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Climate risk and global economic policy uncertainty asymmetric spillover on global energy mix

Khadim Hussain[a], Zhong Jian[a*], Anwar Khan[b]

a. College of Economics, Shenzhen University, Shenzhen, Guangdong, China
b. School of Economics, Xiamen University, Xiamen, Fujian 361005, China

Abstract: Climate risks and economic uncertainties have been the triggering points of energy price spillovers, which are crucial to determining the global development path. Therefore, this study is designed to experiment with the diverse transmission patterns and interconnections between physical climate (PCR), transitional climate risks (TCR), and global economic policy uncertainty (GEPU) concerning various energy commodities. The study employs time and frequency domain econometric methodologies across two different monthly sample sizes. Our findings suggest that the overall connectedness for PCR, TCR, GEPU and energy prices has shown an increasing trend as we move from a shorter time frame to a longer one. It indicates that the magnitude of connectedness between these factors and energy prices tends to be stronger. Across all timelines, GEPU shows the highest connectedness with COAL, ULSD, BRENT, WTI, and NG compared to climate risk. Both PCR and TCR show similar connectedness patterns to energy prices, with a slightly higher value for TCR in most cases. Additionally, PCR serves as a net transmitter of all five energy prices only for 1 month and 1- 3 months, while TCR is a net transmitter to only ULSD across the short, medium, and long-run frequency bands. However, GEPU is not a net transmitter for ULSD at all frequencies and is transmitting net spillover on other energy prices. Its net transmission is more pronounced on COAL, BRENT, and WTI for 1 month, 1-3months, and 3-6months, respectively. These outcomes are further validated by employing the frequency domain causality test, which discloses that PCR, TCR, and GEPU are Granger causes of energy prices across different frequencies.

1. Introduction:

Energy is a crucial component of a country's economic system and has a significant impact that ripples beyond national borders, influencing geopolitics and reshaping the fundamental foundation of stability and economic prosperity worldwide [1].The global energy mix is a complex interplay of renewable and nonrenewable resources, where fossil fuels still dominating and their prices directly influence energy consumption and investment decision, impacting both energy transition and environmental justice by shaping access to clean energy and sustainable practices [2]. Energy has changed from being only a resource for production and consumption. This transformation has been fueled by the development of international financial markets and the introduction of new investment paradigms. It is a physical investment and an essential natural resource (Zhang, 2018). However, the dynamics determining fossil fuel energy pricing are complex and susceptible to a wide range of factors as commodities travel great distances and are frequently imported from unstable political environments; therefore, energy prices remain volatile due to political instabilities (European Commission 2023). The complex web that affects energy prices comprises various factors, including supply and demand dynamics, geopolitical events, decisions made by the Organization of the Petroleum Exporting Countries (OPEC), and weather patterns [3]. Collectively, these factors exert considerable influence over the intricate equilibrium of vital energy markets, determining the fluctuations in their costs with noteworthy consequences[4].

Climate risk, specifically physical climate risk (PCR), transitional climate risk (TCR), and global economic policy uncertainty (GEPU) significantly impacts growth and energy transitions by shaping investment decisions and influencing financial markets, including stock returns [5]. Meanwhile, nonrenewable energy sources like coal,

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Corresponding email: zhongj@szu.edu.cn (Zhong Jian)
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ultra-low sulfur diesel (ULSD), Brent oil, West Texas Intermediate (WTI) crude oil, and natural gas remain central to policymakers and public discourse due to their significant adverse environmental impacts and the urgent need for sustainable alternatives. In literature, many studies primarily focus on the spillover and connectedness between climate risk and market returns on stocks and energy markets using methods such as the cross-quantilogram approach and MGARCH [6], time-varying parameter vector autoregression (Guo et al., 2024), or exploring the effect of climate risk on energy equity (Li et al., 2024), climate risk effects on the dynamic conditional correlation between clean and dirty energy prices using NARDL/ARDL (Li et al., 2024), and dynamic dependencies of fossil energy and investor [7]. However, the connectedness and spillover between PCR, TCR, GEPU, and dirty energy prices remain unresolve, which serves as the major research motivation for this study[8].In the intricate relationship between energy and finance, the main issue is the risk ingrained in energy pricing; this is a known aspect that clouds the financing of energy projects. Price swings in the energy market can substantially impact several areas, including the financial system, food security, business profits, stock prices, energy generation intensity, and import-export trade dynamics. Previous studies have carefully examined macroeconomic factors as risk factors for energy prices [9],[10],11]. Moreover, a near-term trend suggests an increasing danger to energy security attributed to climate-related variables [12] This relationship between energy costs and weather extremes takes center stage in energy-finance studies. Droughts and decreased rainfall are two events that significantly influence the risks associated with energy costs [13]. Furthermore, the trend of climate risk indicates that the frequency of catastrophic weather events will increase energy cost volatility [14].

The energy industry is heavily impacted by geopolitical and climate risks, including the possibility of weather-related disasters or future developments that exacerbate their long- term effects [15]. This effect impacts energy production, supply, and the durability of both the present and future energy frame. Extreme weather events such as heat waves and droughts are already burdening current energy generation, which has an immediate effect on the fragile structure of energy systems[16]. Therefore, climate change-induced events disrupt the function of energy systems [17]. There are two types of hazards associated with climate change: transition risks and physical risks. Hurricanes, floods, and heat waves are imminent hazards that fall under the former category and have a tangible impact on the energy industry. On the other hand, transition risks centre on changes in government regulations, tax laws, and technology that try to reclassify carbon-intensive assets as conventional assets. These factors can magnify losses due to their interdependence within the financial system [18]. When assessing the impact of both forms of climate risk on the energy industry and developing resilient plans for the future, a comprehensive evaluation and deliberate mitigation of these risks are essential[19].

The previous study by In et al. (2022) explored that renewable energy investment is more resilient than carbon-intensive fossil energy assets due to rising climate risks. Similarly, Reboredo and Ugolini (2022) noted that firms with the lowest climate risks perform better financially. Dutta et al. (2023) noted that high climate risk raises the prices of green energy products with less volatility. Similarly, the study of (Shafiullah et al., 2021) witnessed that economic policy uncertainty (EPU) significantly affected renewable energy consumption in the United States. The study of Wang et al. (2023) reported significant correlations between economic policy uncertainty and energy markets at various stages. Similar findings have also been explored in the study of Li et al. (2023a), while the study of Yi et al. (2023) noted that EPU is responsible for reducing renewable energy consumption. These findings from the empirical work have signaled that climate risk and EPU are significant contributors in determining the energy demand and supply in global markets, which calls for appropriate attention[20].

From the previous discussion, we noted that this research starts the initial debate on the spillovers from physical climate risk, transitional climate risk, and GEPU to global energy market, including coal, gas, diesel and oil, by a comprehensive climate uncertainty index (physical and transitional climate risks) and monthly global economic policy uncertainty (GEPU) through time-frequency decomposition paradigm instrumented by Diebold and Yılmaz (2014) and Barun´ık and Kˇrehl´ık (2018) for global energy market[21]. From this perspective, our contributions encompass a threefold advancement in the academic domain. Firstly, we expand the existing scholarly discourse concerning the impact of climate change on international energy prices, furthering the exploration of how climate variations are re- shaping diverse energy markets. Secondly, we augment the body of research highlighting the influence of text-based uncertainty metrics—such as economic policy uncertainty and geopolitical risks—on energy prices. Thirdly, and notably, our most pivotal contribution lies in our investigation into the asymmetric spillover triggered by monthly fluctuations in physical climate risk

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(PCR), transitional climate risk (TCR), and global economic policy uncertainty (GEPU) onto energy prices, coupled with scrutiny of frequency-based Granger causality stemming from these emissions to energy prices. As per the authors' knowledge, limited literature has delved into the spillover effects of monthly PCR, TCR, and GEPU on energy prices, making this inquiry a novel and significant addition to the existing literature.
The rest of the paper is structured as follows: The second part analyses past literature[22]. The third part explains data and methods, the fourth part explains the results and discusses the obtained results and the final part summarizes the results with future recommendations[23].

2. Literature Review

The actual impacts of climate change are visible, and international organizations are seriously working on mitigating the effects of climate change [24]. The effects of climate change have been perceptible in many dimensions, including the crucial impacts on economic systems [25]. Climate risk uncertainty has become a global concern regarding its challenges towards energy prices and has become a center of researchers' attention. Therefore, the worldwide transition to clean and renewable energy become an emerging phenomenon while the uncertainties in climate policies are also surging [26]. Globally, the energy policy is instrumented to alleviate the consumption of fossil fuels and limit greenhouse gas emissions. In contrast, climate uncertainty entails changes in the supply and demand of energy prices, leading to fluctuations in energy rice prices in the global market. Similarly, the spillover effects of the speculations in energy prices have marked significant volatility in global energy prices [27]. Therefore, bringing fresh insight into the effects of climate and economic policy uncertainties on energy spillover effects is essential to build consensus among global policymakers[28]. Conducting a pre- and post-COVID scenario, Raza and Khan (2024) concluded that climate uncertainty remains crucial in determining the price volatility of precious metals. By bringing the Quantile on Quantile regression in the application, Cheng et al. (2023) showed that climate change uncertainty, economic policy uncertainty and energy price volatility are intertwined. From these points, the current study distributes the existing literature and discusses the PCR, TCR, and GEPU on various energy indicators[29].

The first stream of research highlighted the impacts of climate policy uncertainty on the energy and financial market variables, including energy consumption, returns and volatility of green and brown energy stock, and other parameters used to gauge the energy markets. For example, employing the time- varying Granger causality approach [30], it was narrated that climate policy uncertainty and energy markets have feedback effects with a time-varying pattern. Their study further disclosed a significant Granger causality when climate policies are enacted or changing weather patterns are observed. Studying the US data in the Vector Autoregressive (VAR) model, Li et al. (2023b) concluded that climate policy uncertainty and renewable energy have positive and negative connections; for example, when the authorities are inclined towards climate policies, the relationship becomes positive and vice versa. Similarly, applying the time-varying VAR approach, Zhou et al. (2023) stated that CPU, renewable energy and oil prices have time-varying relationships[31]. Their findings stated that in most periods, the CPU positively influences oil prices and renewable energy in the short and long-run. Using the novel econometric approaches, including wavelet and quantile on-quantile analysis, the study by Siddique et al. (2023) tested the effects of CPU on energy, renewable energy and low carbon energy, implying that a CPU negatively influences fossil fuels at various quantiles and frequencies, whereas, their response to renewable energy remains positive at various quantiles and frequencies[32]. Another asymmetric analysis by Karim et al. (2023) on CPU and energy metals in a cross-quantilogram approach pronounced a significant interaction between the two variables. Further, Syed et al. (2023) observed that the climate policy uncertainty impedes renewable energy consumption for the United States using the Fourier Augmented ARDL model. Similarly, Sarker et al. (2023) found spillover effects of the CPU on clean energy prices in the United States. Furthermore, using the monthly data between August 2005 and March 2021 (Hoque et al., 2023), it was further reported that shocks to the CPU transmit to the energy markets, supporting the spillover effects of the CPU on energy. In these studies, we have noted that little consensus has been built on the spillover effects of CPU on energy markets, which is the primary objective of the current study[33].

In a second stream, we highlighted research, determining the interrelationship between GEPU and energy indicators. For instance, the study by Wang et al. (2023) using the quantile on-quantile regression finds that economic policy uncertainty has positive and significant impacts on the energy markets. Similarly, Mokni et al.

(2024) reported that climate and economic policy uncertainty are interconnected at various quantiles. The spillover effects of economic and climate change policies are observed for the G7 countries[34]. Testing the impact of EPU on renewable energy consumption using the monthly data between 2003 and 2020 in the CS-ARDL model Yi et al. (2023) discovered that EPU negatively influences renewable energy consumption. At the same time, the study of Zhang et al. (2023) recognizes the EPU as the significant predictor of energy prices. Likewise, testing Sub-Saharan African data using CS-ARDL Ogede et al. (2023) found that EPU raises energy poverty in the study area. Ivanovski and Marinucci (2021), applying various econometric approaches, reported that EPU is highly reluctant to use renewable energy, highlighting that higher uncertainties dampen the uptake of renewable energy[35]. Most of the studies in the past have been devoted to reflecting the effects of EPU on environmental indicators or targeting the energy consumption and renewable energy consumption dimensions. However, their response to the energy markets, especially the spillover effects of EPU in energy markets, remains undressed. Therefore, the current research would undoubtedly bring a fruitful consensus[36].

