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Climate Risk and Global Economic Policy Uncertainty Asymmetric Spillover on Global Energy Mix

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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 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 patterns of association with energy prices, with TCR showing a slightly higher value in most cases. Additionally, PCR serves as a net transmitter of all five energy prices for only 1 month and 1-3 months, while TCR is a net transmitter of ULSD across the short-, medium-, and long-run frequency bands. However, GEPU is not a net transmitter of ULSD at any frequency and is transmitting net spillover onto 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 the frequency-domain causality test, which indicates that PCR, TCR, and GEPU are Granger causes of energy prices across different frequencies.
Keywords: Climate risk, economic policy uncertainty, energy prices, spillover effects, frequency domain connectedness

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 (Le et al., 2021). The global energy mix is a complex interplay of renewable and nonrenewable resources, where fossil fuels still dominate, and their prices directly influence energy consumption and investment decisions, impacting both energy transition and environmental justice by shaping access to clean energy and sustainable practices (Ndlovu et al., 2020). 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 (Li et al., 2024). However, the dynamics determining fossil fuel energy pricing are complex and susceptible to a wide range of factors, as commodities travel long distances and are frequently imported from unstable political environments; therefore, energy prices remain volatile due to political instability (European Commission 2023). The complex web of factors that affects energy prices includes supply and demand dynamics, geopolitical events, decisions by the Organization of the Petroleum Exporting Countries (OPEC), and weather patterns (Zhang & D, 2018). Collectively, these factors exert considerable influence on the intricate equilibrium of vital energy markets, shaping fluctuations in their costs with noteworthy consequences (European, 2023).

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

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influencing financial markets, including stock returns (Shipley, 2023). Meanwhile, nonrenewable energy sources like coal, 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 (Rao et al., 2023), time-varying parameter vector autoregression or exploring the effect of climate risk on energy equity, climate risk effects on the dynamic conditional correlation between clean and dirty energy prices using NARDL/ARDL (Bouri et al., 2023), and dynamic dependencies of fossil energy and investor (Ahmad & W, 2017). However, the connectedness and spillover between PCR, TCR, GEPU, and dirty energy prices remain unresolved, which serves as the major research motivation for this study (Guo et al., 2024). In the intricate relationship between energy and finance, the main issue is the risk inherent in energy pricing, a known factor 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 (Song et al., 2019). Moreover, a near-term trend indicates an increasing threat to energy security driven by climate-related factors (Ashfaq et al., 2019). This relationship between energy costs and weather extremes takes center stage in energy-finance studies. Droughts and reduced rainfall are two factors that significantly influence energy costs (Guo et al., 2023). Furthermore, the trend of climate risk indicates that the frequency of catastrophic weather events will increase energy cost volatility (Humphreys et al., 1998).

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 (Oberndorfer & U, 2009). 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 systems, with immediate effects on their fragile structure (Taghizadeh et al., 2019). Therefore, climate change-induced events disrupt the function of energy systems (Arndt & C, 2023). 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 (F. Li, Zhang, J., Li, X.,, 2023). 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 (Wen et al., 2021b).

Previous studies have shown that renewable energy investments are more resilient than carbon-intensive fossil fuel assets due to increasing climate risks (Hasegawa et al., 2021). Firms exposed to lower climate risks have also been found to exhibit superior financial performance. High climate risk has been associated with higher prices for green energy products but lower volatility (Song & renewable energy stock markets. Energy Economics). Economic policy uncertainty (EPU) has been shown to significantly affect renewable energy consumption in the United States (Siddique, M.A, & et al., 2023). Significant correlations between EPU and energy markets at different stages have also been documented (Brás et al., 2023). Similar results have been reported in other studies (Yalew et al., 2020), while recent evidence indicates that EPU contributes to a reduction in renewable energy consumption (In et al., 2022). Overall, empirical findings suggest that climate risk and EPU play crucial roles in shaping global energy demand and supply, warranting further attention (Reboredo et al., 2022).

Building on this literature, the present study initiates a systematic examination of spillover effects from physical climate risk, transitional climate risk, and global economic policy uncertainty (GEPU) on global energy markets, including coal, gas, diesel, and oil. A comprehensive climate uncertainty index and monthly GEPU are employed within a time–frequency decomposition framework, following the methodologies proposed in previous studies (Dutta et al., 2023). From this perspective, the study makes three primary contributions. First, it extends the existing literature on the impact of climate change on international energy prices by examining how climate-related risks reshape global energy markets. Second, it contributes to the growing body of research on the role of text-based uncertainty measures, such as EPU and geopolitical risk, in influencing energy prices. Third, and most importantly, it provides novel evidence on asymmetric spillovers arising from monthly variations in physical climate risk, transitional climate risk, and GEPU to energy prices, along with frequency-based Granger causality analysis (Shafiullah et al., 2021). To the best of the authors' knowledge, the spillover effects of monthly physical and transitional climate risks and GEPU on energy prices have not been previously explored, making this study a significant addition to the literature. The remainder of the paper is organized as follows: Section 2 reviews the relevant literature; Section 3 describes the data and methodology; Section 4 presents and discusses the empirical results; and Section 5 concludes with policy implications and future research directions (Wang et al., 2023).

