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Asymmetric spillover and network connectedness of policy uncertainty, fossil fuel energy, and global ESG investment

Ling Lin [a,b], Yong Jiang [c], Zhongbao Zhou [d,*]

[a] School of Economics, Hunan Agricultural University, Changsha 410128, China
[b] School of Social Science, Nanyang Technological University, 639798, Singapore
[c] School of Finance, Nanjing Audit University, Nanjing 211815, China
[d] School of Business Administration, Hunan University, Changsha 410082, China

HIGHLIGHTS

- Energy risks cause direct spillover to the global ESG investment when the economy runs smoothly.
- Different forms of spillovers from the EPU to the global ESG investment during downtowns.
- Asymmetric spillovers from the natural gas market and the US EPU occur in irregular events.
- China's EPU and US MPU cause asymmetric spillovers in different ways under extreme events.
- The crude oil market can directly transmit a common risk to global ESG investment.

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ABSTRACT

This study investigates the asymmetric spillover network connectedness of policy uncertainty, the fossil fuel energy market, and global ESG investment by using a time-frequency domain analysis. The study employs a time-varying filter for the empirical mode decomposition method and Pearson correlation coefficient to distinguish signals' dynamic frequency and amplitude. We combine a two-state fractionally integrated asymmetric power autoregressive conditional heteroskedasticity with asymmetric time-varying parameter vector autoregression and vector autoregression-common factor variance decomposition. The Vector Auto Regression-common factor model is also considered. The results demonstrate that when the economy runs smoothly, risks originating from the natural gas market have indirect spillover effects on emerging economies' ESG investment. When normal economic fluctuations occur, risks arising from fossil fuel energy markets and US climate policy uncertainty exert separate direct and indirect spillovers to the global ESG investment. Second, when the economy declines, different types of spillovers occur from US economic policy uncertainty (EPU) to global ESG investment. During the recession, greater risks in the crude oil market and the uncertainty in China's economic policy caused separate indirect spillovers to advanced economies' ESG investment. Third, with the continuous occurrence of irregular events, asymmetric spillovers can originate from the natural gas market and US EPU. When extreme events occur, positive risks from China's economic policy can be indirectly transmitted to emerging economies' ESG investment, while negative risks from the US monetary policy can be directly transferred to global ESG investment. Finally, the crude oil market can directly transmit an idiosyncratic risk to global ESG investment.

1. Introduction

The global financial crisis (GFC) in 2008 and the European debt crisis in 2010 caused turmoil in the world economy, along with the existing international economic order and the globalization process [1,2]. As the integration of financial markets rapidly progressed, regulators and supranational agencies became increasingly worried about systemic risk [3]. Governments worldwide introduced a series of policies to stimulate the economy, and developed economies adopted quantitative easing monetary policies and a weak exchange rate policy. Emerging

* Corresponding author.
E-mail address: zzbhndxggy@163.com (Z. Zhou).

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economies did the opposite, smoothing interest rates afterward [4,5]. In the postcrisis era, black swan events hit in succession, and the overall world economy remains vulnerable to even more predictable disruptions [6–8], and the system itself continued to be fragile and vulnerable to large macroeconomic shocks [9]. The World Bank downgraded its global economic growth forecasts for 2024, reflecting heightened uncertainties concerning advanced economies. To reduce inflation pressure, a sustained Fed rate rise in the US has been affecting global interest rates and the direction of international capital flow, which affected banks' policies resulting in a severe credit and liquidity crisis in financial markets. This type of risk, wherein the entire financial system, including multiple markets and institutions, is simultaneously distressed, has generally been described as systemic risk [10]. The development of emerging economies is considerably affected by all kinds of domestic and foreign policies. To mitigate the risks to the global economy, governments should consider flexible policymaking and undertake extraordinary actions to support macroeconomic functioning [11–13].

Furthermore, environmental challenges also disrupt the global economy. In the context of climate change, the world has entered a low-carbon age [14–17]. The 27th United Nations Climate Change Conference deepened worldwide cooperation to reach net zero emissions, climate adaptation, investment, and financing. The climate red line brought new propositions for green development is the primary goal of economic transformation, which is an irreversible trend in the world. Keeping global temperature rise well below 2 °C requires a reduction of greenhouse gas emissions. The urgent need to develop low-pollution, low-emissions energy has placed enormous pressure on fossil fuel-based economic development and energy consumption structures [18–21]. Changing climate policies will have significant impacts on economic agents' practices and the environmental system. Nevertheless, global temperatures are likely to rise by 3 °C by 2100, according to the draft of the fourth report by the Intergovernmental Panel on Climate Change of the United Nations [22], which will inevitably impose a far-reaching influence on global green development. Advancing climate change mitigation and adaptation requires a shift of capital allocation from traditional polluting approaches to green infrastructures and technologies. Accelerated low-carbon economic transformation has triggered an emerging global energy crisis, increasing the uncertainty of green development and the complexity of selecting the timing and pace of policy transformation [23,24]. Emerging economies are facing the dual challenges of maintaining stable growth and transforming green investment. Limitations in the known reserves of fossil fuel energy challenge the energy required by rapid economic development. However, emissions have been falling gradually in recent years in most advanced economies, in part because of the global economy's weakness but also because of strengthened climate policies. Advanced economies should provide economic and technological support to emerging economies for energy upgrading and transformation [25–27] as a lack of climate policy coordination could pose a huge potential threat to sustained global economic development.

Stock markets are the barometers of national economies. As a relatively new form of green investment, the ESG stock index (referencing enterprises' efforts in environmental, social, and corporate governance) has become the most popular investment mode in the world. >60 countries and regions have introduced ESG information disclosure requirements. The practice of the ESG investment concept aligns with the requirements of the modern era of global social, environmental, and economic development, presenting a system for implementing and tracking green and sustainable development concepts. This approach helps to improve financial market and enterprise efficiency, guiding capital from the micro market, and promoting improved economic structure and development patterns [28,29]. Some researchers have quantified the policy risks associated with green investment and fossil fuel energy markets for the last few years, using green bonds and clean energy stocks as indicators. Studies have determined that uncertainty is a key risk factor affecting policy implementation effectiveness, which involves economic, monetary, and climate uncertainty. Such uncertainties cannot be eliminated when the global economy is mired in a financial crisis. However, effective, and accurate quantitative characterization of uncertainty can significantly improve strategic policy implementation to reduce the impact of policy uncertainty on steady and sustainable global economic development and contribute to green investment [30–36]. Therefore, it is crucial to determine how policy uncertainty (economic, monetary, and climate) and fossil fuel energy (crude oil and natural gas) generate varying degrees of risk spillover with global ESG investment.