2.1 Literature gap

From the literature review above, climate change uncertainty and economic uncertainties are crucial in affecting the supply and demand mechanism and the speculation and spillover effects of energy prices in global markets. The existing literature pointed out various channels of energy price volatility and tried to explain the spillover effects of energy prices to other markets[37]. However, limited literature has emphasized the impacts of climate policy (PCR and TCR) and economic policy uncertainty on energy markets, directly influencing energy prices. Accordingly, building consensus to explain the CPU and EPU spillover effects on the energy market is essential. This will provide a basis for international investors to plan and invest in more productive, climate-friendly, clean and green energy services to achieve carbon neutrality[38]. Similarly, facilitating a stable economic paradigm will help policymakers deal with climate policy-related issues determining the market demand and supply of energy products[39].

3. Data and Methodology

The Materials and Methods should be described with sufficient details to allow others to replicate and build on the published results. Please note that the publication of your manuscript implies that you must make all materials, data, computer code, and protocols associated with the publication available to readers. Please disclose at the submission stage any restrictions on the availability of materials or information. New methods and protocols should be described in detail while well-established methods can be briefly described and appropriately cited.

3.1 Data

The article extends the work of Rao et al. (2023), focusing on how physical climate risk (PCR), transitional climate risk (TCR), and global economic policy uncertainty (GEPU) influence worldwide energy prices. It examines the effect of these factors on different energy commodities: COAL; Ultra-low Sulphur Diesel (ULSD) in New York, the US Gulf Coast, and Los Angeles; Brent oil (BRENT); West Texas Intermediate Crude Oil (WTI); and the global price of Natural Gas (NG). The energy prices we focus on are critical in shaping the global energy landscape, with significant implication for both the environment and the climate economy. WTI is a major global oil benchmark, crucial for setting oil prices and forming the basis of oil futures contracts on the New York Mercantile Exchange. Similarly, BRENT is crucial, as it prices approximately two-thirds of the world's internationally traded crude oil. Its influence extends across Europe, Africa, and the Middle East, making it a central reference point in the global oil market. According to the International Energy Agency (IEA) from 1990 to 2020, the role of NG and COAL in global energy generation market increased significantly, with growth rate of 262.4% and 113.4%, respectively. Conversely, oil's contribution to energy generation dropped by 49.5% during the same periodFor our research we used two sets of monthly data. The first set, covering PCR and TCR, ranges from January 2000 to November 2019. Physical climate risk and transitional climate risk data are obtained from the study of Faccini et al. (2023). These metrics are calculated using Latent Dirichlet Allocation (LDA), an unsupervised machine learning model. PCR is measured based on indicators like global warming, extreme weather events, and natural disasters. In contrast, TCR is gauged by Analyzing U.S. climate policy and international summits[40]. We aggregated daily data into monthly datasets for our analysis. While the second set focuses on GEPU from January 1997 to September 2023. Detailed information on these variables, including their units, frequency, and sources, are shown in Table 1.

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Table 1: Description, frequency, and source of the variables

Variables	Description	Frequency	Source
PCR	Physical climate risk	Monthly	Faccini et al. (2023)
TCR	Transitional climate risk	Monthly	Faccini et al. (2023)
GEPU	Global Economic Policy Uncertainty Index-adjusted GDP	Monthly	Policy uncertainty
COAL	Global price of coal, U.S. Dollars per Metric Ton	Monthly	FRED
USD	Spot price of Ultra-low Sulphur Diesel of New York, US Gulf Coast and Los Angeles CA ULSD (USD/- Gallon)	Monthly	FRED
BRENT	Global price of BRENT (U.S. dollars per Barrel)	Monthly	FRED
WTI	Global price of WTI Crude Oil (U.S. Dollars per Barrel)	Monthly	FRED
NG	Global Price of Natural Gas, USD/ Million Btu	Monthly	FRED

3.2 Methodology

The theoretical foundation of this research is based on the theory of integration and price transmissions. Market integration refers to the extent to which the prices of various goods and commodities in different market are interconnected. It also assesses the degree to which prices, supply, and demand in one market are influenced by prices and conditions in other related markets. Additionally, price transmission theory examines the elasticity of price fluctuations between various markets, providing insights into how changes in one market are transmitted to another. The theory of economic information systems explores how the flow of information affects an economy and the decisions made to sustain it. In this context, the relationships among PCR, TCR, and GEPU with global energy prices are considered an integral part of the information economic system. For our study, we constructed three sets of models.

Model 1: PCR = COAL + ULSD + BRENT + WTI + NG
Model 2: TCR = COAL + ULSD + BRENT + WTI + NG
Model 3: GEPU = COAL + ULSD + BRENT + WTI + NG

Models 1, 2, and 3 examine the monthly spillover effects of PCR, TCR, and GEPU on the global energy prices of COAL, ULSD, BRENT, WTI, and NG, respectively.
To examine the interconnectedness among PCR, TCR, GEPU, and global energy prices, we utilize the methodological framework developed by [41],[42]. Connectedness measures only the pairwise association and is primarily wed to linear. To address this issue DY proposed a unified approach and framework for empirical measurement and conceptualization of connectedness at a diverse level. This framework is based on the VAR model's variance decomposition, which is closely linked to modern network theory. Variance decomposition provides imperative information to measure the future uncertainty of a particular variable of interest stemming from a shock in another variable[43]. DY framework is built upon the tradition of dynamic predictive modeling under misspecification and assess the share of forecast error variation in diverse location due to shocks arising elsewhere[44]. On the other hand, to understand the source of connectedness we also utilize BY model. As shock to economic activity has a mixed effect on variables at various frequency with various strength[45]. So, BK proposed framework has the ability to measure the level of connectedness in long, medium, and short-term frequency response to shocks., and short-term frequency response to shocks[46].

3.2.1

DY framework is built on the concept of variance decomposition in econometrics. This approach breaks down the forecast error variance of a particular variable, labelled as 'i', into components linked to the other variables in the system. This decomposition aims to analyze the forecast error variance derived from a generalized vector autoregression model, focusing on examining the interconnectedness within the system. The connectedness metrics range from basic to comprehensive system-wide analyses, emphasizing the variance decomposition from "non-own" or "cross" contributions[47]. We started our spillover analysis considering the following VAR model with order p.

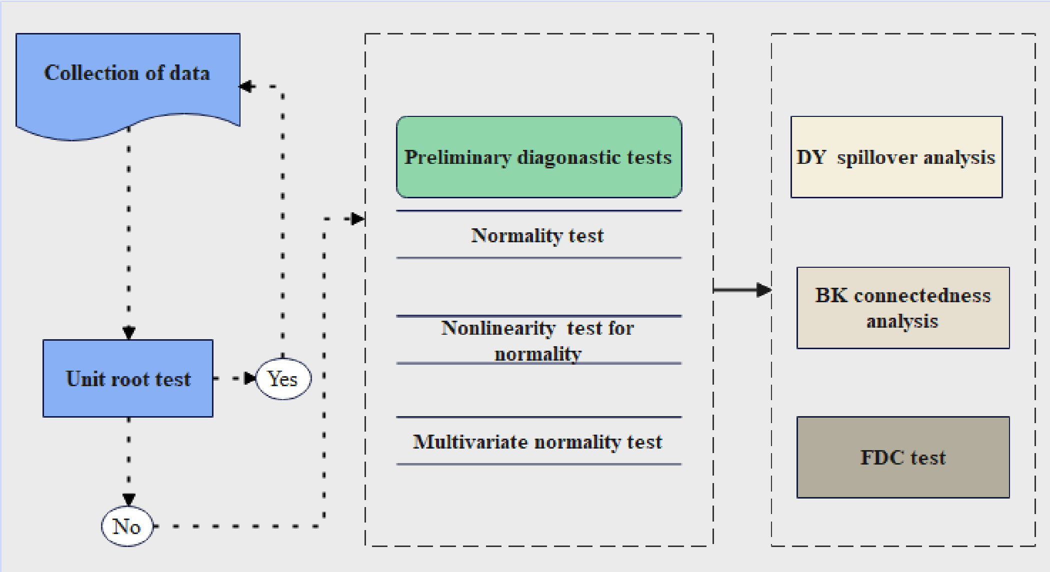

Figure 1: Empirical scheme

$$x_t = \beta + B_1x_{t-1} + B_2x_{t-2} \dots \dots \dots \dots \dots B_p x_{t-p}\, \mu_t \qquad (1)$$

Where x_t is a $K \times 1$ vector at time t and β represents the constants of the vector, and B is the coefficient of variables. Transforming equation 1 into the matrix form, we get:

$$X_t = D + BX_{t-1} + U_t \qquad (2)$$

In Equation 2 B is equal to $pK \times pK$ matrix and

$$X = \begin{bmatrix} x_t \\ x_{t-1} \\ . \\ . \\ . \\ x_{t-p} \end{bmatrix}, D = \begin{bmatrix} d \\ 0 \\ . \\ . \\ . \\ 0 \end{bmatrix}, B = \begin{bmatrix} B_1 & B_2 & . & B_{p-1} & B_p \\ I_K & 0 & . & 0 & 0 \\ 0 & I_K & 0 & 0 & . \\ & & & & \\ 0 & 0 & & I_K & 0 \end{bmatrix} \qquad (3)$$

Equation 3 is used to analyze the spillover effects of PCR, TCR, and GEPU on energy prices of the VAR model by decomposing their variance. This decomposition helps us to understand the extent to which each variable contributes to the variance of others. The next step is to calculate the H-step ahead forecast for x_t, which is denoted as $\hat{X}_{t+H/t}$, is accompanied by a measure of uncertainty, and expressed using the Mean Square Error (MSE). The H-step ahead forecast is obtained using Equation 4:

$MSE|y_{i,t}(H)| = \sum_{j=0}^{H-1} \sum_{k=1}^{k} (\acute{e}_i \Theta_j e_k)^2$ (4)Where e_i presents the ith column of I_K, and $\Theta j = \phi jP$, with P being the lower triangular matrix. The value of P is calculated following Pesaran and Shin (1998) and is utilized to estimate the variance-covariance matrix of $\Psi u = E(u_t u')$ in the generalized decomposition. Additionally, $\phi = JB^j \acute{J}$, where $J = |I_K, \ 0, \dots . 0|$.

$$\gamma_{ik,H} = \frac{\sum_{j=1}^{H-1} (\acute{e}_i \Theta_j e_k)^2}{MSE|y_{i,t}(H)|} \qquad (5)$$

Then the measure of connectedness is obtained through equation 6

$$D_H = \frac{1}{K} \sum_{ij=1}^{K} \gamma_{ij=1}^{K} \ (and\ i \neq j) \qquad (6)$$

3.2.2

BK introduced an innovative approach for assessing connectedness, emerging from diverse frequency reactions to shocks within a system. This approach is grounded in the spectral analysis of variance decompositions. By

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incorporating frequency dynamics into the assessment of connectedness, their study further explores the influence of cross-sectional correlations on connectedness. It is important to note that a high level of simultaneous correlation does not automatically imply connectedness in how it is conventionally understood in the field. Our objective is to identify the frequency at which spillover peaks occur, aiding policymakers in deciding which frequency should be given precedence.