2. Literature Review

The impacts of climate change are increasingly evident, and international organizations are actively engaged in mitigation efforts (Yi et al., 2023). Climate change has affected multiple dimensions of society, including its substantial influence on economic systems . Climate risk uncertainty has emerged as a global concern due to its effects on energy prices, attracting growing scholarly attention. Consequently, the global transition toward clean, renewable energy has gained momentum, while uncertainty surrounding climate policies has intensified (Diebold et al., 2014). Globally, energy policies aim to reduce fossil fuel consumption and limit greenhouse gas emissions. However, climate-related uncertainty induces fluctuations in energy supply and demand, leading to volatility in global energy prices. Additionally, speculative activities in energy markets generate spillover effects that further amplify price volatility (Baruník et al., 2018).

Against this background, providing new insights into the effects of climate-related and economic policy uncertainties on energy spillovers is essential for fostering consensus among global policymakers (Liu et al., 2023). Using a pre- and post-COVID framework, one study concluded that climate uncertainty plays a critical role in determining the volatility of precious metal prices (Hansen & L.P, 2022). By employing the quantile-on-quantile regression approach, it has been demonstrated that climate change uncertainty, economic policy uncertainty, and energy price volatility are closely interconnected (Sarker et al., 2023). Building on this literature, the present study reviews existing research and examines physical climate risk (PCR), transitional climate risk (TCR), and global economic policy uncertainty (GEPU) across various energy indicators (Guo et al., 2023).

The first stream of literature focuses on the effects of climate policy uncertainty on energy and financial market variables, including energy consumption, returns, and the volatility of green and brown energy stocks. Using a time-varying Granger causality framework, previous research identified bidirectional, time-varying feedback between climate policy uncertainty and energy markets, with stronger causality observed during periods of policy implementation and extreme weather (Yi et al.). Employing a vector autoregressive model with U.S. data, another study reported both positive and negative relationships between climate policy uncertainty and renewable energy, depending on policymakers' stance toward climate initiatives (Raza et al., 2024). Similarly, time-varying VAR analysis revealed dynamic interlinkages among climate policy uncertainty, renewable energy, and oil prices (Cheng et al., 2023).

Empirical evidence further suggests that climate policy uncertainty generally exerts a positive influence on oil prices and renewable energy in both the short- and long-run. Using advanced econometric techniques such as wavelet and quantile-on-quantile analyses, previous studies found that climate policy uncertainty negatively affects fossil fuel markets across multiple quantiles and frequencies, while its impact on renewable energy remains predominantly positive (Ren et al., 2023). Asymmetric analysis using a cross-quantile approach also confirmed significant interactions between climate policy uncertainty and energy metals (Z. Z. Li, Su, C.W., Moldovan, N.C., Umar, M.,`, 2023). Additional evidence indicates that climate policy uncertainty hampers renewable energy consumption in the United States and spillovers onto clean energy prices (Siddique, M.A, Nobanee, et al., 2023; Zhou et al., 2023). Moreover, shocks to climate policy uncertainty have been shown to transmit to energy markets, reinforcing the presence of spillover effects (Karim et al., 2023). Despite these findings, there is limited consensus on the magnitude and direction of climate policy uncertainty spillovers, which motivates the present study (Syed et al., 2023).

The second stream of research examines the relationship between global economic policy uncertainty and energy indicators. Quantile-on-quantile regression evidence suggests that economic policy uncertainty has a positive and significant effect on energy markets (Hoque et al., 2023). Other studies document interconnectedness between climate-related and economic policy uncertainties across different quantiles (Yi et al.), as well as spillover effects of climate and economic policies within G7 economies (Mokni et al., 2024). Using monthly data and the CS-ARDL approach, research has shown that economic policy uncertainty negatively affects renewable energy consumption (Ogede et al., 2023). Similarly, economic policy uncertainty has been identified as a strong predictor of energy prices and a contributor to increased energy poverty in Sub-Saharan Africa (Faccini et al., 2023; Ivanovski et al., 2021).

Further evidence indicates that heightened economic policy uncertainty discourages renewable energy adoption, as greater uncertainty suppresses investment incentives (Farnè et al., 2022). While much of the existing literature focuses on environmental indicators or energy consumption dynamics, the spillover effects of economic policy uncertainty on energy markets remain underexplored. Accordingly, the present study aims to address this gap and contribute to a more comprehensive understanding of uncertainty-driven spillovers in global energy markets (Croux et al., 2013).

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 has identified various channels of energy price volatility and has explained the spillover effects of energy prices on other markets (Breitung et al., 2006; Salisu et al., 2023).

However, the literature has paid limited attention to the impacts of climate policy (PCR and TCR) and economic policy uncertainty on energy markets, which directly influence 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 (Wen et al., 2021a). Similarly, a stable economic paradigm will help policymakers address climate-related issues by determining energy product demand and supply (Zhang et al., 2023).