2. Literature review

Policy uncertainty can cause microeconomic entities to reduce investment and indirectly affect the financial system and the economic cycle stability through investment and financing channels, causing fluctuations in energy markets and global green investment.

Previous research has demonstrated that varying degrees of risk spillovers are caused by policy uncertainty and fossil fuel energy markets. Ji et al. [37] applied four types of delta conditional value-at-risk (ΔCoVaR) using six time-varying copulas to consider negative risk spillovers between energy returns (crude oil and natural gas) and changes in economic policy uncertainty (EPU). Chen et al. [38] examined spillover effects from a multiscale perspective using a wavelet-based BEKK-GARCH, determining that the spillover effects between the Brent crude oil market and EPU in Brazil, Russia, India, and China (BRIC countries) are time-varying across different wavelet scales in terms of direction and strength. Mokni et al. [39] employed time-varying parameter vector autoregression combined with measures of spillover variance decomposition (Diebold and Yílmaz [40]). The results revealed significant effects of the EPU on the connectedness of the oil market in static and regime-switching frameworks. Apostolakis et al. [41] examined the risk spillovers of EPU and the nonfinancial Brent oil market and its prices. The dynamic analysis indicates that spillovers increased substantially during the COVID-19 pandemic, but did not exceed the level during the 2009 GFC. He et al. [42] applied the TVP-FAVAR model, finding severe volatility spillover between the EPU and the energy market (oil importing and exporting) was stronger during crisis periods, such as the debt crisis, energy contention, and oil price turbulence. Huang et al. [43] used a spillover directional measure to investigate the cross-category spillovers between crude oil markets and EPU. The results revealed the spillover effects based on the time-domain framework showed a strong connectedness between EPU and crude oil markets. Ren et al. [44] proposed a rolling tail-event-driven network technique, determining that the effect of EPU on the risk spillover of the crude oil futures is asymmetric and heterogeneous. Dai and Zhu [45] applied a combination of quantile VAR and TVP-VAR models based on generalized forecast error variance decomposition. The results suggest that the risk spillover of proxies under 0.01-quantile and 0.99-quantile are much larger than those under mean and median (0.5-quantile). [46–48]) employed quantile connectedness to examine the dynamic spillover between climate policy uncertainty (CPU) and crude oil market uncertainty. The results demonstrated higher spillovers at extreme quantiles.

Ongoing environmental deterioration and the depletion of conventional resources promote the development of new energy is promoted. In recent years, the development of green financial systems has accelerated, and green low-carbon industries have flourished, providing strong motivation for the development of green investment.

Some studies have explored the spillover effects between policy uncertainty and green investment. Lundgren et al. [49] apply nonlinear causality and connectedness to examine the spillovers between EPU and green investment (clean energy and renewable energy–stock indices). The authors determine that most EPU concerns were net transmitters of volatility connectedness during the GFC and European sovereign debt crisis. Yang et al. [50] measured four types of (normalized) ΔCoVaR incorporating variational mode decomposition and time-varying copula approaches. The results revealed that significant risk spillovers from geopolitical risk (GPR) to the renewable energy–-stock markets and the risk spillovers do not exhibit a clear positive or negative pattern. Long et al. [30] investigated the quantile connectedness between EPU and green bonds in the US, Europe, and China using a quantile VAR model-based connectedness approach, finding that spillover effects under extreme market conditions were significantly higher than those under normal market conditions. Cepni et al. [51] examined the spillover effects of climate uncertainty across the conventional European ESG financial markets. The results demonstrated that ESG bonds are particularly useful for managing transition risk exposure concerning environmental policies. Lorente et al. [52] used quantile vector autoregression and wavelet coherence, finding that green bonds are negatively connected to GPR at extreme 10th and 90th quantiles. Ren et al. [35] used dynamic bidirectional causality between CPU and traditional energy, represented by oil and natural gas and green bonds, determining that CPU is more inclined to act as a risk recipient than a sender of market volatility spillover. Xia et al. [53] applied asymmetric time-varying connectedness and EGARCH models, demonstrating asymmetric connectedness between green bonds and EPU. Uddin et al. [54] constructed a high-dimensional network between firms using generalized error decomposition and a sparse vector autoregression framework with a latent common factor. The results showed that the renewable energy subsector has the highest uncertainty transmission compared with other underlying subsectors. Lucey et al. [55] used a time-varying copula approach to compare the interconnectedness and risk profiles of green assets with others. The findings revealed that green assets' relationships with conventional commodities and markets can shift significantly during extreme uncertainty.

As described above, some studies have focused on the risk spillovers between policy uncertainty, energy markets, and green investment. However, limited research has included the critical issue of risk spillover between policy uncertainty (monetary or climate), fossil fuel energy (crude oil and natural gas), and global (emerging and advanced economies) ESG investment. Moreover, suffering from multiple black swan events worldwide, the volatility of policy uncertainty, fossil fuel energy, and green investment undergoes periodic transitions, long-term memory, and asymmetrical features, including the dual characteristics of time and frequency domains [35,56,57]. Hence, wavelet multiscale and the time-domain framework have been applied widely. Although these methods can distinguish volatilities of sample size between long and short-term observations from a multiscale perspective, minimal research has quantified periodic volatilities using time-frequency domain analysis, as such risk spillovers based on time-frequency domains are challenging to capture. Furthermore, TVP-VAR and quantile regression serial model combined with variance decomposition have been broadly applied to capture dynamic and asymmetrical risk spillovers. While such models are effective for capturing time-varying asymmetry characteristics during the mean process, they are inefficient for tracking time-varying periodical, long-term memory, and asymmetrical volatility in the process of variance. Therefore, these models can be inaccurate in determining the periodic and asymmetrical volatility risk spillovers for accurate time-frequency analysis. In addition, certain factors in macroeconomic and financial markets can lead to policy uncertainty, as well as common substantial fluctuations in fossil energy markets and global ESG investments. However, few literatures consider the common factor of high-volatility state spillovers between them in the time-frequency analysis.