Spectral decomposition of variance and indices of interconnectedness measurements.
The BK method breaks down the original DY spillover across various frequencies. Specifically, their method hinges on a spectral approach to variance decomposition. The spectral representation focuses on the frequency response to shocks rather than relying on the impulse response function, which offers several advantages. This approach enhances the clarity of cyclical data analysis, enables detailed decomposition of variability, and adeptly captures heterogeneous temporal responses. Additionally, it offers crucial insights for policymakers and is robust against model uncertainties, providing a sophisticated tool for assessing system dynamics and resilience across time scales. We start considering the below impulse response function.

$$\Phi(\mathrm{e}^{-\mathrm{i}\omega}) = \sum_k e^{-\omega \mathrm{i}} \Phi_k \qquad (7)$$

Equation 7 is estimated as a Fourier transform of the coefficients Φ_k with $i = \sqrt{-1}$. The spectral density of x_t at frequency ω, can then be conveniently defined as a Fourier transform of MA (∞) filtered series as

$$S_X(\omega) = \sum_{\mathrm{k}=-\infty}^{\infty} E\left(X_t X_{t-k}^{\prime}\right) e^{-i\omega \mathrm{k}} = \Phi(\mathrm{e}^{-\mathrm{i}\omega}) \acute{\Phi}(\mathrm{e}^{+\mathrm{i}\omega}) \qquad (8)$$

The spectrum of generalized causality across the frequency domain, where ω spans the interval (−π, π), is given by:

$$(f\ (\omega))_{j,k} = \frac{\sigma_{kk}^{-1}\ |(\Phi(e^{-i\omega})\Sigma)j,k|^2}{\Phi(e - i\omega)\Sigma\Phi'(ei\omega))_{j,j}} \qquad (9)$$

Where $\Phi(e^{-i\omega}) = \sum_k e^{-i\omega k}\, \Phi k$ is the Fourier transform of the impulse response Φk. The measure $(f\,(\omega))_{j,k}$ is the proportion of the influence of the k-th variable on the spectral density of the j-th variable at frequency ω. This term reflects intra-frequency causality, given that the denominator encompasses the spectral density of the jth variable at the specific frequency ω. To disentangle the variance contributions across the frequency spectrum, the measure can be weighted by the relative variance of the jth variable at the respective frequency. The corresponding weighting function is outlined as.

$$\Gamma j(\omega) = \frac{\left(\Phi(e^{-i\omega})\Sigma'(e^{i\omega})\right)j,j}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\Phi(e^{-i\lambda})\Sigma'(e^{i\lambda})\right)j,j\ d\lambda}, \qquad (10)$$

Equation 10 delineates the spectral power of the jth variable at a specific frequency, integrating across the frequency spectrum to yield a consistent value of 2π. It is important to recognize that the Fourier transform of the impulse response typically yields a complex value. However, the spectrum of generalized causation is derived from the squared magnitude of these weighted complex numbers, resulting in a real-valued metric. The ensuing theorem articulates the spectral decomposition of the variance contribution from the j-th to the k-th variable, forming the cornerstone of our connectedness metrics within the frequency domain. It is crucial to understand how the variance decomposition and volatilities in the frequency domain from j to k interact with each other to measure connectedness in the spectral domain. The frequency band is rigorously defined within the interval d = (a, b) where a, b (π, π) and a < b. Within this specified band, Equation 10 provides the generalized variance decomposition as follows:

$$(\theta_d)_{j,k} = \frac{1}{2\pi}\int_d \Gamma_j(\omega)\left(f(\omega)\right)_{j,k} d_\omega \qquad (11)$$

Then we have defined the generalized variance decomposition on the defined frequency band used in Equation 11 as

$$(\hat{\theta}d)i,k = (\theta_d)_{i,k} \sum\nolimits_k (\theta_\infty)_{j,k} , \qquad (12)$$

Where θd and θ∞ are defined by Equation (11). The frequency connectedness on the frequency band d is then defined as

$$C_d^F = \left(\frac{\sum \hat{\theta} d}{\sum \theta_\infty} - \frac{\mathrm{Tr}(\hat{\theta} d)}{\mathrm{Tr}(\theta_\infty)} \right) = C_d^W . \frac{\sum \hat{\theta} d}{\sum \theta_\infty} , \qquad (13)$$

Where Tr(.) is operator, and $\sum \hat{\theta}_d$ signifies the sum of all elements of the $\hat{\theta} d$ matrix.
Figure 1 illustrates the procedure employed in the empirical work, which aligns with that of Rao et al. (2023). Before proceeding to spillover, a stationary test is conducted using the ADF, KPSS, and PP tests to prevent inconsistent and biased results from DY and BK models. The results of the unit root test are shown in the supplementary material.

3.2.3 Frequency domain causality test

For the robustness of the empirical outcomes obtained from DY and BK spillovers, this study also utilizes the frequency domain causality test (FDC) proposed by Croux and Reusens (2013) following the outline proposed by [48]. Prior to investigating FDC, we applied the Hodrick-Prescott filter to all the series, using the canonical value of λ = 1600 to eliminate any trend and isolate the cyclical components. The outcomes are illustrated in the supplementary documents, from Figure B.1 to B.2, for the PCR, TCR, and GEPU models. Our lag selection procedure chooses one lag for the PCR and TCR models and three for the GEPU model. We opted for the Bayesian Information Criterion (BIC) for lag selection, as it provides a more accurate estimate of the unknown number of delays compared to the Akaike Information Criterion (AIC), which tends to overestimate it [49]. The outcomes of VAR with the selected lags are shown in Table C.2 for all three models. Finally, we utilize the FDC test proposed by Croux and Reusens (2013) based on Breitung and Candelon (2006) for the robustness of our empirical results obtained from DY and BK[50].

4. Empirical results and discussion

4.1 Diagnostic test results

Table 2 presents the descriptive statistics for the monthly variables of the energy market's PCR, TCR, and GEPU models. For the PCR and TCR models, the lowest mean value for monthly energy price change is reported for NG, with a mean value of 0.007, while the highest change is noted for USLD (0.377), followed by COAL (0.188). Simultaneously, the percentage change in physical climate risk (PCR) is approximately 105.26% higher than in transitional climate risk (TCR). Conversely, TCR shows higher volatility in monthly changes (57.36%) than PCR. NG exhibits the highest volatility in monthly price changes within the energy market, followed by COAL, with standard deviations of 14.950 and 7.131, respectively. The kurtosis value for all energy prices is more significant than two, indicating a certain level of data peaked ness. On another note, COAL is reported with a minimum value of -160.330 in the GEPU model, whereas BRENT has the highest minimum value of -26.792. All kurtosis values in the GEPU model are greater than three, suggesting that the change in monthly energy prices has heavier tails.

Table 2: Descriptive Statistics

Var	Mean	Max	Min	Std.Dev	Skew	Kurt	N
			Model-1&2: PCR, TCR and Energy Prices				
PCR	0.156	25.636	-32.439	7.822	-0.479	2.971	**238**
COAL	0.188	43.402	-45.132	7.131	0.12	13.524	**238**
ULSD	0.377	55.987	-54.573	14.95	-0.131	2.491	**238**
BRENT	0.156	13.829	-26.792	5.513	-1.222	3.406	**238**
WTI	0.124	13.522	-28.16	5.439	-1.205	3.907	**238**
NG	0.007	2.46	-3	0.576	-0.786	7.866	**238**
TCR	0.076	49.311	-31.177	12.309	0.424	1.786	**238**
			Model-3: GEPU and Energy Prices				

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GEPU	0.531	131.382	-93.199	28.044	0.643	3.97	**320**
COAL	0.416	83.776	-160.33	15.826	-2.544	39.634	**320**
ULSD	0.599	92.867	-54.573	15.995	0.448	5.159	**320**
BRENT	0.216	18.173	-26.792	5.468	-1.062	3.484	**320**
WTI	0.2	16.791	-28.16	5.485	-1.008	3.541	**320**
NG	0.026	18.831	-34.372	3.187	-3.032	53.57	320

Note: For the PCR (Physical Climate Risk), TCR (Transitional Climate Risk), and GEPU (Global Economic Policy Uncertainty) models, COAL, ULSD, BRENT, WTI, and NG represent the monthly fluctuations in their respective prices.

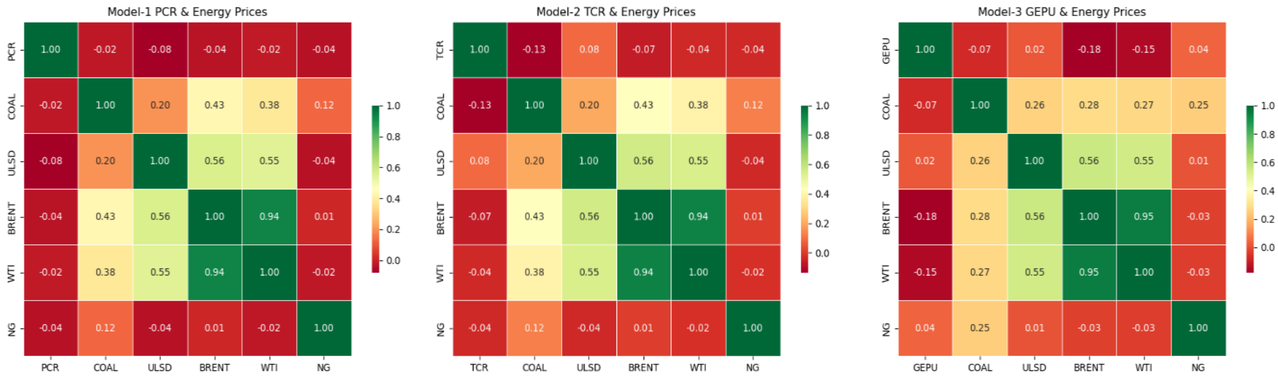

Figure 2: Cluster Heatmaps of Models 1, 2, and 3

Figure 2 presents the pairwise correlation heatmap for monthly PCR, TCR, and GEPU models. The heatmap illustrates that PCR and TCR have a negative correlation with all energy prices. Notably, the West Texas Intermediate (WTI) exhibits a more pronounced correlation with PCR and TCR than other monthly energy price changes. Meanwhile, the GEPU model exhibits a positive correlation with NG and ULSD, but a negative correlation with COAL and BRENT.
Table 3 is organized into three sections: Section A presents the results of normality tests, Section B details nonlinear tests for normality, and Section C contains the results for multivariate normality tests, each applied to the PCR, TCR, and GEPU models, respectively. The Bartels test, Robust Jarque-Bera (RJB) test, and Shapiro-Johnson (SJ) test consistently show statistical significance, marked by asterisks denoting significance levels of 1% (***). Based on the test results, we accept the alternative hypothesis of a normal distribution for PCR, TCR, COAL, ULSD, BRENT, and WTI, suggesting that these time series do not follow a normal distribution. However, the Bootstrap Symmetry test, Difference Sign test, Mann-Kendall (MK) test, and Runs test for PCR and WTI do not show such levels of significance across all tests, implying a mixed outcome regarding the normality of these series. For Model-3 (GEPU and Energy Prices), the GEPU variable and its relations with energy prices reveal statistically significant deviations from normality in several tests, notably in the RJB and SJ tests at the 1% level. In summary, the preponderance of statistically significant results in the normality tests suggests a departure from the normal distribution for the PCR, TCR, and GEPU models concerning energy prices. Provide foundational support for further exploring asymmetric spillovers in the energy market, as DY and BK's framework posited. This evidence of non-normality is crucial, as it suggests the potential for nonlinear dynamics and asymmetrical relationships in the impact of climate risks and policy uncertainty on energy markets, reinforcing the relevance of employing models that capture these complexities.

Section B of Table 3 reveals the outcomes from nonlinearity tests for normality, with most variables within the PCR, TCR, and GEPU models demonstrating statistically significant deviations from normality, particularly in the Ter¨asvirta, White, and Tsay tests. This further suggests the presence of nonlinear behaviour in the data, aligning with conventional advanced studies investigating complex dynamics in financial markets. These findings underscore the necessity of considering nonlinearity when analyzing the influences of climate risks and economic policy uncertainty, a concept BK and DY's research on asymmetric spillovers has brought to the forefront of energy economics. Finally, Section C of Table 3 indicates the results of multivariate normality tests for the PCR, TCR, and GEPU models. The Energy Test yields highly significant E-statistics for all three models (PCR: 9.3667, TCR: 8.222, GEPU: 29.831) with p-values less than 2.2e-16, implying a solid rejection of the null hypothesis of multivariate normal distribution. This suggests that the variables within each model are collectively non-normally distributed. Additionally, the Mardia Kurtosis test results for skewness and kurtosis across the models further validate this finding, with p-values indicating significance at the 1% level. As highlighted in advanced econometric research, these results reinforce the importance of using methods that capture the non-normal distribution and potential asymmetric relationships within the energy market. Based on the results above indicating non-normality, we have sufficient statistical justification for selecting a Vector Autoregression (VAR) model for our spillover analysis.

