.32**	2.17**	0.47	1.81**	1.13	0.71	1.98**	2.38***	2.22**	1.2	1.16	0.9	1.04	0.66	1.34*	1.61*	1.1	1.54*
0.2	0.7	1.27	2.14**	1.76**	0.53	1.46*	1.18	0.63	2.4***	2.69***	2.02**	1.28	1.45*	0.83	1.05	0.83	1.66**	1.59*	1.67**	1.35*
0.25	0.63	0.84	2.25**	2.1**	0.69	1.46*	1.61*	0.71	2.75***	3.41***	2.16**	1.5*	1.41*	0.7	1.04	1.06	1.62*	1.41*	1.8**	0.91
0.3	0.68	0.7	2.56***	2.92***	0.66	2**	1.85**	0.57	3.61***	3.55***	2.17**	1.71**	1.49*	0.81	1.1	1.71**	1.54*	1.51*	1.49*	1.06
0.35	0.77	0.6	2.61***	3.18***	0.55	1.57*	1.33*	0.49	4.28***	3.97***	2.48***	1.43*	1.38*	0.89	0.95	2.04**	1.41*	1.62*	1.05	1.26
0.4	0.62	0.62	3.11***	3.08***	0.45	1.2	1.37*	0.57	4.24***	3.95***	2.69***	1.29*	1.4*	0.89	0.79	1.52*	1.51*	1.47*	0.87	1.59*
0.45	0.6	0.73	3.46***	3.23***	0.33	1.07	1.63*	0.73	4.08***	4.25***	2.54***	1.63*	1.59*	1.04	0.84	1.38*	1.03	1.51*	1.18	1.43*
0.5	0.59	1.02	3.17***	3.11***	0.24	1.01	1.64*	0.95	4.3***	3.66***	2.71***	1.57*	1.61*	1.05	0.77	1.46*	1.18	1.3*	1.04	1.39*
0.55	0.42	0.93	3.44***	3.05***	0.25	0.85	1.46*	0.96	3.42***	3.54***	2.75***	1.6*	1.71**	1.07	1.16	2.02**	1.82**	1.18	1	1.5*
0.6	0.38	0.85	2.74***	3.19***	0.32	0.92	1.41*	0.97	3.17***	3.95***	2.71***	1.44*	1.55*	1.36*	1.44*	1.91**	1.65**	1.36*	1.26	1.54*
0.65	0.4	0.8	2.9***	2.86***	0.3	0.99	1.58*	0.88	3.26***	3.9***	2.54***	1.29*	1.79**	1.39*	1.1	1.9**	1.46*	1.22	1.03	1.48*
0.7	0.56	0.72	2.63***	2.74***	0.39	1.25	1.59*	0.81	3.37***	3.42***	2.32**	1.17	1.46*	1.13	1.04	1.29*	0.91	1.26	0.8	1.62*
0.75	0.47	0.91	2.11**	2.21**	0.4	1.35*	1.32*	0.77	2.91***	2.91***	2.2**	1.05	1.57*	1.06	1.3*	0.93	0.96	1.25	0.73	1.5*
0.8	0.4	0.74	2.07**	1.96**	0.3	0.87	1.08	0.51	2.64***	2.51***	2.03**	1.18	1.3*	0.9	0.93	0.69	0.61	1.38*	0.83	1.38*
0.85	0.36	0.45	1.71**	1.65**	0.19	0.65	0.77	0.46	2.13**	2.34***	1.94**	1.04	0.95	0.54	0.55	0.64	0.82	1.36*	0.49	0.87
0.9	0.24	0.65	1.27	1.52*	0.11	0.39	0.56	0.24	1.95**	1.86**	1.39*	0.98	0.89	0.69	0.59	0.78	1.04	1.28	0.27	0.52
0.95	0.37	0.56	2.7***	3.6***	0.33	0.91	0.56	0.4	1.57*	1.22	1.94**	1.04	2.27**	1.48*	0.85	0.55	0.5	0.82	0.42	0.44

Note: Results are based on the estimation following the quantile Granger casualty test (Troster, 2018). ***, **, and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. τ = the range of quantiles from 0.05 to 0.95.