3. Data and Methodology

The Materials and Methods should be described with sufficient detail 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. This study extends previous research by examining the effects of physical climate risk (PCR), transitional climate risk (TCR), and global economic policy uncertainty (GEPU) on global energy prices (Perera et al., 2020). Specifically, it investigates the impact of these factors on several major energy commodities, including coal; ultra-low sulfur diesel (ULSD) traded in New York, the U.S. Gulf Coast, and Los Angeles; Brent crude oil (BRENT); West Texas Intermediate crude oil (WTI); and the global price of natural gas (NG). These energy prices play a critical role in shaping the global energy landscape and have substantial implications for both environmental sustainability and the climate economy. WTI serves as a key global oil benchmark, underpinning oil futures contracts traded on the New York Mercantile Exchange. Similarly, BRENT is a dominant benchmark that determines the pricing of approximately two-thirds of globally traded crude oil, with influence extending across Europe, Africa, and the Middle East.

According to the International Energy Agency, the contribution of natural gas and coal to global energy generation increased significantly between 1990 and 2020, with growth rates of 262.4% and 113.4%, respectively. In contrast, oil's share in global energy generation declined by 49.5% over the same period. The empirical analysis in this study relies on two sets of monthly data. The first dataset covers PCR and TCR from January 2000 to November 2019 and is obtained from established climate risk indices (Ashfaq). These indices are constructed using Latent Dirichlet Allocation, an unsupervised machine learning technique. Physical climate risk is measured using indicators related to global warming, extreme weather events, and natural disasters, while transitional climate risk is captured through textual analysis of U.S. climate policies and international climate summits (Li). Daily observations are aggregated into monthly series for consistency. The second dataset comprises monthly GEPU data spanning from January 1997 to September 2023. Detailed descriptions of all variables, including measurement units, frequency, and data sources, are provided 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 in 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 markets are interconnected. It also assesses the extent to which prices, supply, and demand in one market are influenced by those in related markets.

Additionally, price transmission theory examines the elasticity of price fluctuations across markets, providing insights into how changes in one market are transmitted to others. 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 (Zhou & renewable energy consumption. Renewable Energy). Connectedness measures only pairwise association and is primarily wed to linear models.

To address this issue, DY proposed a unified approach and framework for empirically measuring and conceptually defining connectedness across diverse levels. This framework is based on the VAR model's variance decomposition, which is closely linked to modern network theory. Variance decomposition provides essential information for measuring the future uncertainty of a variable of interest stemming from a shock in another variable (Karim & energy metals. Finance Research).

The DY framework is built on the tradition of dynamic predictive modeling under misspecification and assesses the share of forecast-error variation across diverse locations due to shocks arising elsewhere (Syed & renewable energy in the). On the other hand, to understand the source of connectedness, we also utilize the BY model. A shock to economic activity has mixed effects on variables at different frequencies, with varying magnitudes (Hoque & Pollution Research).

So, BK's proposed framework can measure the level of connectedness in the long-, medium-, and short-term frequency responses to shocks (Mokni & economic uncertainty. Journal of Environmental). The 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 analyzes the forecast-error variance from a generalized vector autoregression model, focusing on the system's interconnectedness. The connectedness metrics range from basic to comprehensive, system-wide analyses, emphasizing variance decomposition of "non-own" or "cross" contributions (Ogede & energy poverty. Energy). We started our spillover analysis considering the following VAR model with order p.

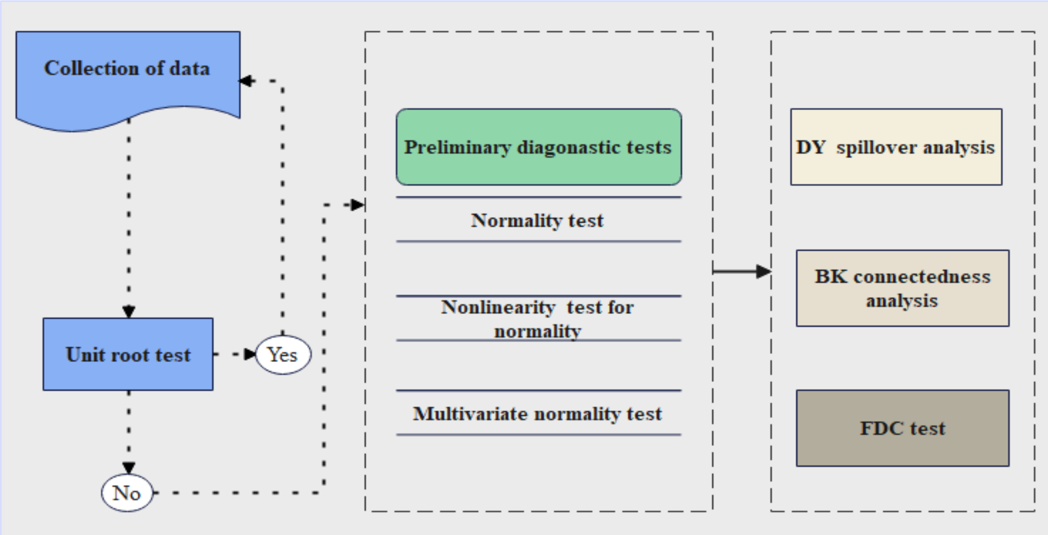

Figure 1: Empirical scheme

$$x_t = \beta + B_1 x_{t-1} + B_2 x_{t-2} \dots \dots \dots \dots \dots B_p x_{t-p}\, \mu_t \qquad (1)$$