Table 3: Diagnostic Tests

Var	**Bartels Test**	**RJB Test**	**SJ Test**	**Boot Symmetry Test**	**Difference Sign Test**	**MK Test**	**Runs Test**	
PCR	**5.501*** **	220.501***	8.893***	-0.369	3.697***	0.358	**3.897*** **	
COAL	**-5.380*** **	12655.344	23.044***	0.441	-0.227	-1.377	**-4.157*** **	
ULSD	**3.950*** **	197.135***	10.172***	-0.612	0.784	0.055**	**3.378*** **	
BRENT	**-3.003*** **	301.057***	7.263***	-3.062***	1.456	-0.251	**-1.169**	
WTI	**-2.130*** **	407.122***	8.516	-3.197***	0.112	-0.207	**-0.390**	
NG	**-2.694*** **	12063.580***	31.180***	0.395	0.851	-2.642***	**-3.923*** **	
TCR	**5.156*** **	57.170***	4.969***	1.669	1.456	-0.215	**3.508*** **	
Model-3 GEPU and Energy Prices								
GEPU	**2.897*** **	645.922***	12.888***	1.913	2.417***	-0.152	**2.464**	
COAL	**-6.304*** **	1736495.000	63.091	1.208	0.199	1.371	**-5.296*** **	
ULSD	**4.986*** **	1293.491***	16.037***	0.406	1.450	0.739	**3.807***	
BRENT	**-3.676*** **	395.969***	8.742***	-2.650***	1.450	1.186	**-1.680***	
WTI	**-2.926*** **	445.091***	9.776***	-2.851***	-0.290	1.177	**-0.784**	
NG	**-3.236*** **	52699120.000	118.756***	0.541	1.674*	-0.705	**-4.285*** **	
Section B: Nonlinearity test for normality								
		Model-1				Model-2		
	Teraesvirta NN Test	White NN Test	Keenan Test	Tsay Test	Teraesvirta NN Test	White NN Test	Keenan Test	**Tsay Test**
PCR	**27.202*** **	34.683***	6.215***	3.245***				
TCR					3.929	8.384***	0.382	**1.614*** **
COAL	**11.394*** **	14.692***	8.401***	4.038***	11.394***	14.692***	8.401***	**4.038*** **
ULSD	**9.638*** **	8.425***	0.041	2.279***	9.638***	8.425***	0.041	**2.279*** **
BRENT	**10.757*** **	10.981***	6.730***	9.594***	10.757***	10.981***	6.730***	**9.594*** **
WTI	**11.109*** **	16.316***	7.564***	10.19***	11.109***	16.316***	7.564***	**10.19*** **
NG	**12.385*** **	10.329***	4.481**	4.441***	12.385***	10.329***	4.481**	**4.441*** **
Model-3					**Section C: Multivariate Normality Test of Model-1**			
GEPU	**6.887***	4.283	1.541	NaN		**Energy Test=29.831*** **		
COAL	**5.0667***	3.42	57.343***	14.45***	**Mardia Kurtosis Test**			
ULSD	**3.76**	4.586	0.393	2.36***		Beta hat	Kappa	**P values**
BRENT	**10.905*** **	7.744**	7.232***	10.88***	Skewness	10.202	404.684	**0.000**
WTI	**11.370*** **	11.782***	6.987***	10.31***	Kurtosis	92.533	35.059	**0.000**
NG	**44.161*** **	23.540***	39.937***	105***				
Section C: Multivariate Normality test Of Model 2 & 3								
		Model-2				**Model-3**		
Energy Test		8.222***				Energy Test=29.831***		
Mardia Kurtosis Test		β^	Kappa	P Values	β^	Kappa	**P values**	
Skewness		10.254	406.73882	0.000	30.3494	1618.637	**0.000**	
Kurtosis		**92.898**	**35.467**	**0.000**	**190.321**	**129.921**	**0.000**	

Note: Note: ***, **, and * indicate level significance at the 0.01, 0.05, and 0.1.

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Section A: Normality Tests: (Model-1 & 2) PCR, TCR and Energy Prices

4.2 DY spillover results

The results of the Diebold and Yılmaz (2014) Spillover analysis, grounded on a Vector Autoregression (VAR) model with a maximum lag of two and a constant term, are exhibited in Table 4. This analysis summarizes our models, integrating physical and transitional climate risks and global economic policy uncertainty. It examines their monthly impact on the prices of five key indicators in the energy market (NG, COAL, WTI, BRENT, and ULSD). The values in each row measure how much other variables affect the predictability of a particular energy sector's future value changes. In contrast, the column values focus on the impact of a single variable on the forecast of error of another. PCR contributes to a modest but notable portion of the variance in other energy commodities. It accounts for 0.29% of COAL returns, 2.55% of ULSD, 1.53% of BRENT, 0.56% of WTI, and 0.44% of NG. This influence spread underscores PCR's relative importance in the energy market dynamics, albeit overshadowed by other larger contributors. In the broader context, PCR's impact on NG (0.44%) is particularly significant. This could reflect the sensitivity of natural gas consumption to climate risk factors, potentially influenced by consumer demand for heating or cooling due to fluctuating temperatures. The COAL market, with a spillover contribution of 0.84% to NG, may indicate the interplay between traditional energy sources, possibly reflecting shifts in energy usage patterns or substitution effects in response to climate policy and market changes.

In Model 2, the TCR spillover matrix for the energy market, diagonal elements (like 95.57 for TCR and 65.66 for COAL) indicate the self-connectedness of each variable, reflecting their contribution to their forecast error variance. Off-diagonal elements represent the spillover effect between different variables. The concertedness from TCR to the energy market is stronger with COAL (3.02%) and 2.44% from ULSD to TCR. In models one and two, the contribution of PCR and TCR is highest for BRENT (0.74%) and NG (1.53%) among all other variables, respectively. At the same time, the contribution from the energy market to PCR and TCR is highest from BRENT (1.53%) and USLD (2.44).

In the GEPU model, NG is reported to have the highest self-connectedness, and BRENT has the lowest prices within the energy market. Interestingly, GEPU contributes equally to COAL and BRENT with a 2.07% contribution to their dependence and the highest observed pair-wise connectedness from GEPU to the energy market. This confirms that COAL and BRENT are integral to the global energy mix, sensitive to policy changes, and vital to industrial activities and power generation, making them susceptible to changes in economic policies and global market sentiments. Conversely, the row sum of pairwise connectedness is highest for BRENT, followed by WTI, which measures the received share of volatility from others. The total directional connectedness in the FROM column ranges between 2.16% to 9.96%. The share of directional volatility from the energy market to GEPU is highest for BERNT, followed by COAL.

Figures 3, 4 and 5 show the overall connectedness of PCR. TCR and GEPU models, respectively. The magnitude of overall connectedness and time are labelled on the Y and X axes. The circle's diameter shows the magnitude of the connectedness of the variable in the model. We observe that the overall connectedness in all three models increases with time. The TCR model has the lowest connectedness, while the GEPU model exhibits maximum connectedness with a magnitude of 17.89% and 28.43% in one month. In the climate risk framework, the PCR model shows relatively higher connectedness than the TCR model in one moth. From 1-3 months to 6 months and beyond, the overall connectedness of the GEPU model remains relatively higher than other models, with magnitude values of 31.91%, 48.65%, and 53.87%. The period transitional climate risk model shows higher overall connectedness than physical climate risk. Additionally, the increasing overall cone
cuteness in both PCR and TCR models is aligned with the empirical result of [51].

Table 4: DY Spillover

Model-1 PCR							
Var	**PCR**	**COAL**	**ULSD**	**BRENT**	**WTI**	**NG**	**FROM**
PCR	94.63	0.29	2.55	1.53	0.56	0.44	**0.9**

COAL	0.33	66.27	4.88	15.33	12.36	0.84	**5.62**
ULSD	0.60	3.74	51	22.43	20.7	1.54	**8.17**
BRENT	0.74	5.99	15.44	40.72	35.2	1.91	**9.88**
WTI	0.33	5.05	13.57	36.85	41.69	2.51	**9.72**
NG	0.25	5.5	1.03	0.8	1.05	91.37	**1.44**
TO	0.37	3.43	6.24	12.82	11.65	1.21	**35.72**
Model-2 TCR							
	TCR	COAL	ULSD	BRENT	WTI	NG	**FROM**
TCR	95.57	0.78	2.44	0.4	0.45	0.36	**0.74**
COAL	3.02	65.66	4.34	14.58	11.72	0.68	**5.72**
ULSD	0.28	3.58	50.88	22.77	21.02	1.46	**8.19**
BRENT	0.88	5.7	15.26	40.95	35.26	1.93	**9.84**
WTI	0.82	4.76	13.33	36.78	41.68	2.63	**9.72**
NG	1.53	5.39	1	0.88	1.27	89.93	**1.68**
TO	1.09	3.37	6.06	12.57	11.62	1.18	**35.89**
Model-3 GEPU							
	GEPU	COAL	ULSD	BRENT	WTI	NG	**FROM**
GEPU	87.06	3.65	0.55	4.28	3.49	0.97	**2.16**
COAL	2.07	59.01	9.69	10.16	8.66	10.41	**6.83**
ULSD	0.93	6.16	51.33	21.72	19.63	0.23	**8.11**
BRENT	2.07	5.3	16.44	40.25	35.58	0.35	**9.96**
WTI	1.81	4.64	14.97	37.25	41.05	0.29	**9.83**
NG	0.62	11.04	3.43	1.89	2.14	80.87	**3.19**
TO	**1.25**	**5.13**	**7.51**	**12.55**	**11.58**	**2.04**	**40.07**

Note: For PCR (physical climate risk), TCR (transitional climate risk), and GEPU (Global Economic Policy Uncertainty) models: COAL, ULSD, BRENT, WTI, and NG represent the monthly fluctuations in their respective prices.

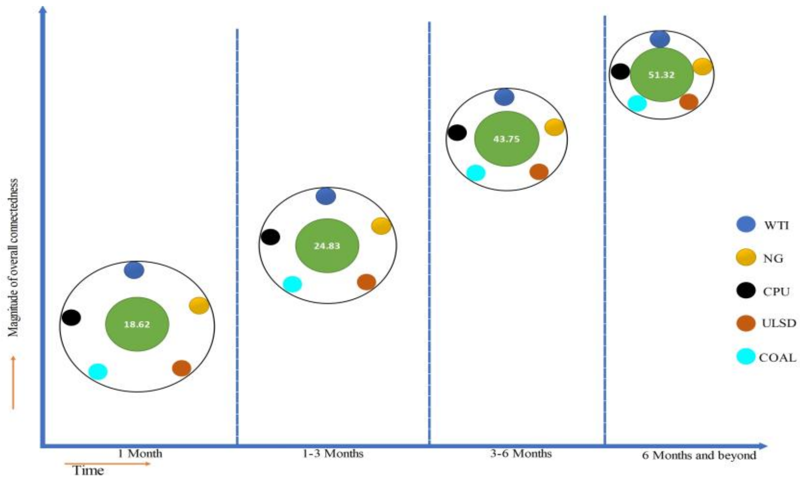

Figure 2: Physical climate risk and energy prices Overall connectedness

4.3 Barun´ık and K˘rehl´ık Spillover result

Tables 5, 6, and 7 depict the comprehensive connectedness among the PCR, TCR, and GEPU models across four distinct time horizons. Table 5 explicitly presents the frequency spillover between PCR and five principal energy commodities, utilizing the methodology developed by [52],[53].The spillover effects between physical climate risk and the energy market are detailed for the following durations: 1 Month, 1-3 Months, 3- 6 Months, and 6 Months and beyond. Initially, at the 1-Month horizon, the spillover impact from PCR to the energy market is markedly minimal, indicating that PCR contributes insignificantly to the price fluctuations of the energy commodities under examination[54]. Compared to the 1-Month horizon, the spillover effects of PCR on the energy market increase over the 1-3 Month period. BRENT experiences the most substantial impact, followed by ULSD, with contributions of 0.24% and 0.23%, respectively, within this timeframe[55]. Over the 1-3 Month period, the spillover from the energy market to PCR is more pronounced than in the 1 Month, with ULSD contributing 2.37% to PCR. During this period, the self-connectedness of PCR and NG notably increases, while other energy commodities show a marked decrease in self-connectedness compared to the preceding time horizon. In the 3–6-month timeframe, the spillover effects from PCR to COAL, ULSD, BRENT, WTI, and NG are 0.07%, 0.14%, 0.19%, 0.08%, and 0.02%, respectively. Notably, the spillover from PCR to COAL remains constant, while there is a significant decrease in its impact on other energy prices compared to the 1–3-month period. Progressing to the six-month and beyond horizon, the spillover impact of PCR on NG stays stable, whereas it increases substantially for the other energy commodities. In summary, the spillover effects of PCR on the price movements of various energy commodities demonstrate a varied pattern across different periods[56],[57]. However, overall, there is an increase in the cumulative spillover effect, as indicated by the rising sum in the "FROM" column, from 18.62% to 51.35%.

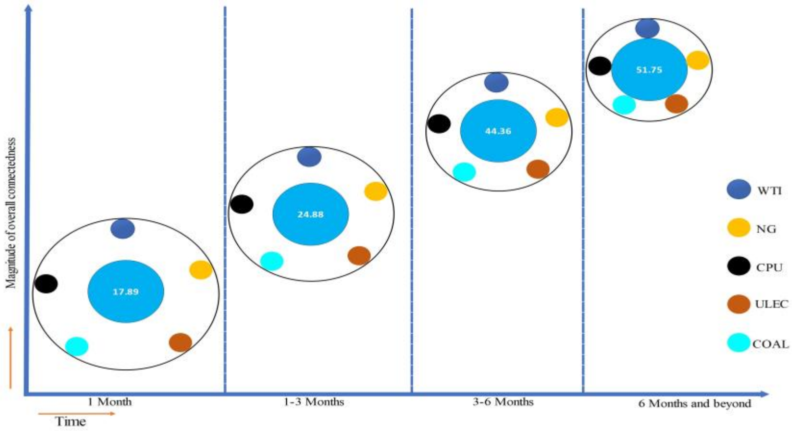

Figure 3: Overall connectedness of transitional climate risk and energy prices

In contrast, Table 6 reveals that the spillover effect of transitional climate risk (TCR) on the prices of five energy commodities is relatively higher for one month than the PCR model, with a specific impact on BRENT of 0.02%. TCR's higher initial spillover impact compared to PCR is likely due to the more immediate and direct influence of policy decisions, regulatory changes, and technological innovations intrinsic to transitional climate strategies. For instance, a new policy promoting renewable energy or imposing carbon taxes can quickly alter energy prices, reflecting the market's swift response to regulatory changes. Over the 1–3-month period, TCR's spillover to COAL is 2.03%, to ULSD is 0.22%, to BRENT is 0.72%, to WTI is 0.59%, and to NG is 0.88%. Natural Gas exhibits the highest self-connectedness during this timeframe, while BRENT shows the lowest among the energy commodities.