Table 10
Granger causality test results from changes in climate transition risk to changes in energy market tail risk.

	ΔTRI→ΔBrent		ΔTRI→ΔCoal		ΔTRI→ΔCO.Dubai		ΔTRI→ΔCO.Oman		ΔTRI→ΔGasoline		ΔTRI→ΔHeating Oil		ΔTRI→ΔNatural Gas		ΔTRI→ΔOPEC Oil		ΔTRI→ΔPropane		ΔTRI→ΔWTI	
	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside
0.05	3.94***	3.92***	4.27***	5.05***	4.52***	4.73***	4.15***	4.33***	4.46***	4.6***	4.21***	4.28***	4.78***	4.73***	4.37***	4.66***	3.84***	4.23***	3.82***	3.85***
0.1	2.4***	2.56***	2.48***	2.98***	2.67***	2.95***	2.03**	2.06**	2.64***	2.71***	2.31**	2.54***	2.78***	2.83***	2.19**	2.61***	2.41***	2.54***	2.05**	2.12**
0.15	1.64*	1.89**	1.78**	2.35***	1.84**	2.11**	1.6*	1.6*	2.01**	2.19**	2.02**	2.15**	2.39***	2.58***	1.81**	2.05**	1.96**	2.1**	1.65**	1.58*
0.2	1.74**	1.97**	1.76**	2**	1.89**	2.28**	1.43*	1.2	1.99**	2.2**	2.36***	2.28**	2.29**	2.48***	1.8**	2.22**	2.16**	2.06**	2.09**	1.77**
0.25	1.62*	1.85**	1.83**	1.98**	1.73**	2.33**	1.44*	1.39*	2.09**	2.49***	2.44***	2.54***	2.74***	2.95***	1.76**	2.07**	1.9**	1.93**	1.99**	2.12**
0.3	1.53*	1.62*	2.35***	2.31**	2.37***	2.82***	1.99**	1.83**	2.3**	2.31**	2.47***	3.25***	2.2**	2.44***	1.98**	2.32**	2.3**	2.36***	2.01**	2.12**
0.35	1.75**	1.87**	2.34***	2.44***	2.5***	2.95***	2.02**	1.98**	2.08**	2.32**	2.39***	2.89***	2.2**	2.47***	2.15**	2.7***	2.39***	2.35***	2.23**	2.42***
0.4	1.75**	2.09**	2.23**	2.52***	2.83***	2.92***	2.28**	2.43***	2.2**	2.22**	2.36***	2.89***	2.76***	3.13***	2.1**	2.79***	2.36***	2.4***	2.46***	2.66***
0.45	2.12**	2.24**	2.3**	2.46***	3.24***	3.38***	2.59***	2.9***	2.48***	2.3**	2.47***	3.01***	2.87***	3.32***	2.19**	2.82***	2.3**	2.61***	2.53***	2.7***
0.5	2.39***	2.65***	2.68***	2.98***	3.48***	3.27***	2.99***	2.98***	2.73***	2.52***	2.52***	3.31***	3.11***	3.53***	2.43***	3.05***	2.79***	2.88***	3.24***	3.13***
0.55	2.52***	2.56***	2.73***	3.3***	3.4***	3.43***	3.01***	2.83***	2.74***	2.49***	2.8***	3.64***	3.14***	3.66***	2.46***	2.9***	2.79***	3.18***	2.89***	2.7***
0.6	6.58***	6.35***	6.76***	7.75***	6.88***	6.81***	6.3***	6.43***	6.04***	5.96***	6.26***	7.17***	6.51***	7.14***	5.97***	6.48***	6.69***	7.05***	6.18***	5.95***
0.65	5.49***	5.04***	5.77***	6.8***	6***	5.76***	5.18***	5.34***	5.17***	5.13***	5.23***	6.16***	5.33***	5.72***	5.05***	5.61***	5.4***	5.46***	5.32***	5.09***
0.7	4.21***	4.17***	4.71***	5.75***	5.16***	5.01***	4.21***	4.45***	4.47***	4.33***	4.71***	5.68***	4.78***	5.1***	4.16***	4.48***	4.57***	4.48***	4.43***	4.09***
0.75	2.71***	2.82***	3.77***	5.12***	3.6***	3.52***	2.99***	3.04***	3.59***	3.51***	4.01***	4.31***	3.82***	3.91***	3.1***	3.5***	3.7***	3.6***	3.35***	2.88***
0.8	1.83**	1.98**	2.85***	3.6***	2.6***	2.66***	2.11**	2.31**	2.53***	2.66***	3.16***	3.48***	2.81***	2.9***	2.28**	2.61***	2.76***	2.64***	2.37***	2.09**
0.85	1.36*	1.47*	1.87**	2.35***	1.66**	1.88**	1.82**	1.88**	2.18**	2.21**	2.38***	2.64***	2.22**	2.32**	1.56*	1.61*	1.8**	1.89**	1.71**	1.58*
0.9	1.18	1.38*	1.42*	1.59*	1.31*	1.29*	1.76**	1.6*	1.83**	1.79**	1.91**	2.19**	2.03**	2.05**	1.21	1.37*	1.44*	1.53*	1.4*	1.26
0.95	1.19	1.06	1.25	1.31*	1.11	1.05	1.33*	1.37*	1.29*	1.21	1.63*	1.56*	1.52*	1.52*	1.31*	1.26	1.14	1.14	1.13	1.1