This study makes several contributions in this regard. First, we provide novel empirical evidence concerning the spillover network between policy uncertainty, fossil fuel energy, and global ESG investment. Although some researchers have recently focused on the impacts of different policy uncertainties and fossil fuel energy on ESG performance, ESG scores have primarily been represented by individual companies' stocks based on various country's ESG considerations [51,58–64]. Limited evidence has been provided analyzing the risk spillover between various policy uncertainties and global ESG investment in emerging and advanced economies. Our results from investigating this issue can provide countries around the world with valuable insights to strategically establish new economic development models, invest in addressing climate change, promote green economic growth and employment, restore the natural ecosystems that support the global economy, and advance economic transformation to achieve sustainable development.

Second, this study accurately identifies time-varying irregular and extreme volatilities by introducing a combined time-series wavelet decomposition (TVF-EMD) model and Pearson correlation coefficient (PCC) algorithm. In recent years, the global economy and financial markets have been frequently impacted by uncertain events (such as regional wars, financial crises, debt crises, global economic slowdowns, meteorological factors, natural disasters, and other economic shocks), with a higher probability of outliers appearing in data than that of normal distributions. The clustering nature of economic fluctuations generates numerous outliers that deviate from the mean and appear in clusters. In other words, some uncertain events can cause short-term, nonsystemic risk spillovers, whereas others can cause significant long-term systemic risk spillovers. Therefore, it is particularly crucial to conduct in-depth research on the risk spillovers of abnormal (irregular and extreme) fluctuations in economic and financial markets using wavelet analysis as a research method.

Third, this study contributes to advancing research approaches by establishing a long memory and asymmetric GARCH model combined with Markov switching vector autoregression and asymmetric TVP-VAR variance decomposition. In addition, this study uses a high-dimensional network using generalized error decomposition and a sparse vector autoregression framework with a latent common factor [54,65]. When policy uncertainty increases, it will generate some risk spillovers on global macro factors such as countries' market rates, resident consumption, enterprise production, and cross-border capital flow, which can subsequently impose different risks and affect enterprises' decision-making and practices concerning green investment. Furthermore, with the occurrence of global economic and financial crises, extreme weather, and other natural disasters, energy supply and demand can become seriously unbalanced, which raises green energy prices increasing production costs. This slows down the pace of enterprises' green innovation and energy transformation, which exacerbates the complexity of policy uncertainties. Our network analysis enables us to determine the interconnectedness of systemic and nonsystemic risk from policy uncertainty, fossil fuel energy, and global ESG investment.

This study yields some notable results. First, core risks from the natural gas market can directly or indirectly promote global ESG investment, regardless of how great the short-term economic changes are. Second, when the economy slows, risks from US EPU can individually intensify the uncertainty in China's economic policy. Therefore, US monetary policy can deeply influence advanced economies' ESG investment. Furthermore, US EPU can have direct spillover effects on emerging economies' ESG investment. Moreover, during the economic recession, the risk of significant turbulence from China's economic policy can be conveyed to the US's CPU, which can considerably influence advanced economies' ESG investment. Third, when irregular events occur, positive risks can be shaped by US EPU, and negative risks can arise in the natural gas market. Finally, when extreme events emerge, the significantly positive risk from China's EPU can simultaneously exacerbate US EPU, with a strong influence on emerging economies' ESG investment. However, negative spillover from US monetary policy uncertainty (MPU) can directly transmit to global ESG investment.

The remainder of this paper is organized as follows. Section 3 introduces the methodology of the study. Section 4 details the data description. Section 5 presents the empirical results. Section 6 imparts concluding remarks and policy implications.

3. Methodology

3.1. Time-varying filter-based empirical mode decomposition

Recently, the world has entered an era in which systemic risk is high and unpredictable. The global economy remains full of uncertainty, which enhances the volatilities in the macroeconomy and financial markets. EMD (empirical mode decomposition) is proposed to deal with the nonlinear and nonstationary indicators. This means the method can continuously separate unstable signals from the original sequence, and it can also identify spatial inconsistencies and structural transformation intervals from the original sequence.

Huang et al. [66] proposed the EMD, the purpose of this algorithm is to decompose the poorly performing signals into a set of well-performing IMFs (intrinsic mode functions). The IMF must meet two properties: Firstly, the number of extreme points (maximum or minimum) of the signal is equal to or significantly different from the number of zero crossing points. Secondly, the average value of the upper envelope composed of local maxima and the lower envelope composed of local minima is zero. The steps of the EMD algorithm are as follows: First, calculate all the maximum and minimum points of the original data series, fit them into the upper and lower envelopes of the series with cubic spline functions, and obtain the average value of the upper and lower envelopes M_t. The original data series obtained a new sequence H_t.Since not a stationary time series, the above process needs to be repeated to obtain the first intrinsic mode function component C_1, which represents the highest time-frequency component of the data. Then, the original data sequences are subtracted to get a new data sequence R_t. Repeat the above operation to obtain the second intrinsic mode function component C_2. Afterward, repeat the above operation until the last data sequence cannot be decomposed. At this moment, R_n represents the trend of the original data series X_t. However, the EMD method has some shortcomings. For instance, due to the non-uniform distribution of signal extreme points, mode mixing may occur in IMFs. To address this issue, Wu and Huang [67] proposed the EEMD (Ensemble Empirical Mode Decomposition) method. The basic principle is to add a set of white noise to the original signal, decompose the signal with white noise by using EMD, and then repeat the above steps. However, the EEMD method still has some shortcomings. For example, as the number of white noise increases, the speed of the EEMD algorithm will inevitably decrease. If white noise is added multiple times, the reconstruction error will increase.