Moreover, the spillover from TCR to all energy commodities significantly decreases in the 3-6 month period relative to the 1-3 month period, with coal experiencing the highest spillover from TCR. In the 6-month and beyond timeframe, the spillover impact from TCR to COAL is 0.55%, to NG is 0.47%, and to WTI is 0.14%. Notably, the spillover from TCR to COAL shows a considerable increase from 0.01% in the one-month period to 2.03% in the 1-3 month period. Compared to other energy commodities, the significant and sustained increase in spillover from TCR to COAL across all time frames likely reflects coal's heightened sensitivity to transitional climate policies, which often target carbon-intensive sectors for early and substantial reductions in emissions. It underscores the need for targeted strategies in the coal sector to manage the impacts of transitional climate policies and adapt to the shifting energy landscape. Table 7 shows the BK spillover effects from global economic policy uncertainty on essential energy commodities, including COAL, ULSD, BRENT, WTI, and NG. In the initial 1-month period, the minimal impact suggests that energy markets may take time to react to policy changes or global economic uncertainties. However, as the timeframe extends to 1-3 Months, the observed increase in GEPU's influence, particularly on COAL, is 1.83%, NG is 0.5%, ULSD is 0.57%, BRENT is 0.84%, and WTI is 0.67%. This could be due to the market's gradual adjustment of policy changes and the adjustments in supply and demand dynamics. In the 3-6 Month and beyond horizons, the pronounced spillover effects, especially on BRENT, are 0.47%, and on WTI are 0.41%, likely reflecting the cumulative and lagged responses of the energy sector to ongoing global economic shifts. This delayed reaction could be linked to the time required for policy decisions to permeate the energy sector, affecting operational strategies, investment decisions, and consumer behavior. The analysis indicates that the energy market's responsiveness to GEPU varies over time, aligning with the evolving nature of policy impacts and market adjustments. The spillover from GEPU to all under study energy prices is observed to be relatively higher in the short run than in climate risk models 1 and 2. Additionally, Table 7 reveals an increase in the self-connectedness of GEPU and NG, from 2.4% and 0.43% in the 1-month timeframe to 68.8% and 62.23% in the 1–3 months period, respectively. Subsequently, there is a decline to 7.77% and 7.41% in the 6 months and beyond time frame.

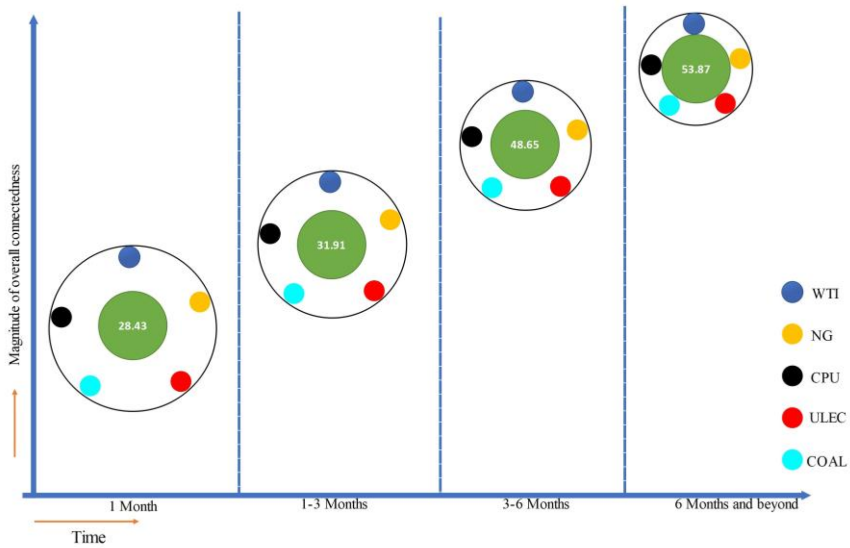

Figure 5: Global economic policy uncertainty and energy prices overall connectedness

Table 8, comparative analysis across four time periods (1 Month, 1-3 Months, 3-6 Months, and 6 Months and Beyond) for the GEPU, PCR, and TCR models reveals distinct spillover impacts on five essential energy commodities. The table effectively summarizes the short-run, medium-term, and long-run spillover effects of GEPU, PCR, and TCR across various energy market prices. In the initial month, the spillover effect of GEPU is predominantly greater than both PCR and TCR for COAL and ULSD, indicating an immediate and significant influence of global economic policy uncertainty in these markets. In contrast, TCR shows a greater spillover than PCR in all commodities except ULSD. Over the 1-3 months, the impact of GEPU relative to PCR and TCR diminishes for COAL but remains strong for ULSD, BRENT, and WTI. The spillover of TCR surpasses PCR in COAL, NG, and ULSD (1-3 Months) and in NG (3-6 Months), suggesting a more pronounced transitional climate risk impact on these commodities in the medium term. In the long term (6 months and beyond), GEPU continues to exert a greater influence on BRENT and WTI than PCR and TCR. At the same time, TCR exhibits a greater spillover effect than PCR in NG, underscoring the enduring impact of transitional climate risks on the natural gas market.

Table 5: BK spillover for Model 1-PCR.

1 Month								
Var	**PCR**	**COAL**	**ULSD**	**BRENT**	**WTI**	**NG**	**FROM_ABS**	**FROM_WTH**
PCR	2.84	0.03	0.17	0.01	0.00	0.04	0.04	2.77
COAL	0.00	0.91	0.01	0.06	0.03	0.02	0.02	1.29
ULSD	0.00	0.08	1.49	0.08	0.04	0.05	0.04	2.68
BRENT	0.00	0.06	0.09	0.37	0.32	0.01	0.08	5.36
WTI	0.00	0.06	0.11	0.39	0.47	0.00	0.09	6.23
NG	0.00	0.02	0.01	0.00	0.00	1.28	0.00	0.29
TO_ABS	0.00	0.04	0.06	0.09	0.07	0.02	0.28	
TO_WTH	0.13	2.65	4.20	5.96	4.40	1.28		18.62
1 to 3 Month								

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PCR	80.77	0.21	2.37	1.46	0.53	0.39	0.83	1.59
COAL	0.07	32.74	0.72	2.80	1.90	0.50	1.00	1.92
ULSD	0.23	1.07	36.39	8.92	8.38	0.80	3.24	6.22
BRENT	0.24	1.75	6.32	17.28	14.70	0.65	3.94	7.58
WTI	0.06	1.24	5.55	14.81	17.71	0.48	3.69	7.09
NG	0.21	0.42	0.51	0.03	0.18	49.70	0.23	0.43
TO_ABS	0.13	0.78	2.58	4.67	4.28	0.47	12.92	
TO_WTH	0.26	1.50	4.96	8.98	8.23	0.90		24.83
3 to 6 Month								
PCR	6.07	0.02	0.01	0.03	0.01	0.01	0.01	0.08
COAL	0.07	12.15	1.24	3.57	2.96	0.19	1.34	7.64
ULSD	0.14	0.85	5.38	4.86	4.49	0.21	1.76	10.03
BRENT	0.19	1.40	3.51	8.73	7.61	0.44	2.19	12.50
WTI	0.08	1.22	2.84	7.57	8.49	0.65	2.06	11.77
NG	0.02	1.26	0.10	0.16	0.29	18.33	0.30	1.74
TO_ABS ⁻	0.08	0.79	1.28	2.70	2.56	0.25	7.67	
TO_WTH	0.46	4.51	7.33	15.41	14.60	1.42		43.75
6 Month & Beyond								
PCR	4.94	0.04	0.00	0.02	0.02	0.00	0.01	0.05
COAL	0.18	20.46	2.91	8.90	7.47	0.13	3.27	11.28
ULSD	0.23	1.73	7.74	8.56	7.80	0.48	3.13	10.83
BRENT	0.32	2.79	5.51	14.34	12.57	0.82	3.67	12.66
WTI	0.19	2.53	5.07	14.07	15.02	1.38	3.87	13.38
NG	0.02	3.81	0.41	0.61	0.58	22.06	0.90	3.12
TO_ABS	0.15	1.82	2.32	5.36	4.74	0.47	14.86	
TO_WTH	0.53	6.27	8.01	18.52	16.37	1.62		51.32

Note: For PCR (Physical Climate Risk), TCR (transitional climate risk), and GEPU (Global Economic Policy Uncertainty) models: COAL, ULSD, BRENT, WTI, and NG represent the monthly fluctuations in their respective prices.

In Figures 6, 7, and 8 of the network diagrams, we can observe spillover effects from PCR, TCR, and GEPU onto five key energy market variables across different time frames. These time frames include 3.14 (1 month), 3.14 to 1.05(1-3 months), 1.05 to 0.52 (3-6 months), and 0.52 to 0 (6 months and beyond). Analyzing Figure 6, we discover that within the frequency bands of 3.14 and 3.14 to 1.05, PCR significantly influences the monthly changes in all five energy market prices. Specifically, ULSD experiences the highest spillover effect over one month, followed by NG and COAL, while WTI registers the least spillover impact from physical climate risk. This could be due to the vulnerability of these energy sources to physical climate risks such as extreme weather events or supply chain disruptions. As Salisu et al. (2023) noted, climate change can escalate global crude oil market uncertainties. In the 3.14 to 1.05 frequency band, ULSD continues to be the primary recipient of spillover from PCR, with BRENT and WTI following in terms of influence. However, none of the energy prices exhibit any significant changes or spillover effects in the remaining frequency bands. From Figure 7, it is evident that TCR acts as the primary driver of monthly changes in ULSD across all frequency bands. This aligns with the findings of Salisu et al. (2023), which indicated that TCR offers better predictive accuracy for energy market volatility in out-of-sample forecasts compared to PCR.

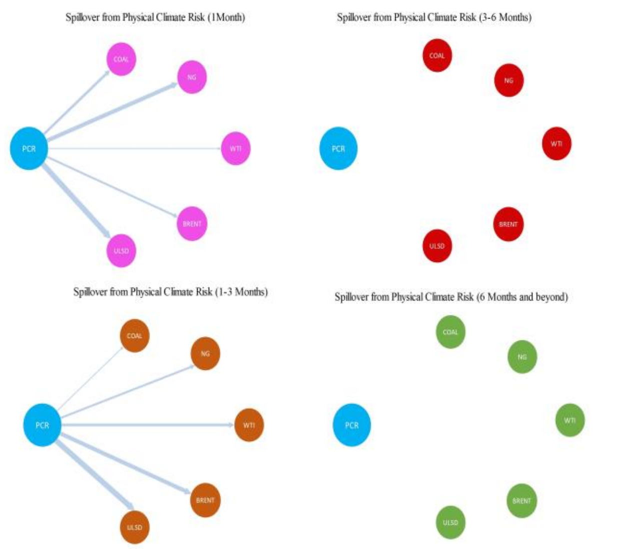

Figure 4: Spillover from PCR to energy market

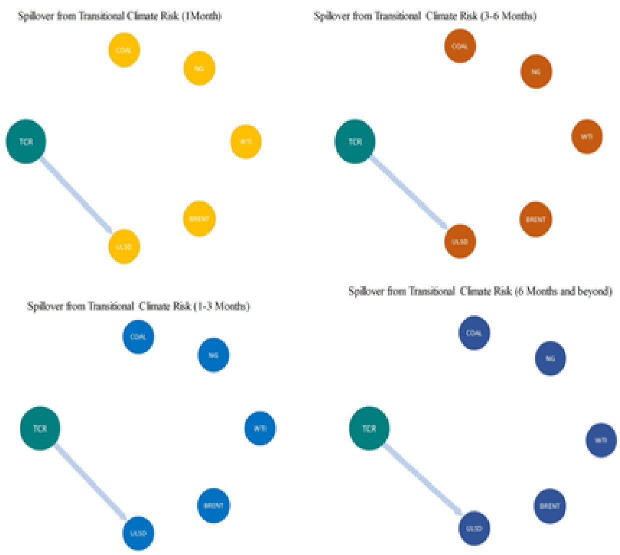

Figure 7: Spillover from TCR to energy market

Furthermore, Figure 8 illustrates the net impact of global economic policy uncertainty (GEPU) on COAL, NG, WTI, BRENT, and ULSD, highlighting the swift influence of policy uncertainty on energy prices. In the initial frequency band, GEPU solely affects the monthly COAL, NG, and BRENT changes. Notably, COAL experienced the most significant spillover from GEPU, followed by BRENT, within the first month. As we move into the medium-term 1-3 months, the maximum spillover shifts from COAL to BRENT. Moreover, the influence extends to four energy prices, including WTI within the network. BRENT received more substantial spillover effects during this time than NG, COAL, and WTI. In the longer term, specifically within the frequency bands of 1.05 to 0.52 and 0.52 to 0.00, GEPU continues to transmit spillover effects to the changes in COAL, NG, WTI, and BRENT. However, an interesting contrast is worth noting: ULSD no longer receives spillover from GEPU in the long term, in contrast to its short-term behavior.