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 the 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 the VAR model's energy prices by decomposing their variances. 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 Squared Error (MSE). The H-step ahead forecast is obtained using Equation 4:

$$MSE|y_{i,t}(H)| = \sum_{j=0}^{H-1} \sum_{k=1}^{k} (\acute{e}_i \Theta_j e_k)^2 \qquad (4)$$

Where e_i presents the ith column of I_K, and $\Theta j = \phi j P$, with P being the lower triangular matrix. The value of P is calculated following, 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

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

BK introduced an innovative approach to assessing connectedness, based on diverse frequency responses to shocks within a system. This approach is grounded in the spectral analysis of variance decompositions. By 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, by itself, imply the connectedness conventionally understood in the field. Our objective is to identify the frequency of spillover peaks, 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 on the impulse response function, offering 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 following 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 the 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, since the denominator includes the spectral density of the jth variable at the frequency ω. To disentangle variance contributions across the frequency spectrum, the measure can be weighted by the relative variance of the jth variable at each 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 magnitudes of these weighted complex numbers, yielding a real-valued metric. The ensuing theorem articulates the spectral decomposition of the variance contribution from the j-th to the k-th variable, which serves as the cornerstone of our connectedness metrics in the frequency domain. It is crucial to understand how the variance decomposition and the frequency-domain volatilities from j to k interact 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:

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

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

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

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 empirical procedure adopted in this study, which follows the methodological framework proposed in earlier work (Sarker et al.). Prior to conducting the spillover analysis, stationarity tests are performed using the Augmented Dickey–Fuller (ADF), Kwiatkowski–Phillips–Schmidt–Shin (KPSS), and Phillips–Perron (PP) tests to avoid inconsistent and biased estimates in the Diebold–Yılmaz (DY) and Baruník–Křehlík (BK) models. The results of the unit root tests are reported in the supplementary material.

3.2.3 Frequency domain causality test

To assess the robustness of the empirical outcomes from DY and BK spillovers, this study also uses the frequency-domain causality test (FDC) proposed by Croux and Reusens (Ahmad et al.), following the outline outlined by (Ivanovski et al.). Before investigating FDC, we applied the Hodrick-Prescott filter to all the series, using the canonical value of λ = 1600 to remove the trend and isolate the cyclical components.

The results for the PCR, TCR, and GEPU models are reported in the supplementary materials. The lag selection procedure identifies one lag for the PCR and TCR models and three lags for the GEPU model. The Bayesian Information Criterion (BIC) is used for lag selection, as it provides a more accurate estimate of the true lag length than the Akaike Information Criterion (AIC), which tends to overestimate the number of lags (Faccini & Finance). The vector autoregressive (VAR) estimation results using the selected lag lengths are presented in Table C.2 for all three models. Finally, the frequency-domain causality (FDC) test proposed by Croux and Reusens, which builds on the approach of Breitung and Candelon, is applied to assess the robustness of the empirical findings from the DY and BK frameworks (Farnè).

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 monthly energy price change is reported for NG (0.007), followed by USLD (0.377) and 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 greater monthly volatility (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 values for all energy prices exceed 2, indicating a degree of peakedness in the data. On another note, COAL reports a minimum value of -160.330 in the GEPU model, whereas BRENT reports the highest minimum value of -26.792. All kurtosis values in the GEPU model exceed 3, 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**

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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				
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 price fluctuations of their respective commodities.