The calculation and use of the local mean function in traditional EMD methods can be seen as a low-pass filtering process. In the TVF-EMD method, B-spline filters are used as low-pass filters to filter out low-frequency components and achieve the same effect as local mean functions. Compared to traditional linear filters, B-spline filters are relatively easy to construct cutoff frequencies and can adaptively change over time, giving them better capabilities for nonlinear and non-stationary signals (Chaitanya et al. [68], Song et al. [69] , Guermoui et al. [70] , Jamie et al. [71] , Song et al. [72] , [46–48]). Furthermore, compared with conventional fixed learning rate algorithms, adaptive optimization algorithms have the following advantages: firstly, they can dynamically adjust the learning rate based on the characteristics of parameters, improving the convergence speed and performance of model training. The second is the ability to cope with gradient changes of different parameters, improving the robustness and generalization ability of the model (Ye et al. [73] , Ranjan et al. [74] , Zhou et al. [75] , Yu et al. [76]). However, adaptive optimization algorithms also face challenges such as hyperparameter selection and overfitting, requiring reasonable parameter tuning and optimization in practical applications.

Based on this point, we select the TVF-EMD model proposed by Li et al. [77]. The main idea of this method is centered on the localized cutoff frequency and then proceeds with a time-varying filtering procedure. Compared with EMD and EEMD, TVF-EMD not only solves the problems of modal separation and signal intermittency but also solves the problem of modal aliasing and preserves the time-varying characteristics of the signal. The detailed steps of this method can be listed as follows.

(a) Calculate local cutoff frequency

First, calculate the instantaneous amplitude and instantaneous phase and frequency from the original signal. Then, based on the local maximum and local minimum, the interpolation operation can be obtained. Simultaneously, by utilizing the local maximum and minimum values of instantaneous amplitude $A(t)$, the instantaneous mean and instantaneous envelope are obtained through interpolation operations. Finally, calculate the local cutoff frequency $\varphi_{bis}^{'}(t)$.

$$\varphi_1^{'}(t) = \frac{\eta_1(t)}{2a_1^2(t) - 2a_1(t)a_2(t)} + \frac{\eta_2(t)}{2a_1^2(t) + 2a_1(t)a_2(t)} \tag{1}$$

$$\varphi_2^{'}(t) = \frac{\eta_1(t)}{2a_2^2(t) - 2a_1(t)a_2(t)} + \frac{\eta_2(t)}{2a_2^2(t) + 2a_1(t)a_2(t)} \tag{2}$$

$$\varphi_{bis}^{'} = \frac{\varphi_1^{'}(t) + \acute{\varphi}_2(t)}{2} = \frac{\eta_2(t) - \eta_1(t)}{4a_1(t)a_2(t)} \tag{3}$$

(b) Signal reconstruction

Rearrange to solve intermittent problems and reconstruct the signal $h(t)$ based on the adjusted cutoff frequency.

$$h(t) = cos\left[\int \varphi_{bis}\acute{(t)}dt\right] \tag{4}$$

(c) Cut-off criteria

Take the extreme point as a node and use spline interpolation B for signal approximation $x(t)$. The approximation result and the calculation cut-off criteria are $\theta(t)$. If it is satisfied, and there is a given bandwidth threshold. Then is an IMF. If not, let $x_1(t) \ = x(t) - y(t)$, repeat the above steps.

$$\theta(t) = \frac{B_{Loughlin}(t)}{\varphi_{avg}(t)} \tag{5}$$

In the above equation, $B_{Loughlin}(t)$ is the Loughlin instantaneous bandwidth of the component signal. $\varphi_{avg}(t)$ is the weighted mean of instantaneous phase and frequency.

$$\varphi_{avg}(t) = \frac{a_1^2(t)\acute{\varphi}_1^2(t)}{a_1^2(t) + a_2^2(t)} \tag{6}$$

$$B_{Louglin}(t) = \sqrt{\frac{\acute{a}_1^2(t) + \acute{a}_2^2(t)}{a_1^2(t) + a_2^2(t)} + \frac{a_1^2(t)a_2^2(t)[\acute{\varphi}_1(t) - \acute{\varphi}_2(t)]^2}{[a_1^2(t) + a_2^2(t)]^2}} \tag{7}$$

3.2. Pearson correlation coefficient

The Pearson correlation coefficient is used to measure whether two datasets are on the same line, and it can measure the relationship between two random variables (real-valued vectors). Based on the TVF-EMD method, the variables of policy uncertainty, fossil energy, and global ESG investment can be divided into different IMF components. Then the Pearson correlation coefficient of IMF components for two of them can be expressed as the covariance of the two IMFs, which can be divided by the product of their standard deviations. It can be computed as follows:

$$r = \frac{N\sum c_i \acute{c}_i - \sum c_i \sum \acute{c}_i}{\sqrt{N\sum c_i^2 - \left(\sum c_i\right)^2} - \sqrt{N\sum \acute{c}_i^2 - \left(\sum \acute{c}_i\right)^2}} \tag{8}$$

Indicate the different IMFs and N indicates the number of IMFs. The coefficient ranges from -1 to 1, and it is invariant to linear transformations of either variable. If satisfied, it can only be said that there is no linear correlation between and y, and it cannot be said that there is no correlation. The absolute value of the correlation coefficient is larger, the correlation is stronger: the correlation coefficient is nearer to 1 or $-$ 1, the correlation is stronger, the correlation coefficient is nearer to 0, and the correlation is weaker. Based on the Pearson correlation coefficient, the IMF components can be reconstructed into high-frequency components, low-frequency components, and long-term trends.

3.3. Markov switching autoregression long memory and asymmetry GARCH

A matrix contains a time series that follows a vector autoregressive system with $\phi_{s(t)}$ as the matrix of parameters:

$$c_t = \phi_{s(t)} c_{t-1} + \varepsilon_t \tag{9}$$

Changes in the state of the vector c_t (indicate the high frequency or low frequency of the policy uncertainty, fossil energy, and global ESG investment) in the Markov chain with the time step is called evolution or transition, which means the low volatility and high volatility. Since the state space of the Markov chain is set to be limited, the transition probabilities of all states can be arranged in a matrix in a single-step evolution, and the following stochastic matrix can be obtained as follows:

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \tag{10}$$

Where the two-state transition probabilities are expressed as follows: This means that the probability of a switch from state 2 to state 1 between time t and $t+1$ will be given by p_{12}. $\phi_{s(t)}$ indicates the vector autoregressive coefficient of lagged variables under a state transition regime-switching process.