Note: Results are based on the estimation following the quantile Granger casualty test (Troster, 2018). ***, **, and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. τ = the range of quantiles from 0.05 to 0.95.

Table 11
Granger causality test results from changes in energy market tail risk to changes in climate transition risk.

	ΔBrent→ΔTRI		ΔCoal→ΔTRI		ΔCO.Dubai→ΔTRI		ΔCO.Oman→ΔTRI		ΔGasoline→ΔTRI		ΔHeating Oil→ΔTRI		ΔNatural Gas→ΔTRI		ΔOPEC Oil→ΔTRI		ΔPropane→ΔTRI		ΔWTI→ΔTRI	
	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside	Upside	Downside
0.05	0.49	0.64	3.36***	3.36***	0.47	0.69	0.97	0.84	1.85**	2.26**	1.57*	1.18	1.3*	0.9	0.78	0.62	1.04	0.49	1.11	1.14
0.1	0.45	1.37*	2.39***	2.26**	0.32	0.7	1.6*	0.47	2.08**	2.67***	1.79**	1.67**	1.36*	1.18	0.75	0.86	0.59	0.87	1.43*	1.45*
0.15	0.62	1.43*	1.9**	1.92**	0.52	0.76	1.3*	0.45	2.84***	2.8***	2.13**	1.85**	1.56*	0.96	0.86	0.78	0.81	1.71**	1.84**	1.64*
0.2	0.83	1.64*	2.22**	2.13**	0.57	1.07	1.47*	0.45	3.02***	3.07***	2.44***	1.42*	1.88**	1.32*	0.99	0.81	1.22	2.07**	1.64*	1.95**
0.25	1.58*	1.51*	2.46***	2.22**	0.64	1.03	1.62*	0.76	2.79***	3.54***	2.43***	1.18	2**	1.56*	0.98	0.87	1.08	2.53***	2.14**	1.33*
0.3	1.37*	1.44*	2.91***	2.66***	1.24	1.13	1.73**	0.81	3.1***	3.38***	2.49***	1.37*	1.93**	1.44*	0.92	0.87	1.87**	2.37***	2.06**	1.92**
0.35	1.85**	1.09	2.84***	3.29***	1.52*	1.34*	1.64*	0.85	4.14***	3.71***	2.41***	1.32*	2.54***	1.66**	1.13	0.89	2.32**	1.93**	1.84**	1.77**
0.4	1.08	1.04	3.13***	3.38***	1.02	1.13	1.48*	0.76	4.18***	3.88***	2.48***	1.46*	2.07**	1.3*	0.94	0.94	1.56*	1.85**	1.83**	1.73**
0.45	0.78	1.44*	3.03***	3.34***	0.82	1.48*	1.29*	0.8	4.13***	4.16***	2.58***	1.65**	2.02**	1.68**	0.96	1.28	1.34*	1.59*	2.17**	1.75**
0.5	0.83	1.09	2.93***	3.54***	0.9	1.59*	1.35*	0.82	4.01***	4.03***	2.81***	2.14**	2.39***	1.71**	1.2	1.17	1.08	1.48*	2.02**	2.01**
0.55	0.81	1.17	3.66***	3.59***	1.1	2.06**	1.14	0.83	3.69***	4.28***	2.65***	2.31**	2.34***	1.57*	1.22	1.33*	1.34*	1.86**	1.72**	1.98**
0.6	0.78	1.64*	3.38***	3.97***	0.85	1.62*	1.14	0.96	3.86***	4.21***	2.38***	2.36***	2.52***	1.58*	1.07	1.36*	1.07	1.31*	2.05**	1.8**
0.65	0.79	1.11	3.18***	2.9***	0.63	1.55*	0.94	0.88	3.85***	4.06***	2.57***	2.1**	2.41***	1.9**	0.88	1.47*	1.52*	1.48*	1.38*	1.69**