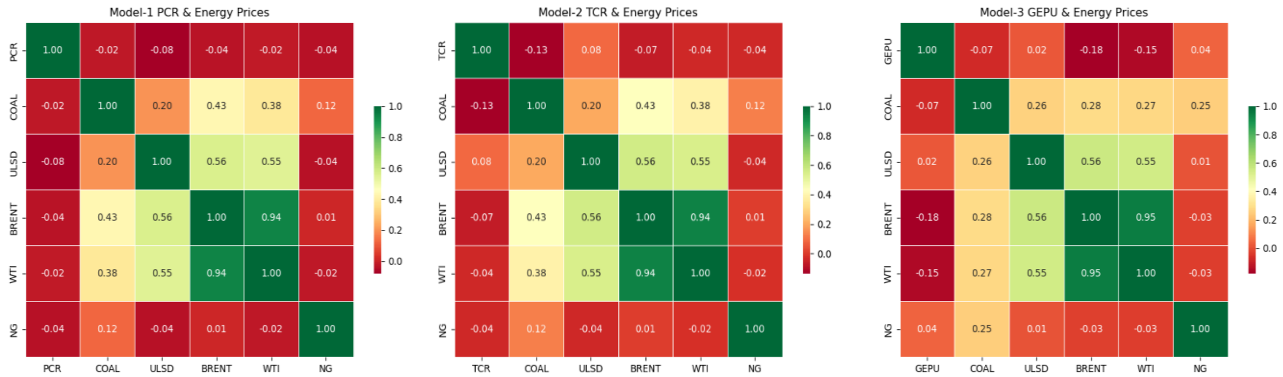

Figure 2: Cluster Heatmaps of Models 1, 2, and 3

Figure 2 presents the pairwise correlation heatmap for monthly PCR, TCR, and GEPU models. The heatmap shows that PCR and TCR are negatively correlated with all energy prices. Notably, West Texas Intermediate (WTI) shows a stronger correlation with PCR and TCR than other monthly energy prices. 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 of 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, as indicated by asterisks denoting a 1% significance level (***). Based on the test results, we accept the alternative hypothesis that the distributions of PCR, TCR, COAL, ULSD, BRENT, and WTI are not normal, indicating that these time series do not follow normal distributions. 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 relationship with energy prices show statistically significant departures from normality in several tests, notably 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 normality for the PCR, TCR, and GEPU models regarding 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 need to employ models that capture these complexities.

Section B of Table 3 presents the outcomes of nonnormality tests; most variables in the PCR, TCR, and GEPU models exhibit statistically significant deviations from normality, particularly in the Teräsvirta, 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, indicating strong rejection of the null hypothesis of a 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 account for non-normal distributions and potential asymmetries in 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	β̂	Kappa	P Values	β̂	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: ***, **, and * indicate level significance at the 0.01, 0.05, and 0.1.
Section A: Normality Tests: (Model-1 & 2) PCR, TCR and Energy Prices

4.2 DY spillover results

The results of the Diebold and Yılmaz spillover analysis, based on a vector autoregression (VAR) model with a maximum lag length of two and a constant term, are presented in Table 4 (Guo). This analysis summarizes the estimated models that incorporate physical climate risk (PCR), transitional climate risk (TCR), and global economic policy uncertainty (GEPU). It evaluates their monthly spillover effects on five major energy market indicators: natural gas (NG), coal (COAL), West Texas Intermediate crude oil (WTI), Brent crude oil (BRENT), and ultra-low sulfur diesel (ULSD).

The row-wise values represent the extent to which shocks from other variables contribute to the forecast error variance of a given energy price, whereas the column-wise values capture the contribution of a specific variable to the forecast error variance of other variables. The results indicate that PCR contributes a modest yet non-negligible share of volatility to other energy commodities, accounting for 0.29% of COAL, 2.55% of ULSD, 1.53% of BRENT, 0.56% of WTI, and 0.44% of NG. Although these effects are relatively small compared to dominant market forces, they highlight the role of physical climate risk in shaping energy market dynamics.

Notably, PCR's influence on NG (0.44%) is particularly relevant, reflecting the sensitivity of natural gas demand to climate-related factors, such as temperature fluctuations that affect heating and cooling needs. Furthermore, the spillover from COAL to NG (0.84%) suggests interaction between conventional energy sources, potentially driven by substitution effects and shifts in energy consumption patterns in response to climate policies and market conditions.

In Model 2, the TCR spillover matrix reveals substantial self-connectedness, as indicated by the diagonal elements (e.g., 95.57 for TCR and 65.66 for COAL), which represent each variable's own contribution to its forecast error variance. The off-diagonal elements capture cross-variable spillover effects. The results show stronger spillover coherence between TCR and COAL (3.02%) than between TCR and ULSD (2.44%), indicating that transitional climate risks are more closely linked to coal market dynamics.

Across Models 1 and 2, the highest spillover contributions from PCR and TCR are observed for BRENT (0.74%) and NG (1.53%), respectively. Conversely, spillovers from the energy market to climate risks are strongest from BRENT to PCR (1.53%) and from ULSD to TCR (2.44%), underscoring the bidirectional nature of risk transmission between climate variables and energy prices.

In the GEPU-based model, NG exhibits the highest degree of self-connectedness, whereas BRENT shows the lowest within-market self-dependence. GEPU contributes equally to COAL and BRENT, with spillover effects of 2.07% for each, representing the strongest pairwise connectedness from GEPU to the energy market. This finding underscores the importance of COAL and BRENT in the global energy system, as both are highly sensitive to economic policy changes and global market sentiment, given their central roles in industrial activity and power generation.

Finally, the row-wise sum of pairwise connectedness is highest for BRENT, followed by WTI, indicating that these markets receive the greatest volatility from other sources. The total directional spillovers received from other variables range from 2.16% to 9.96% in the FROM column. In contrast, directional spillovers transmitted

from the energy market to GEPU are strongest for BRENT, followed by COAL, highlighting the feedback effects between energy prices and economic policy uncertainty.
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 indicates the degree of the variable's connection to 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 the highest, reaching 17.89% and 28.43% over one month.

In the climate risk framework, the PCR model shows relatively higher connectedness than the TCR model in one month. From 1-3 months to 6 months and beyond, the overall connectedness of the GEPU model remains relatively higher than that of other models, with magnitudes of 31.91%, 48.65%, and 53.87%. The transitional climate risk model shows higher overall connectedness than the physical climate risk model. Additionally, the increasing overall cone cuteness in both the PCR and TCR models aligns with the empirical result reported in (Croux).

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.