ε_t subjects to normal distribution that follows two-state regime switching behavior with covariance matrix:

$$\varepsilon_t \sim N\left(0, \sum s_t\right) \tag{11}$$

Then, the two-state conditional variance switching model is established as a long memory and asymmetry process:

$$\sigma_{t,s(t)}^{\delta_{s(t)}} = \omega_{s(t)} + \left\{1 - \left[1 - \beta_{s(t)}(L)\right]^{-1} \phi(L)(1-L)^{d_{s(t)}}\right\}\left(|\varepsilon_t| - \gamma_{s(t)}\varepsilon_t\right)^{\delta_{s(t)}} \tag{12}$$

where $\omega_{s(t)} > 0$ must be satisfied in eq. (12). The fractional integral parameter refers to the long memory process in the state $s(t)$. $\gamma_{s(t)}$represents asymmetry parameter in the state $s(t)$. $\sigma_{t,s(t)}^2$ is the state-dependent conditional variance (low volatility and high volatility) at a time for the variables. L is the lag operator.

3.4. High-dimensional VAR with a common factor

By reference to Uddin et al., [54], we consider a p-order vector autorepression (VAR) process with common factors (Miao et al., [65]).

$$c_t = \phi_t c_{t-1} + \Lambda^0 f_0 + \varepsilon_t \tag{13}$$

where c_t indicates the high frequency or low frequency of policy uncertainty, fossil energy, and global ESG investments under a high volatility state. Λ^0 is a factor-loading matrix and is a dimensional vector of common factors.

3.5. TVP-VAR-based asymmetric spillover network approach

To capture the asymmetric spillover and connectedness, we propose the MS-VAR-FIAPARCH and VAR-CF-FIAPARCH combined with the TVP-VAR-DY approach proposed by Antonakakis et al., [78]. Referring to Cheng et al., [79], we introduce the FIAPARCH model with the TVP-VAR-DY to obtain the asymmetric spillover effect and connectedness:

$$c_t = E(c_t|\Omega_{t-1}) + \varepsilon_t \tag{14}$$

$$\sigma_t^\delta = \omega + \left\{1 - [1-\beta(L)]^{-1}\phi(L)(1-L)^d\right\}(|\varepsilon_t| - \gamma\varepsilon_t)^\delta \tag{15}$$

where c_t indicates the policy uncertainty, fossil energy, and global ESG investment variables under time-frequency components. Ω_{t-1} is the information set at a time $t-1$. $E(.|.)$ denotes the conditional expectation operator, $\varepsilon_t$is the disturbance term (or unpredictable part) with $E(\varepsilon_t\varepsilon_s) = 0, \forall t \neq s$. The parameter setting in eq. (15) is like eq. (12). According to the eq. (14) and (15), the conditional volatility can be decomposed into positive volatility (good volatility) and negative volatility (bad volatility).

$$N_t = \begin{cases} 0, if\ V^- = \sigma_t^2 < 0 \\ 1, if\ V^+ = \sigma_t^2 \geq 0 \end{cases} \tag{16}$$

$$\acute{V}^+ = N_t \bullet \sigma_t^2 \tag{17}$$

$$\acute{V}^- = (1 - N_t) \bullet \sigma_t^2 \tag{18}$$

The TVP-VAR based on variance decomposition proposed by Diebold and Yilmaz [80] can be applied to examine the risk spillovers. It captures the time-varying parameters of this model by using the multivariate Kalman filter approach. Hence, the approach can not only solve the problem of selecting the rolling window size but also prevent the loss of valuable observations. Moreover, it can control the extreme values that exist in the parameter estimation process.

The simplified process of TVP-VAR is as follows:

$$V_t = \Phi_{0,t} + \Phi_{1,t}V_{t-1} + \Phi_{2,t}V_{t-2} + \cdots + \Phi_{p,t}V_{t-p} + \varepsilon_t \tag{19}$$

where V_t is the dimensional column vector of conditional volatilities (low volatility, high volatility, positive volatility, and negative volatility). It meets the moving average process:

$$V_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{20}$$

where A_i is the autoregressive coefficient matrix, ε_t is the stochastic disturbance variance. Then calculate the coefficient matrix of the corresponding TVP -VAR model by using a recursive relationship:

$$A_{h,t} = \widehat{\Phi}_{1,t}A_{h-1,t} + \widehat{\Phi}_{2,t}A_{h-2,t} + \cdots + \widehat{\Phi}_{p,t}A_{h-p,t} \tag{21}$$

According to eq. (20), we can calculate the corresponding coefficient matrices $A_{0,t}$, $A_{H-1,t}$ in the H-step forward prediction. The estimated value of the conditional covariance matrix of the disturbance terms $\sum_t = \widehat{C}_t^{t-1}\widehat{D}_t(\widehat{\acute{C}}_t^{t-1})$. The $N \times N$ dimensional generalized variance decomposition matrix can be from the generalized pulse function, the computational formula for the elements in the matrix is as follows:

$$\theta_{ij,t}(H) = \widehat{\sigma}_{jj,t}^{-1} \sum_{h=0}^{H-1} \left(\acute{e}_i \widehat{A}_{h,t} \sum\nolimits_t e_j\right)^2 \Big/ \sum_{h=0}^{H-1} \left(\acute{e}_i \widehat{A}_{h,t}\right) \sum \widehat{A}_{h,i} e_i \tag{22}$$

Among them, $\theta_{ij,t}(H)$ is the element in the row and column of the matrix Θ_t. It represents the proportion of the total predicted variance of the variable affected by the variable. $\widehat{\sigma}_{jj,t}$ is the diagonal element and it denotes the variance of the disturbance term. And it plays a role in selecting vectors. However, the generalized variance decomposition matrix calculated directly from the above equation often does not meet the requirement that the sum of row totals equals 1. Therefore, to align with the economic implications of traditional variance decomposition, we need to standardize the matrix and obtain the transformed generalized variance decomposition matrix $\widetilde{\Theta}_t$. The calculation formula for matrix elements is as follows:

$$\widetilde{\theta}_{ij,t}(H) = \theta_{ij,t}(H) \Big/ \sum_{j=1}^{N} \theta_{ij,t}(H) \tag{23}$$

Calculating the time-varying volatility spillover index based on the transformed generalized variance decomposition matrix $\widetilde{\Theta}_t$:

(a) Total spillover index: summation of all non-diagonal elements of the generalized variance decomposition matrix, then divide by the number of variables to obtain the total spillover effect:

$$TCI = (1/N) \sum_{i,j=1, i \neq j}^{N} \widetilde{\theta}_{ij,t}(H) \tag{24}$$

(b) Single spillover index: reflects the risk spillover relationship between a certain variable and all other variables, including overflow spillover index, inflow spillover index, and net overflow spillover index. Among them, the "spillover index" represents the total spillover effect of the variable on all other variables and it is recorded by $To_{i,t}(H)$. The "spillover index" represents the total spillover effect of the *i–th* variable from all other variables and is recorded by $From_{i,t}(H)$; The "net overflow index" is the overflow index minus the inflow index, it represents the net overflow effect of the variable on all other variables and recorded by $Net_{i,t}(H)$. The corresponding formula is as follows:

$$To_{i,t}(H) = \sum_{j=1, j \neq i}^{N} \widetilde{\theta}_{ji,t}(H) \tag{25}$$

$$From_{i,t}(H) = \sum_{j=1, j \neq i}^{N} \widetilde{\theta}_{ij,t}(H) \tag{26}$$

$$Net_{i,t}(H) = To_{i,t}(H) - From_{i,t}(H) \tag{27}$$

(c) Net Paired Market Spillover Index: it represents the net overflow effect of the $i - th$ variable on the variable:

$$NPDC_{ij}(H) = \widetilde{\theta}_{ji,t}(H) - \widetilde{\theta}_{ij,t}(H) \tag{28}$$

Based on the dynamic spillover indexes, the corresponding dynamic connectedness can be obtained from it.

4. Data description

The study uses monthly policy uncertainty indices (China and US EPU, US MPU, and US CPU), fossil fuel energy prices (WTI crude oil and natural gas), and the global ESG investment index for emerging and advanced economies from November 2014 to April 2023 as the observation samples. Data for policy uncertainty are sourced from the official EPU website (policyuncertainty.com/index.html). Data for WTI crude oil and natural gas are obtained from the official US Department of Energy website (http://www.eia.gov/), the global ESG investment index is from the MSCI ESG Focus website (https://www.msci.com/our-solutions/indexes/esg-focus-indexes). All variables are calculated by using the logarithmic differences:

$$R_t = log(X_t / X_{t-1}) \tag{29}$$

where R_t represents the original data at time t.

Fig. 1 reveals that all variables exhibit significant fluctuations, indicating that countries across the world are bearing double impacts from global economic risks and enhanced financial risks. Furthermore, climate change is correlated with increased global energy prices and can also result in global supply shortages, posing a risk to economic growth with a significant impact on the smooth implementation of global energy conservation and green investment. Fig. 2 illustrates the irregular and extreme risks that can cause all variables to exhibit volatility clustering effects.

Figs. 3 demonstrate the conditional high volatility under time-frequency components based on the MS-VAR-FIAPARCH estimation for policy uncertainty, fossil fuel energy, and ESG investment, revealing consistent irregular and extreme volatility trends. Among them, the fluctuation range of US MPU, the irregular volatility of US CPU, and the extreme volatility of China's EPU is the largest. In addition, the high frequency and large range of fluctuations appear to be normal characteristics of irregular events, but exceeding a certain limit in amplitude and frequency of fluctuations means the aggregation of risks, and extreme fluctuations exhibit cyclical characteristics.

Fig. 4 illustrates the common factors of policy uncertainty, fossil fuel energy, and ESG investment under time-frequency components with high-volatility states. The common factor can consistently identify sources of risk from irregular and extreme events in the short and long term. The findings demonstrate a negative fluctuation trend. Among them, the common factors in the low-frequency component dropped to a relatively low point in 2015 and 2020, respectively, which corresponds with the global economic crisis triggered by the regional stock index crisis and the COVID-19 pandemic. However, common factors in high-frequency components exhibit wave aggregation effects, which correspond to the impact of numerous irregular global economic and financial market events such as natural disasters, the pandemic, and regional conflicts.

Table 1 presents the descriptive statistics regarding policy uncertainty, fossil fuel energy, and ESG investment logarithmic differences, revealing that the mean of the policy uncertainty is larger than fossil fuel energy and ESG investment, and the minimum values are all negative. The volatilities of policy uncertainty and fossil fuel energy measured by the standard deviation are much greater than those of ESG investment. Negative values of skewness show that the probability distributions of fossil fuel energy and ESG investment are skewed to the left. The values of kurtosis indicate that all the variables have leptokurtosis and fatter tails, especially fossil fuel markets. The Jarque–Bera test shows that all the variables differ from the normal distribution, and the Ljung–Box autocorrelation test shows that the variables are serially correlated. Augmented Dickey-Fuller and Kwiatkowski–Phillips–Schmidt–Shin tests confirm the stationarity of all variables.

5. Empirical analysis

5.1. Time-varying filter-based empirical mode decomposition and signal reconstruction

The occurrence of global black swan events (regional wars, economic crises, banking crises, the pandemic, and natural disasters) has had varying degrees of impact on the adjustment of international macroeconomic policies and low-carbon, energy-saving, and environmental protection policy implementation. In this regard, policy uncertainty, traditional energy price, and ESG investment indices all demonstrate abnormal fluctuations, and the wavelet decomposition approach can accurately depict these corresponding fluctuations.

Fig. 5 presents the IMFs of policy uncertainty, fossil fuel energy, and global ESG investment decomposed using the TVF-EMD model. Previous aspects of the IMFs exhibit a characteristic of short-term volatility clustering effects. Periodic and asymmetric volatilities are discernible in the long term in the remaining IMFs. The IMFs decomposed using the TVF-EMD model show different uniform sizes and degrees. To