Overall, Figure 8 suggests that the impact of global economic policy uncertainty on energy market prices varies across different energy commodities and time frames. Policy uncertainty seems to reasonably affect all energy prices equally in the short run. In the medium term, liquid fuels (WTI, BRENT, ULSD) are more affected, while in the long term, solid fuels (COAL) and gases (NG) seem to experience greater spillover effects. This could indicate that market participants might be more concerned about policy changes affecting long-run contracts and investments in these commodities.

Table 6: BK spillover for Model 3-TCR.

1 Month								
Var	**TCR**	**COAL**	**ULSD**	**BRENT**	**WTI**	**NG**	**FROM_ABS**	**FROM_WTH**
TCR	2.02	0.01	0	0	0.01	0.01	0	0.34
COAL	0.01	0.94	0.01	0.05	0.03	0.02	0.02	1.61
ULSD	0	0.07	1.49	0.06	0.03	0.04	0.03	2.45
BRENT	0.02	0.05	0.11	0.36	0.31	0.01	0.08	6.12
WTI	0.01	0.05	0.12	0.38	0.46	0	0.09	7.01
NG	0.01	0.01	0	0	0	1.26	0	0.35
TO_ABS	0.01	0.03	0.04	0.08	0.06	0.01	0.24	
TO_WTH	0.66	2.27	2.95	6.29	4.86	0.85		17.89
1 to 3 Month								
TCR	85.44	0.61	2.25	0.27	0.27	0.34	0.62	1.19

COAL	2.03	31.96	0.75	2.38	1.62	0.38	1.19	2.27
ULSD	0.22	0.94	36.35	9.15	8.6	0.69	3.27	6.21
BRENT	0.72	1.48	6.39	17.1	14.46	0.56	3.93	7.48
WTI	0.59	1.01	5.55	14.5	17.45	0.43	3.68	6.99
NG	0.88	0.42	0.63	0.11	0.33	48.85	0.39	0.75
TO_ABS	0.74	0.74	2.59	4.4	4.21	0.4	13.09	
TO_WTH	1.41	1.41	4.93	8.37	8.01	0.76		24.88
3 to 6 Month								
TCR	4.75	0.04	0.09	0.05	0.08	0	0.04	0.25
COAL	0.42	11.98	1.05	3.43	2.79	0.13	1.3	7.54
ULSD	0.01	0.83	5.43	4.91	4.49	0.22	1.74	10.1
BRENT	0.06	1.37	3.46	8.88	7.65	0.46	2.17	12.54
WTI	0.08	1.18	2.79	7.63	8.51	0.69	2.06	11.93
NG	0.17	1.24	0.08	0.21	0.37	18.13	0.34	1.99
TO_ABS	0.12	0.78	1.24	2.71	2.56	0.25	7.66	
TO_WTH	0.72	4.5	7.2	15.66	14.83	1.45		44.36
6 Month & Beyond								
TCR	3.36	0.11	0.1	0.07	0.1	0.01	0.07	0.23
COAL	0.55	20.78	2.53	8.71	7.28	0.15	3.21	11.14
ULSD	0.05	1.75	7.6	8.65	7.9	0.52	3.14	10.92
BRENT	0.09	2.81	5.31	14.62	12.84	0.91	3.66	12.71
WTI	0.14	2.52	4.88	14.27	15.26	1.5	3.88	13.5
NG	0.47	3.73	0.29	0.56	0.57	21.69	0.94	3.25
TO_ABS	0.22	1.82	2.19	5.38	4.78	0.52	14.89	
TO_WTH	0.75	6.32	7.6	18.68	16.61	1.79		51.75

Note: For PCR (physical climate risk), TCR (Transitional Climate Risk), and GEPU (Global Economic Policy Uncertainty) models: COAL, ULSD, BRENT, WTI, and NG represent the monthly fluctuations in their respective prices.

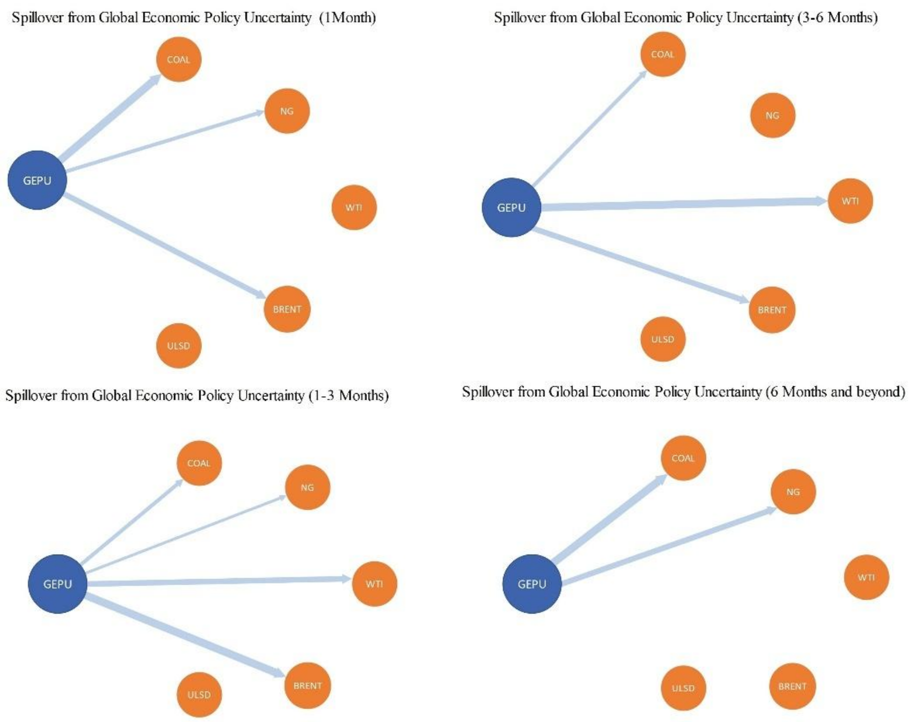

Figure 8: Spillover from GEPU to the energy market

Table 7: Model 3-GEPU BK Spillover

1 Month								
Variables	**GEPU**	**COAL**	**ULSD**	**BRENT**	**WTI**	**NG**	**FROM ABS**	**FROM WTH**
GEPU	2.4	0.04	0	0.02	0	0.01	0.01	0.9
COAL	0.03	0.75	0.22	0.15	0.12	0	0.09	6.11
ULSD	0.03	0.2	1.82	0.25	0.18	0	0.11	7.72
BRENT	0.01	0.03	0.1	0.35	0.32	0.01	0.08	5.35
WTI	0.01	0.03	0.11	0.35	0.41	0	0.08	5.81
NG	0.01	0.16	0.01	0.02	0.02	0.43	0.04	2.52
TO ABS	0.02	0.08	0.08	0.13	0.1	0	0.41	
TO WTH	1.06	5.31	5.23	9.24	7.31	0.27		28.43
1 to 3 Months								
GEPU	68.8	3.13	0.39	2.99	2.19	0.85	1.59	2.79
COAL	1.83	30.28	2.82	3.46	2.92	7.34	3.06	5.37
ULSD	0.57	2.98	36.42	8.62	7.74	0.2	3.35	5.88
BRENT	0.84	2.47	6.66	17.35	15.33	0.34	4.27	7.49
WTI	0.67	2.14	5.81	15.33	17.91	0.24	4.03	7.06
NG	0.5	6.35	2.36	0.95	1.2	62.33	1.9	3.32
TO ABS	0.73	2.84	3.01	5.23	4.9	1.5	18.2	
TO WTH	1.29	4.99	5.27	9.16	8.58	2.62		31.91
3 to 6 Months								
GEPU	8.09	0.27	0.12	0.71	0.7	0.09	0.31	1.81
COAL	0.16	10.6	1.73	1.4	1.25	1.78	1.05	6.08
ULSD	0.14	1.23	5.32	4.89	4.51	0.02	1.8	10.38
BRENT	0.47	1.38	4.13	9.31	8.23	0.01	2.37	13.7
WTI	0.41	1.24	3.76	8.65	9.27	0.03	2.35	13.58

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NG	0.11	1.69	0.75	0.3	0.35	10.69	0.53	3.08
TO ABS	0.21	0.97	1.75	2.66	2.51	0.32	8.42	
TO WTH	1.24	5.6	10.1	15.37	14.5	1.85		48.65
6 Months & Beyond								
GEPU	7.77	0.21	0.04	0.57	0.59	0.02	0.24	0.98
COAL	0.05	17.39	4.91	5.15	4.37	1.29	2.63	11.14
ULSD	0.2	1.75	7.78	8.65	7.9	0.52	3.14	10.92
BRENT	0.75	1.43	5.55	14.62	11.7	0.91	3.24	12.71
WTI	0.72	1.23	5.29	12.92	13.45	0.02	3.36	13.89
NG	0.01	2.84	0.31	0.61	0.57	7.41	0.72	2.99
TO ABS	0.29	1.24	2.68	4.53	4.07	0.22	13.04	
TO WTH	1.19	5.13	11.08	18.72	16.82	0.92		53.87

Note: For PCR (physical climate risk), TCR (transitional climate risk), and GEPU (Global Economic Policy Uncertainty) models: COAL, ULSD, BRENT, WTI, and NG represent the monthly fluctuations in their respective prices.

Table 8: Comparative Analysis of BK Spillovers of Models 1 to 3

	1 Month					**1-3Months**				
	COAL	ULSD	BRENT	WTI	NG	COAL	ULSD	BRENT	WTI	**NG**
GEPU vs Climate Risk	Yes	Yes	No	No	No	No	Yes	Yes	Yes	**No**
TCR vs PCR	Yes	No	Yes	Yes	Yes	Yes	No	No	No	**Yes**
	3-6 Months					**6 Months and Beyond**				
GEPU vs Climate Risk	No	No	Yes	Yes	No	No	No	Yes	Yes	**No**
TCR vs PCR	**No**	**No**	**No**	**No**	**Yes**	**No**	**No**	**No**	**No**	**Yes**

Note: For all energy market prices, instances where GEPU's spillover exceeds both PCR and TCR are marked with "Yes." Similarly, "Yes" also denotes cases where TCR's spillover surpasses that of PCR. In all other scenarios, the response is marked as "No" for both comparisons.

4.4 Frequency domain causality test

To enhance the robustness of our findings regarding DY and BK spillovers, we have conducted a sensitivity analysis using the frequency domain causality (FDC) test. This analytical approach provides additional support for our results. Figures 9, 10, and 11 display the outcomes of the FDC test corresponding to the PCR, TCR, and GEPU models, respectively. In these visual representations, the black dotted line denotes the 5% significance threshold, while the red dashed line represents the incremental R-squared values. The X-axis is labeled with frequencies, and the Y-axis displays the incremental R-squared values. The incremental R-squared measures the disparity between the R-squared (R2) derived from an unrestricted model and the R-squared (R2) derived from a model estimated under specific constraints. This incremental R-squared value quantifies the degree of Granger causality from PCR, TCR, and GEPU to energy prices at a given frequency ω.

In Figure 9, the red dashed line represents the incremental R-square value of PCR compared to the critical value at a 5% significance level. In all five cases, the incremental R-squared equals the critical value, rather than being greater or lesser. Consequently, we cannot reject the null hypothesis of Granger causality from PCR to energy prices. Therefore, we can conclude that PCR plays a significant role in predicting the future values of COAL, ULSD, BRENT, WTI, and NG.