4.3 Barun´ık and Kˇrehl´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 (Breitung & long-run causality. Journal of Econometrics). The spillover effects between physical climate risk and the energy market are detailed for the following time horizons: 1 Month, 1-3 Months, 3-6 Months, and 6 Months and beyond. At the 1-month horizon, the spillover impact of PCR on the energy market is negligible, indicating that PCR contributes insignificantly to the price fluctuations of the energy commodities under examination (Wen & energy price risk. Energy).

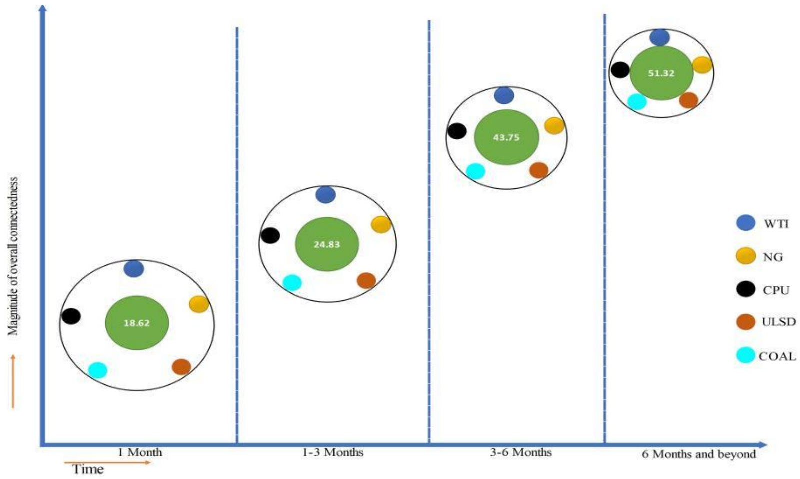

Figure 3: Physical climate risk and energy prices: Overall connectedness

Compared to the 1-month horizon, the spillover effects of PCR on the energy market increase over the 1-3-month period. BRENT has the greatest impact, followed by ULSD, with contributions of 0.24% and 0.23%, respectively, during this timeframe (Zhang & oil volatility. International Journal of Forecasting). Over the 1-3-month period, the spillover from the energy market to PCR is more pronounced than in the 1-month period, 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 its impact on other energy prices decreases significantly compared to the 1–3-month period. Beyond the six-month horizon, the spillover impact of PCR on NG remains 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 exhibit a varied pattern across different periods (Perera). 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%.

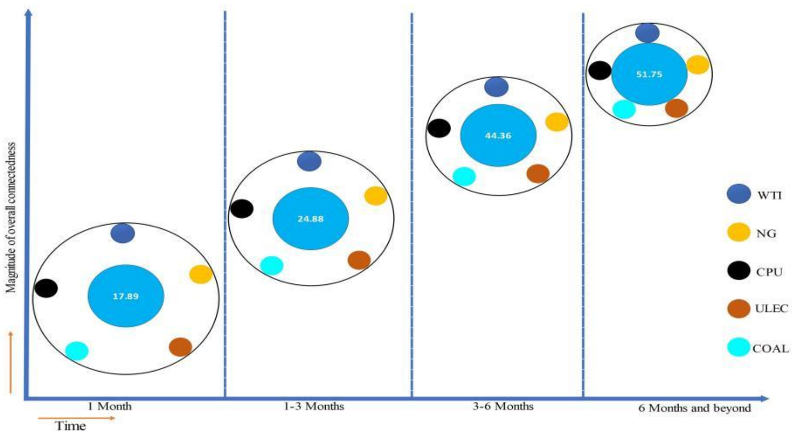

Figure 4: Overall connectedness of transitional climate risk and energy prices

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 decreases significantly in the 3-6 month period relative to the 1-3 month period, with coal experiencing the highest spillover. 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-month and beyond time frame.

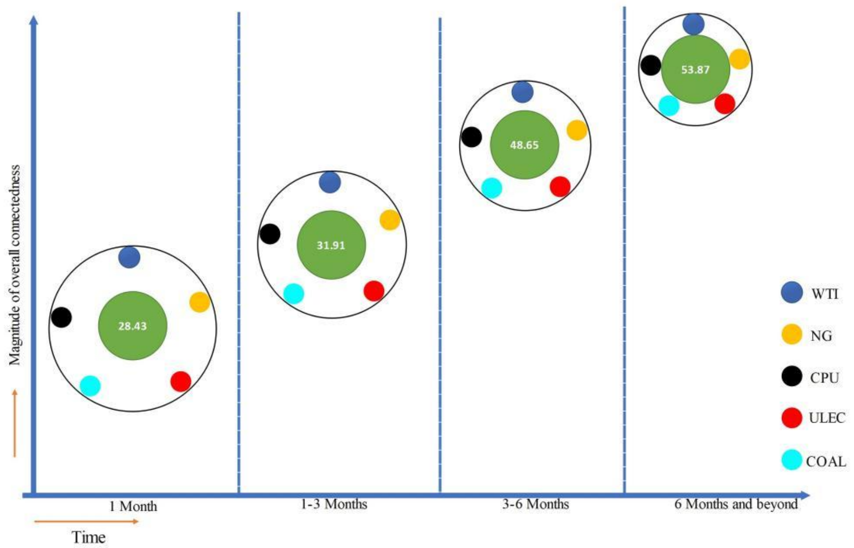

Figure 5: Global economic policy uncertainty and energy prices overall connectedness

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

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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								
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 Months								
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 Months & 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 the PCR (Physical Climate Risk), TCR (transitional climate risk), and GEPU (Global Economic Policy Uncertainty) models, COAL, ULSD, BRENT, WTI, and NG represent 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 find that within the frequency bands 3.14 and 3.14-1.05, 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 noted by Salisu et al. (2023), climate change can heighten global crude oil market uncertainties. In the 3.14 to 1.05 frequency band, ULSD remains 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), who found that TCR offers better predictive accuracy for energy market volatility in out-of-sample forecasts than PCR.