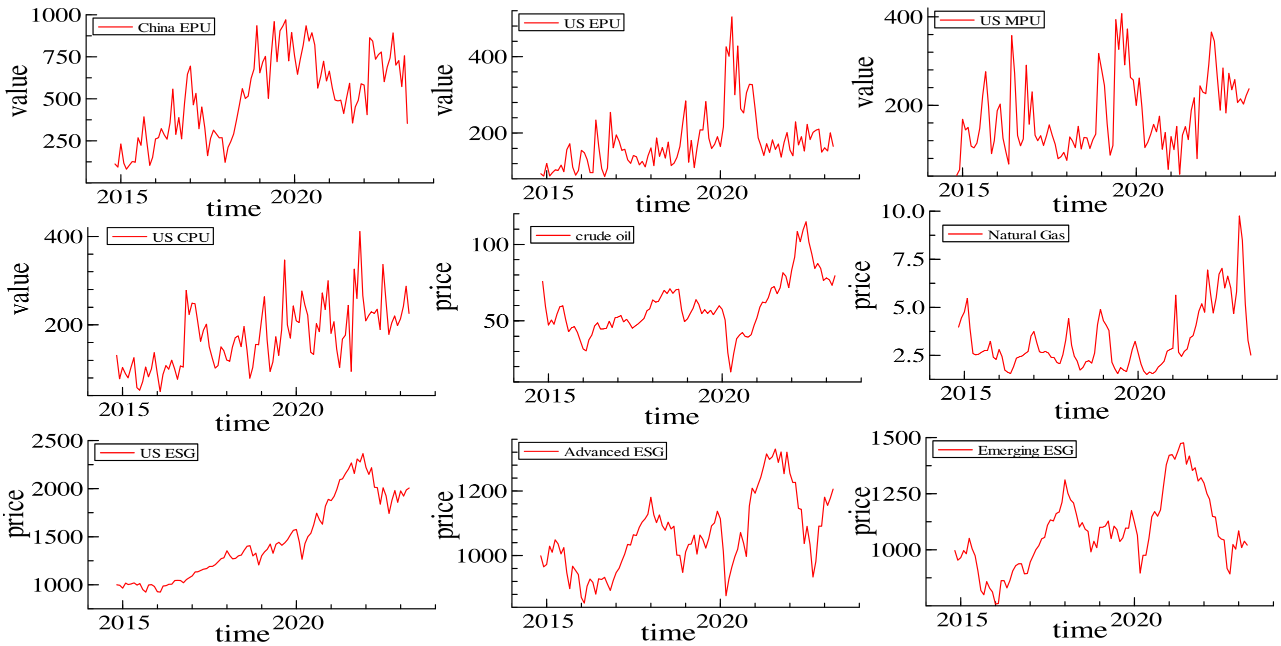


Fig. 1. Policy uncertainty, fossil energy, and ESG investment's value and price.

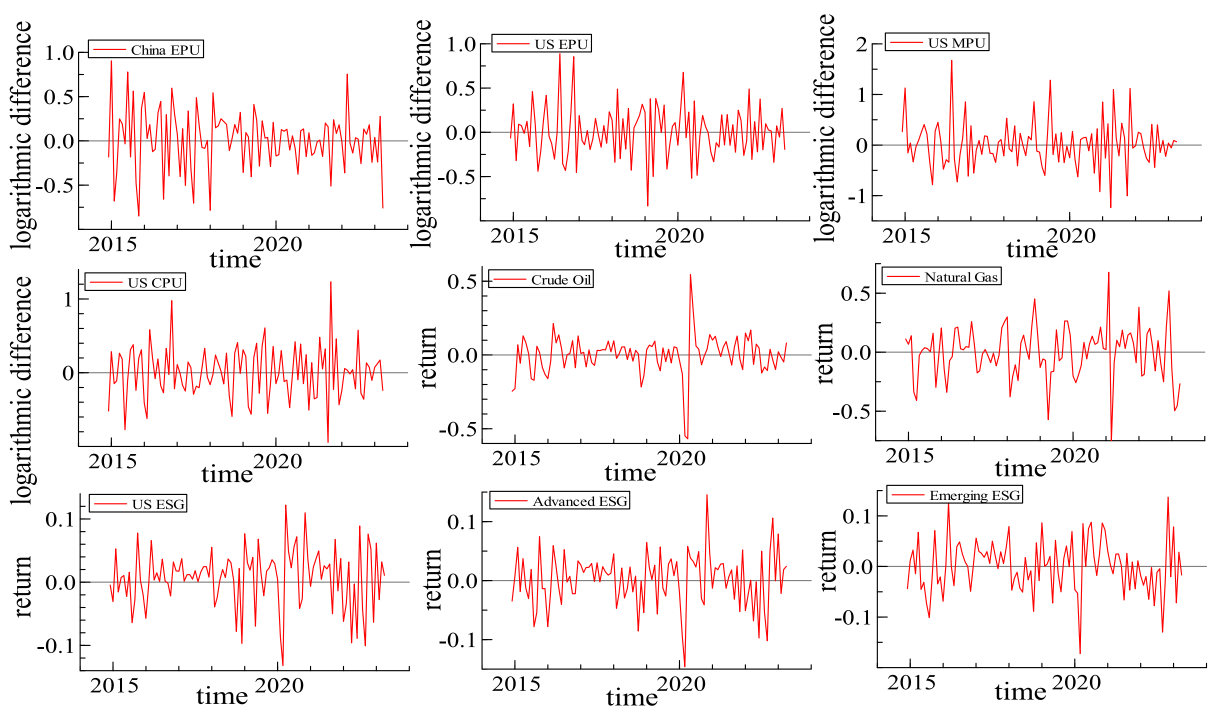
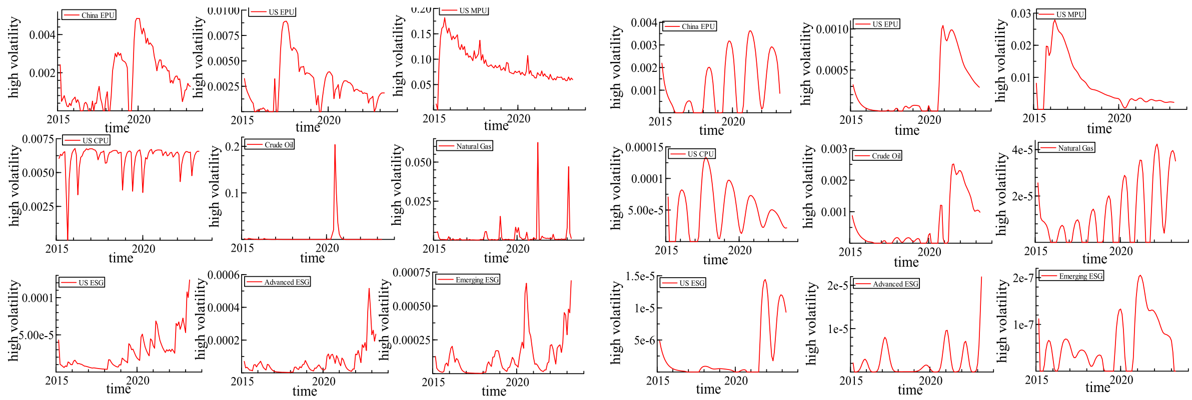


Fig. 2. Policy uncertainty, fossil energy, and ESG investment's logarithmic difference and return.

differentiate the high- and low-frequency components of the IMFs, we next apply the PCC.