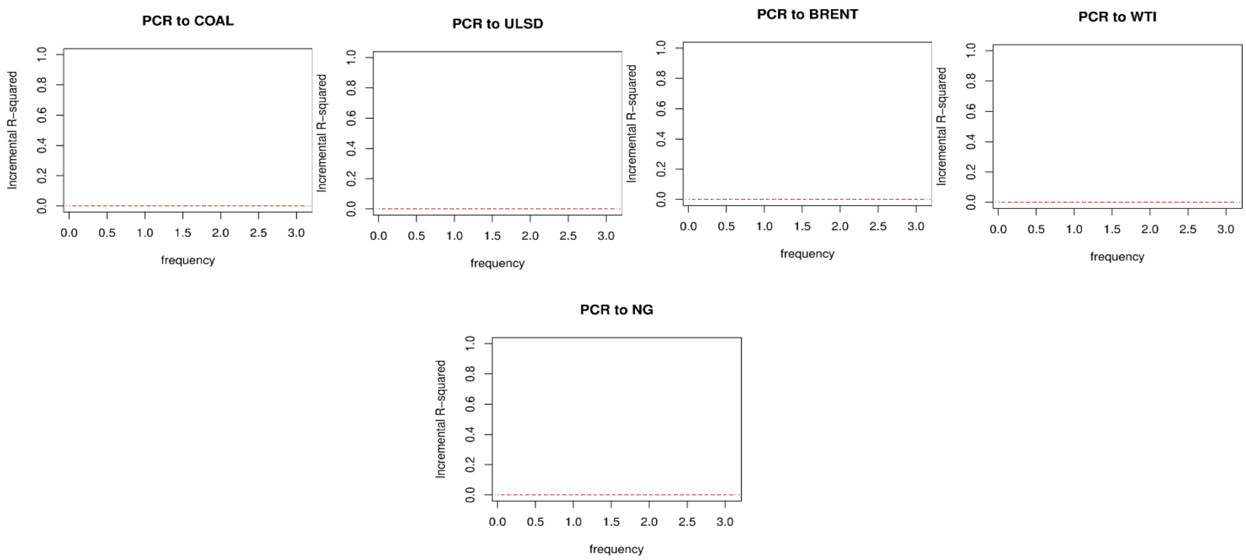

Figure 9: Frequency domain causality from PCR to energy prices

In Figure 10, we plotted the FDC outcomes for TCR to the energy market. This also confirmed that TCR significantly contributes to predicting future values of five key energy prices. These results are in line with (Rao et al., 2023). However, at the lowest frequency, we failed to accept the null hypothesis of Granger causality from TCR to energy prices.

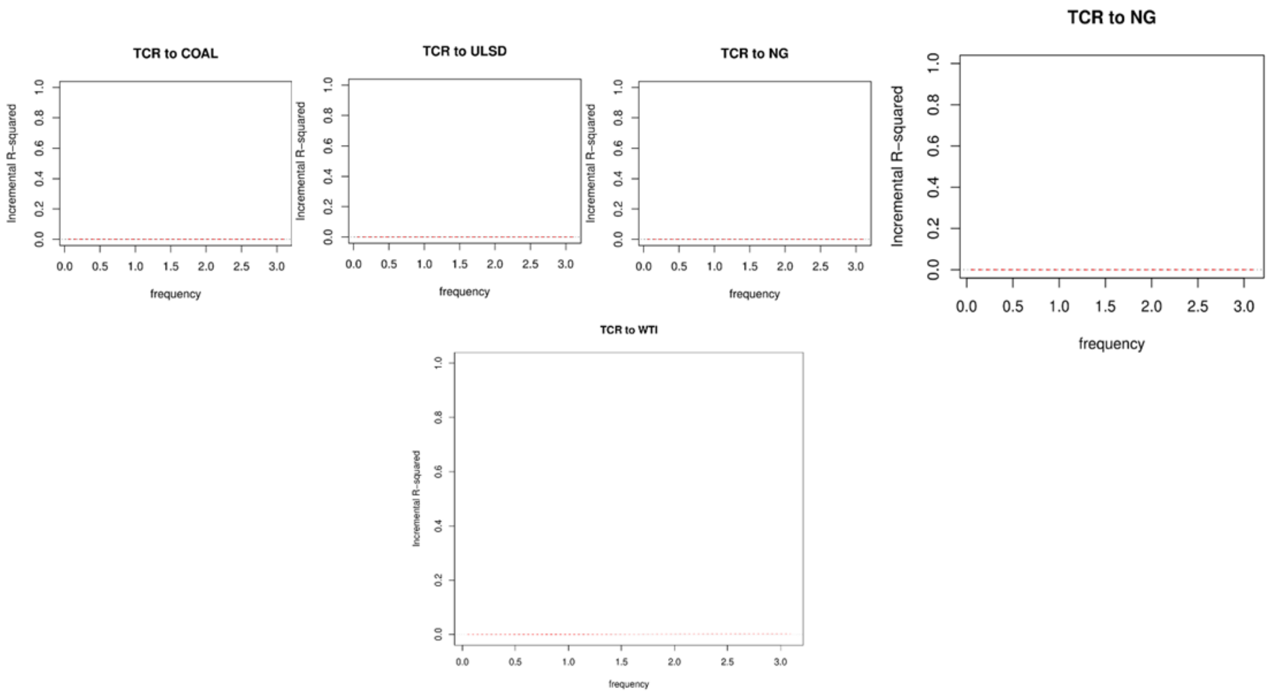

Figure 10: Frequency domain causality from TCR to energy prices

Figure 11 illustrates the frequency domain causality outcomes between global economic policy uncertainty and energy prices. The outcomes confirmed that GEPU makes a significant contribution to predicting the future price of the energy market. To sum up, the casual association from PCR, TCR, and GEPU to COAL, ULSD, BRENT, WTI, and NG is not prominent at the lower and upper-frequency limits. In most cases, the strength of causality remains constant throughout the significant range.

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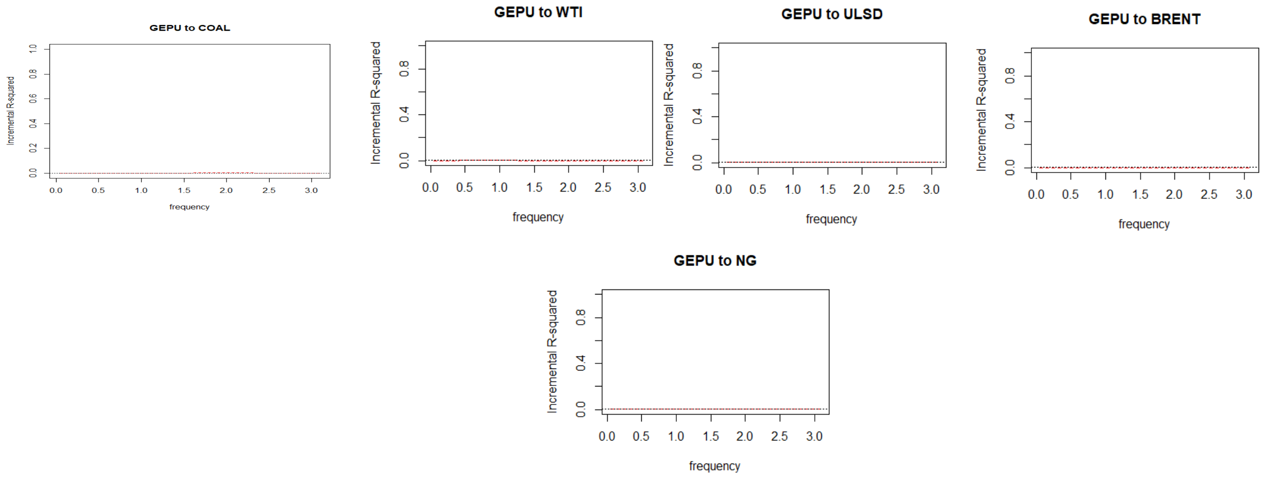

Figure 11: Frequency domain causality from GEPU to energy prices

5. Conclusion and policy recommendation

The energy market faces unprecedented and unpredictable price fluctuations, driven by a complex mix of changing global climate patterns, rapid industrialization, policy uncertainties, and economic growth. These dynamics present significant challenges for investors, particularly in making decisions about future investments. As a result, the associated risks—namely, physical climate risks (PCR) and transitional climate risks (TCR)—have drawn the attention of researchers aiming to support potential investors in navigating these uncertainties.This study set out to explore the intricate relationships between transitional climate risk (TCR), physical climate risk (PCR), global economic policy uncertainty (GEPU), and the prices of key energy commodities, including COAL, ULSD, BRENT, WTI, and NG. By analyzing asymmetric spillover connectedness and utilizing frequency domain causality, we offer empirical insights into energy price fluctuations. Specifically, we examined the overall connectedness and spillover effects using two datasets: one for monthly climate risks and another for global economic policy uncertainty.

Our results, based on DY and BK methodologies, reveal an increasing pattern of overall connectedness over time for PCR, TCR, and GEPU. Among these, GEPU exhibited the highest connectedness for periods of six months and beyond, followed by TCR and PCR, with connectedness magnitudes of 53.87%, 51.75%, and 51.32%, respectively. Notably, TCR maintained higher connectedness than PCR across all time frames except for the one-month period, where TCR showed a lower connectedness of 17.89%. These findings have crucial implications for shaping policies related to both physical and transitional climate risks, as well as addressing uncertainties arising from economic policies. These policies are particularly important as they aim to achieve the dual goals of fostering economic growth while reducing greenhouse gas emissions. Moreover, investors are especially concerned about policy changes, as they impact not only present but also future earnings. This concern is reflected in our findings, where TCR shows greater overall connectedness with energy price volatility compared to PCR.

Our analysis of transmission dynamics further highlights the varying effects of TCR, PCR, and GEPU on energy prices across different time frames. In the short term (1 month and 1-3 months), PCR acts as a net transmitter to all five energy prices, while TCR's transmissions are limited, affecting only ULSD. On the other hand, GEPU demonstrates a more varied transmission pattern: for one month, it is a net transmitter for COAL, NG, and BRENT; for 1-3 months, it transmits to WTI, BRENT, NG, and COAL; and for 3-6 months, it is a net transmitter to COAL, WTI, and BRENT. Beyond six months, GEPU's transmissions diminish, particularly for WTI, BRENT, and ULSD.Given these varied transmission dynamics, policymakers should prioritize diversification of energy sources. In the short term (1-3 months), policy efforts should focus on addressing PCR's net transmission to all

energy prices. For longer time frames (3-6 months and beyond), attention should shift to managing risk factors that disproportionately impact specific energy prices. For example, stabilizing the prices of COAL, WTI, and BRENT could ensure long-term energy price stability. Additionally, developing more robust risk assessment and forecasting tools will allow for proactive policy adjustments to minimize economic disruptions.
Furthermore, our analysis extends to the causal relationships between PCR, TCR, GEPU, and energy prices. Understanding these causal interconnections will empower stakeholders in the energy markets for coal, ULSD, Brent, WTI, and natural gas to devise proactive strategies for managing risks associated with economic and climate policies.

5.1 Limitations and Future Research Directions

While this study provides valuable insights, it is not without limitations. First, the analysis is constrained to a limited set of energy commodities, and future research could expand the scope to include a broader range of energy markets. Second, the frequency domain causality approach, though effective, may not capture all complexities of dynamic interactions over shorter time frames. Future studies could explore alternative methodologies, such as machine learning techniques, for more granular analysis. Lastly, this research focuses on the global perspective; country-specific studies could offer additional insights into how regional policies and risks affect energy prices differently.
By addressing these limitations, future research can further enhance our understanding of the intricate relationships between climate risks, economic policy uncertainty, and energy markets, ultimately leading to more effective policy interventions and investment strategies.

Author Contributions:

Conceptualization, Khadim Hussain and Anwar Khan; methodology, Khadim Hussain and Zhong Jian; software, Khadim Hussain; validation, Zhong Jian; formal analysis, Khadim Hussain; investigation, Khadim Hussain; resources, Zhong Jian; data curation, Khadim Hussain; writing—original draft preparation, Khadim Hussain and Anwar Khan; writing—review and editing, Khadim Hussain; visualization, Khadim Hussain; supervision, Zhong Jian. All authors have read and agreed to the published version of the manuscript.

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Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent

Ethics approval was not required. All participants provided informed consent for participation and publication of anonymized data.

Competing interests

The authors declare no competing interests.