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.

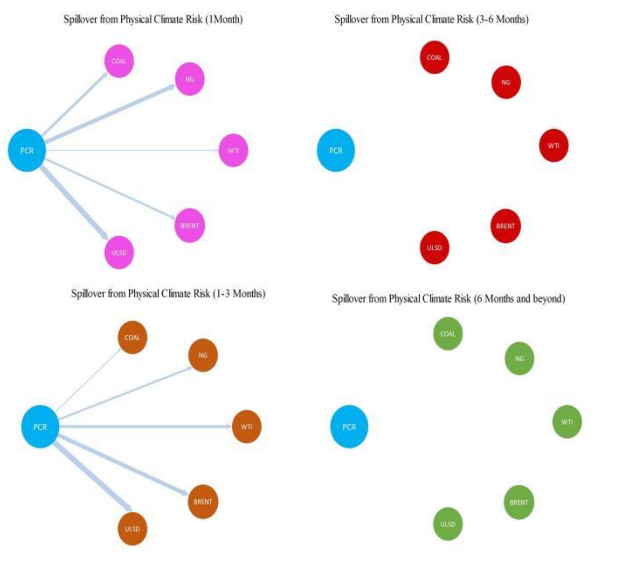

Figure 6: Spillover from PCR to energy market

Figure 7: Spillover from TCR to energy market

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, unlike 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

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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
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 in which TCR's spillover exceeds 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 on 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 show the outcomes of the FDC test for 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 less. 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.

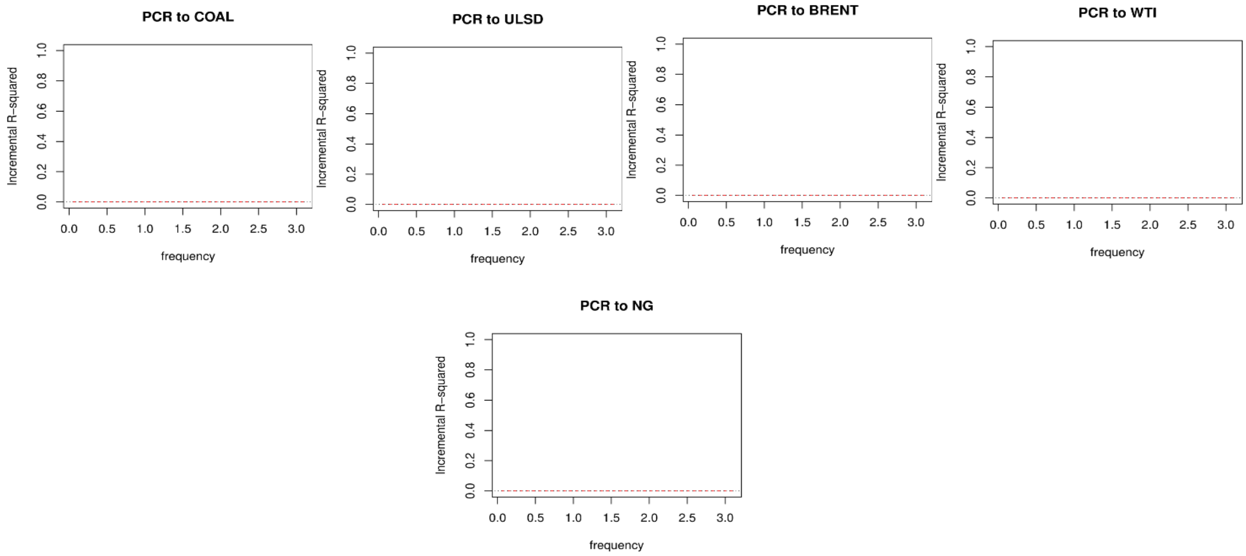

Figure 9: Frequency domain causality from PCR to energy prices

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 (Sarker et al.). However, at the lowest frequency, we failed to accept the null hypothesis of Granger causality from TCR to energy prices.