0.7	0.69	1.08	3.13***	3.18***	0.43	1.21	0.99	1.01	3.46***	3.77***	2.38***	1.69**	2.21**	1.32*	1.21	1.68**	1.31*	1.55*	1.46*	1.78**
0.75	0.87	1.21	2.49***	2.65***	0.56	1.15	1.02	1.34*	3.11***	3.6***	1.82**	1.48*	1.5*	1.07	1.27	1.5*	1.5*	1.75**	1.36*	1.35*
0.8	0.57	1.11	2.65***	2.61***	0.73	1.5*	1.46*	1.89**	2.84***	3.58***	2.13**	1.06	1.34*	0.99	1.18	0.98	1.68**	2.11**	1.06	1.36*
0.85	0.54	0.78	2.11**	1.9**	1.22	1.42*	1.95**	1.46*	2.5***	3.18***	1.78**	0.99	1.07	0.78	1.05	0.83	1.94**	1.86**	1.18	1.52*
0.9	0.33	0.89	1.74**	1.16	1.12	1.32*	1.57*	1	1.82**	2.89***	1.44*	0.88	0.97	0.72	1.23	0.68	1.28*	1.55*	1.11	1.49*
0.95	0.3	0.4	2.73***	3.56***	1.08	1.4*	1.18	1.21	1.49*	1.27	2.09**	1.17	2.48***	1.91**	1.17	0.72	0.72	0.89	0.74	0.48

Note: Results are based on the estimation following the quantile Granger casualty test (Troster, 2018). ***, **, and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. PRI = Physical Risk Index; TRI = Transition Risk Index; WTI = West Texas Intermediate Crude Oil; Brent = Brent Crude Oil; OPEC.Oil = OPEC Crude Oil; CO.Oman = Crude Oil Oman; CO.Dubai = Crude Oil Dubai. Gasoline = Gasoline; Propane = Propane; Natural.Gas = NYMEX Natrual Gas; Coal = NYMEX Coal. τ = the range of quantiles from 0.05 to 0.95.

findings. Investigating the spillover effects within specific energy market sectors, such as renewable energy versus fossil fuels, could provide more granular insights. Extending the analysis to different geographical regions would help understand regional variations in tail risk spillover and connectedness. Additionally, examining the influence of varying climate policies and regulatory frameworks on the spillover effects between climate risks and energy markets would be valuable. These future research directions will deepen our understanding of the intricate relationships between climate risks and energy markets, supporting more effective risk management strategies.

CRediT authorship contribution statement

David Adeabah: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft. **Thu Phuong Pham:** Conceptualization, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.108122.

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