References

[1] Ahmad, W., 2017. On the dynamic dependence and investment performance of crude oil and clean energy stocks. Research in International Business and Finance, 42, 376–389. https://doi.org/10.1016/j.ribaf.2017.07.140
[2] Arndt, C., 2023. Climate change vs energy security? The conditional support for energy sources among Western Europeans. Energy Policy, 174, 113471. doi:10.1016/j.enpol.2023.113471
[3] Ashfaq, S., Tang, Y., Maqbool, R., 2019. Volatility spillover impact of world oil prices on leading Asian energy exporting and importing economies' stock returns. Energy, 188, 116002. doi:10.1016/j.energy.2019.116002
[4] Baruník, J., Křehlík, T., 2018. Measuring the frequency dynamics of financial connectedness and systemic risk. Journal of Financial Econometrics, 16, 271–296. doi:10.1093/jjfinec/nby001
[5] Bouri, E., Rognone, L., Sokhanvar, A., Wang, Z., 2023. From climate risk to the returns and volatility of energy assets and green bonds: A predictability analysis under various conditions. Technological Forecasting and Social Change, 194, 122682. https://doi.org/10.1016/j.techfore.2023.122682

[6] Bras, T.A., Simoes, S., Amorim, F., Fortes, P., 2023. How much extreme weather events have affected European power generation in the past three decades? Renewable and Sustainable Energy Reviews, 183, 113494. doi:10.1016/j.rser.2023.113494
[7] Breitung, J., Candelon, B., 2006. Testing for short-and long-run causality: A frequency-domain approach. Journal of Econometrics, 132, 363–378. doi:10.1016/j.jeconom.2005.02.004
[8] Cheng, J., Mohammed, K.S., Misra, P., Tedeschi, M., Ma, X., 2023. Role of green technologies, climate uncertainties and energy prices on the supply chain: Policy-based analysis through the lens of sustainable development. Technological Forecasting and Social Change, 194, 122705.
[9] Croux, C., Reusens, P., 2013. Do stock prices contain predictive power for the future economic activity? A Granger causality analysis in the frequency domain. Journal of Macroeconomics, 35, 93–103. doi:10.1016/j.jmacro.2012.10.001
[10] Diebold, F.X., Yılmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics, 182, 119–134. doi:10.1016/j.jeconom.2014.04.012
[11] Dutta, A., Bouri, E., Rothovius, T., Uddin, G.S., 2023. Climate risk and green investments: New evidence. Energy, 265, 126376. doi:10.1016/j.energy.2022.126376
[12] Faccini, R., Matin, R., Skiadopoulos, G., 2023. Dissecting climate risks: Are they reflected in stock prices? Journal of Banking & Finance, 155, 106948. doi:10.1016/j.jbankfin.2023.106948
[13] Farnè, M., Montanari, A., 2022. A bootstrap method to test Granger-causality in the frequency domain. Computational Economics, 59, 935–966. doi:10.1007/s10614-021-10112-x
[14] Guo, C., Zhang, X., Iqbal, S., 2023. Does oil price volatility and financial expenditures of the oil industry influence energy generation intensity? Implications for clean energy acquisition. Journal of Cleaner Production, 139907. doi:10.1016/j.jclepro.2023.139907
[15] Guo, C., Zhang, X., Iqbal, S., 2024. Does oil price volatility and financial expenditures of the oil industry influence energy generation intensity? Implications for clean energy acquisition. Journal of Cleaner Production, 434, 139907. doi:10.1016/j.jclepro.2023.139907
[16] Guo, K., Kang, Y., Ma, D., Lei, L., 2024. How do climate risks impact the contagion in China's energy market? Energy Economics, 133, 107450. https://doi.org/10.1016/j.eneco.2024.107450
[17] Hansen, L.P., 2022. Central banking challenges posed by uncertain climate change and natural disasters. Journal of Monetary Economics, 125, 1–15.
[18] Hasegawa, T., Sakurai, G., Fujimori, S., Takahashi, K., Hijioka, Y., Masui, T., 2021. Extreme climate events increase risk of global food insecurity and adaptation needs. Nature Food, 2, 587–595. doi:10.1038/s43016-021-00335-4
[19] Hoque, M.E., Soo-Wah, L., Bilgili, F., Ali, M.H., 2023. Connectedness and spillover effects of US climate policy uncertainty on energy stock, alternative energy stock, and carbon future. Environmental Science and Pollution Research, 30, 18956–18972. doi:10.1007/s11356-022-23464-0
[20] Humphreys, H.B., McClain, K.T., 1998. Reducing the impacts of energy price volatility through dynamic portfolio selection. The Energy Journal, 19, 1–25. doi:10.5547/ISSN0195-6574-EJ-Vol19-No3-6
[21] In, S.Y., Manav, B., Venereau, C.M., Weyant, J.P., et al., 2022. Climate-related financial risk assessment on energy infrastructure investments. Renewable and Sustainable Energy Reviews, 167, 112689. doi:10.1016/j.rser.2022.112689
[22] Ivanovski, K., Marinucci, N., 2021. Policy uncertainty and renewable energy: Exploring the implications for global energy transitions, energy security, and environmental risk management. Energy Research and Social Science, 82, 102415.
[23] Jin, Y., Zhao, H., Bu, L., Zhang, D., 2023. Geopolitical risk, climate risk and energy markets: A dynamic spillover analysis. International Review of Financial Analysis, 87, 102597. doi:10.1016/j.irfa.2023.102597
[24] Karim, S., Naeem, M.A., Shafiullah, M., Lucey, B.M., Ashraf, S., 2023. Asymmetric relationship between climate policy uncertainty and energy metals: Evidence from cross-quantilogram. Finance Research Letters, 54, 103728
[25] Le, T.H., Boubaker, S., Nguyen, C.P., 2021. The energy-growth nexus revisited: An analysis of different types of energy. Journal of Environmental Management, 297, 113351. doi:10.1016/j.jenvman.2021.113351
[26] Li, D., Wu, Z., Tang, Y., 2024. Do climate risks affect dirty–clean energy stock price dynamic correlations? Energy Economics, 136, 107713. https://doi.org/10.1016/j.eneco.2024.107713

[27] Li, F., Zhang, J., Li, X., 2023a. Energy security dilemma and energy transition policy in the context of climate change: A perspective from China. Energy Policy, 181, 113624. doi:10.1016/j.enpol.2023.113624
[28] Li, Z.Z., Su, C.W., Moldovan, N.C., Umar, M., 2023b. Energy consumption within policy uncertainty: Considering the climate and economic factors. Renewable Energy, 208, 567–576
[29] Liu, B., Liao, S., Lund, J.R., Jin, X., Cheng, C., 2023. Economically optimal hydropower development with uncertain climate change. Journal of Hydrology, 627, 130383
[30] Mokni, K., Zaier, L.H., Youssef, M., Jabeur, S.B., 2024. Quantile connectedness between the climate policy and economic uncertainty: Evidence from the G7 countries. Journal of Environmental Management, 351, 119826.
[31] Ndlovu, V., Inglesi-Lotz, R., 2020. The causal relationship between energy and economic growth through research and development (R&D): The case of BRICS and lessons for South Africa. Energy, 199, 117428. doi:10.1016/j.energy.2020.117428

[32] Oberndorfer, U., 2009. Energy prices, volatility, and the stock market: Evidence from the Eurozone. Energy Policy, 37, 5787–5795. doi:10.1016/j.enpol.2009.08.043
[33] Ogede, J.S., Oduola, M.O., Onanuga, A.T., 2023. Deciphering the moderation influence of economic policy uncertainty in the dynamics of energy poverty–government expenditure nexus in SSA. Energy Efficiency, 16, 86.
[34] Perera, A., Nik, V., Chen, D., Scartezzini, J., Hong, T., 2020. Quantifying the impacts of climate change and extreme climate events on energy systems. Nature Energy, 5, 150–159. doi:10.1038/s41560-020-0558-0
[35] Rao, A., Lucey, B., Kumar, S., 2023. Climate risk and carbon emissions: Examining their impact on key energy markets through asymmetric spillovers. Energy Economics, 126, 106970. doi:10.1016/j.eneco.2023.106970
[36] Raza, S.A., Khan, K.A., 2024. Climate policy uncertainty and its relationship with precious metals price volatility: Comparative analysis pre and during COVID-19. Resources Policy, 88, 104465.
[37] Reboredo, J.C., Ugolini, A., 2022. Climate transition risk, profitability and stock prices. International Review of Financial Analysis, 83, 102271. doi:10.1016/j.irfa.2022.102271
[38] Ren, X., Li, J., He, F., Lucey, B., 2023. Impact of climate policy uncertainty on traditional energy and green markets: Evidence from time-varying Granger tests. Renewable and Sustainable Energy Reviews, 173, 113058.
[39] Salisu, A.A., Ndako, U.B., Vo, X.V., 2023. Transition risk, physical risk, and the realized volatility of oil and natural gas prices. Resources Policy, 81, 103383. doi:10.1016/j.resourpol.2023.103383
[40] Sarker, P.K., Bouri, E., Marco, C.K.L., 2023. Asymmetric effects of climate policy uncertainty, geopolitical risk, and crude oil prices on clean energy prices. Environmental Science and Pollution Research, 30, 15797–15807.
[41] Shafiullah, M., Miah, M.D., Alam, M.S., Atif, M., 2021. Does economic policy uncertainty affect renewable energy consumption? Renewable Energy, 179, 1500–1521.
[42] Siddique, M.A., Nobanee, H., Hasan, M.B., Uddin, G.S., Hossain, M.N., Park, D., 2023. How do energy markets react to climate policy uncertainty? Fossil vs. renewable and low-carbon energy assets. Energy Economics, 107195. doi:10.1016/j.eneco.2023.107195
[43] Song, Y., Ji, Q., Du, Y.-J., Geng, J.-B., 2019. The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets. Energy Economics, 84, 104564. https://doi.org/10.1016/j.eneco.2019.104564
[44] Syed, Q.R., Apergis, N., Goh, S.K., 2023. The dynamic relationship between climate policy uncertainty and renewable energy in the US: Applying the novel Fourier augmented autoregressive distributed lags approach. Energy, 275, 127383.
[45] Taghizadeh-Hesary, F., Rasoulinezhad, E., Yoshino, N., 2019. Energy and food security: Linkages through price volatility. Energy Policy, 128, 796–806. doi:10.1016/j.enpol.2018.12.043
[46] Wang, X., Li, J., Ren, X., Bu, R., Jawadi, F., 2023. Economic policy uncertainty and dynamic correlations in energy markets: Assessment and solutions. Energy Economics, 117, 106475.
[47] Wen, J., Zhao, X.X., Chang, C.P., 2021. The impact of extreme events on energy price risk. Energy Economics, 99, 105308. doi:10.1016/j.eneco.2021.105308
[48] Yalew, S.G., van Vliet, M.T., Gernaat, D.E., Ludwig, F., Miara, A., Park, C., Byers, E., De Cian, E., Piontek, F., Iyer, G., et al., 2020. Impacts of climate change on energy systems in global and regional scenarios. Nature Energy, 5, 794–802. doi:10.1038/s41560-020-0664-z

[49] Yi, S., Raghutla, C., Chittedi, K.R., Fareed, Z., 2023. How economic policy uncertainty and financial development contribute to renewable energy consumption? The importance of economic globalization. Renewable Energy, 202, 1357–1367.
[50] Zhang, D., 2018. Energy finance: background, concept, and recent developments. doi:10.1080/1540496X.2018.1466524
[51] Zhang, Y., He, M., Wang, Y., Liang, C., 2023. Global economic policy uncertainty aligned: An informative predictor for crude oil market volatility. International Journal of Forecasting, 39, 1318–1332.
[52] Zhou, D., Siddik, A.B., Guo, L., Li, H., 2023. Dynamic relationship among climate policy uncertainty, oil price and renewable energy consumption—findings from TVP-SV-VAR approach. Renewable Energy, 204, 722–732.
[53] Jiang, Z., Wang, L., Wang, H., Ma, J., Shi, W., Bai. Benefits of pasture construction for comprehensive agricultural development in Duolun agro-pasture ecotone of Inner Mongolia. Animal Husbandry and Feed Science, 2 (10/12), 42–44 (2010).

[54] Liu, Y., Tong. Effects of land use type on soil nutrient distribution in northern agro-pasture ecotone. Ying Yong Sheng Tai Xue Bao = The Journal of Applied Ecology, 16 (10), 1849–1852 (2005).
[55] Yun-Hao, L., Xiao-Bing, S., Pei-Jun, D., Wen, L., Xia. Intra-annual vegetation change characteristics in the NDVI-Ts space: Application to farming-pastoral zone in North China. Animal Husbandry and Feed Science, 45 (10), 1139–1145 (2003).
[56] Zhang, J., Guo, C., Xin, X., Li, H., Xie. Current situation of Chinese Simmental cows breeding in Tongliao of Inner Mongolia. Animal Husbandry and Feed Science (Inner Mongolia), 39 (2), 78–80 (2018)