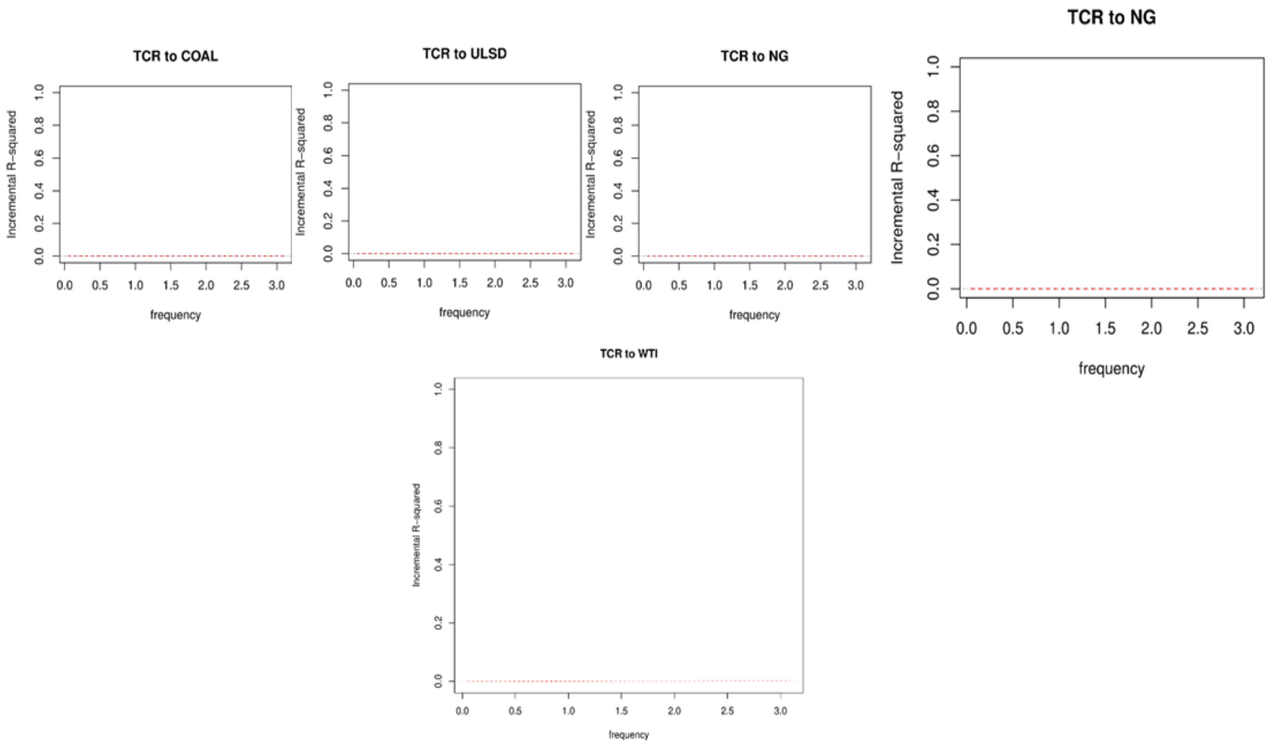

Figure 10: Frequency domain causality from TCR to energy prices

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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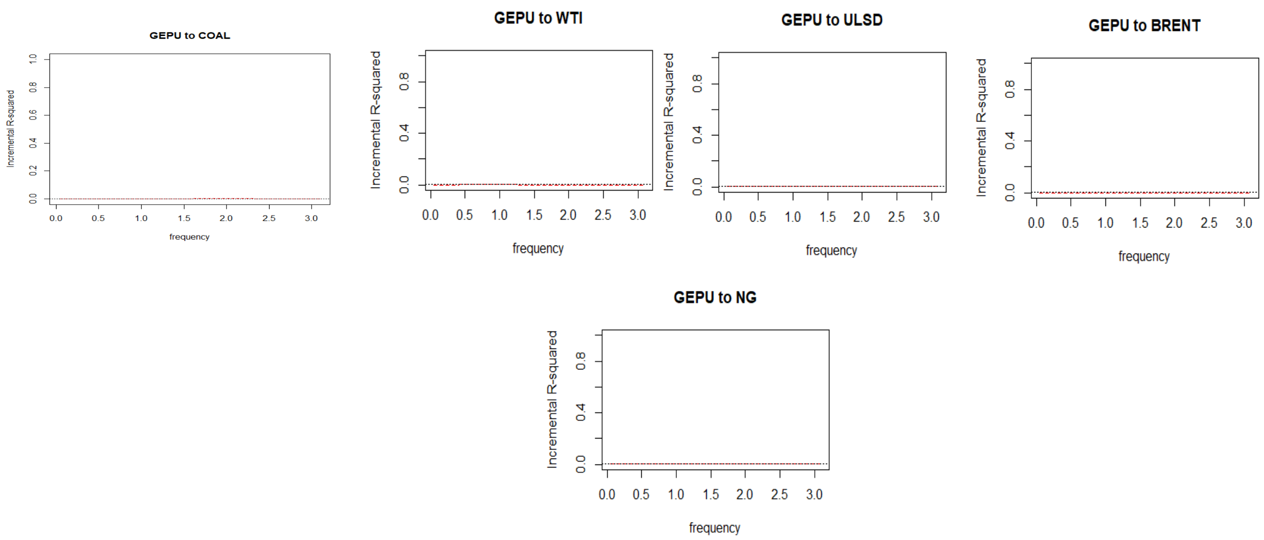

Figure 11: Frequency domain causality from GEPU to energy prices

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 using 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 on both physical and transitional climate risks, as well as for 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, to enable 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.

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