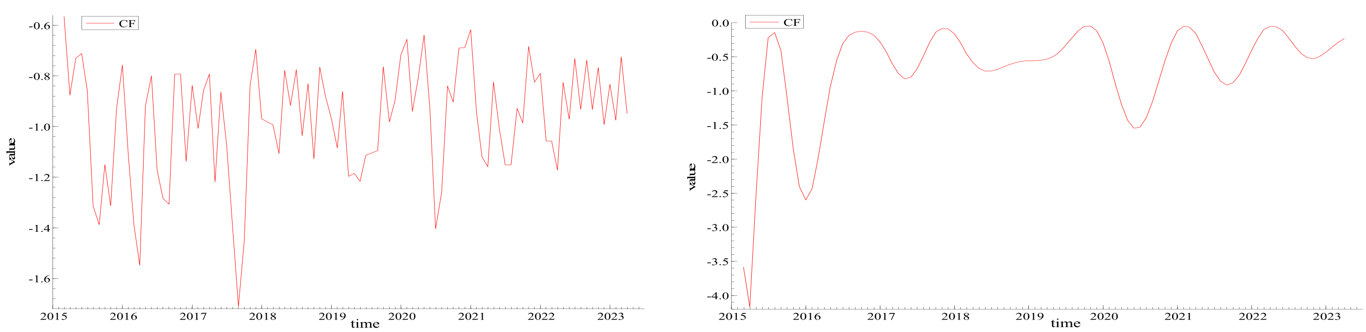
Fig. 6 demonstrates the PCCs of policy uncertainty, fossil fuel energy, and global ESG investment. The PCCs of IMF1 to IMF6 in policy uncertainty and ESG investment (China EPU, US EPU, US MPU, and US ESG) are relatively high. Furthermore, an analogous outcome occurs in IMF1 to IMF7 in US CPU, crude oil, advanced ESG investment, and emerging ESG investment; however, the PCCs of IMF1 to IMF8 in natural gas are relatively high. This indicates IMF1 to IMF6 of the policy uncertainty and the ESG investment (China's EPU, US EPU, US MPU, and US ESG) can be restructured to the high-frequency component, and the remainder, except for the last one, can be restructured to the low-frequency component. Likewise, the other IMFs of policy uncertainty, fossil fuel energy, and ESG investment (US CPU, crude oil, natural gas, advanced ESG, and emerging ESG) can also be restructured as above.

Fig. 7 demonstrates the high-frequency component of policy uncertainty, fossil fuel energy, and global ESG investment, reflecting the inherent contradictions across political, economic, financial, and natural environments, indicating various types of irregular crises, such as frequent adjustments in global policies, geopolitical unrest, natural hazards, and the pandemic. Furthermore, the high-frequency components of policy uncertainty are particularly significant.



Panel a: high volatility under high-frequency component Panel b: high volatility under low-frequency component

Fig. 3. Policy uncertainty, fossil energy, and ESG investment's high volatility under time-frequency components.



Panel a: Common factor under high-frequency component Panel b: Common factor under low-frequency component

Fig. 4. Policy uncertainty, fossil energy, and ESG investment's time-frequency common factor under high volatility state.

Table 1
Descriptive statistics for the policy uncertainty, fossil energy, and ESG investment's logarithmic difference.

	China EPU	US EPU	US MPU	US CPU	Crude Oil	Natural Gas	US ESG	Emerging ESG	Advanced ESG
Min	−0.85	−0.83	−1.24	−0.94	−0.57	−0.75	−0.13	−0.17	−0.15
Max	0.90	0.89	1.67	1.23	0.55	0.68	0.12	0.14	0.15
Mean	0.01	0.01	0.02	0.01	0.001	−0.005	0.007	0.0002	0.002
std. dev	0.33	0.29	0.46	0.35	0.13	0.22	0.05	0.05	0.05
Skewness	−0.20	0.25	0.61**	0.27	−0.79***	−0.28	−0.49**	−0.16	−0.29
Kurtosis	0.39	0.62	1.73***	1.03**	6.75***	1.36***	0.52	0.77	1.06**
Jarque -Bera	1.31	2.65	18.98***	5.66*	202.19***	9.12**	5.21*	2.91	6.16**
ARCH -LM(10)	1.68	1.04	0.54	0.78	15.32**	1.14	1.54	0.53	1.28
Q(20)	41.24**	45.85**	31.10	41.90**	29.08	48.00**	17.38	13.88	9.62
$Q^2(20)$	31.49*	17.83	15.03	15.98	73.37**	18.95	24.22	13.02	17.81
KPSS	0.13***	0.04***	0.04***	0.02***	0.10***	0.05***	0.08***	0.10***	0.05***
ADF	−7.09***	−8.94***	−9.70***	−8.29***	−6.79***	−5.87***	−6.02***	−5.78***	−5.84***

Notes: The table is a report on the policy uncertainty, fossil energy, and ESG investment's logarithmic differences. J-B, Q(20), $Q^2(20)$, and ARCH(10) are respectively represented Jarque-Bera normal distribution test, Ljung-Box auto-correlation test in 20 order, Engle [81] test for conditional heteroscedasticity. Augmented Dickey-Fuller, Kwiatkowski-Phillips-Schmidt-Shin is used to test for unit root and stability. **and *** are represented for statistical significance at the 5% and 1% levels.

Fig. 8 demonstrates the low-frequency component of policy uncertainty, fossil fuel energy, and global ESG investment, revealing that events (economic and banking crises) can generate increasing global systemic risks, causing cyclical and asymmetric fluctuations to occur. The low-frequency components of EPU and fossil fuel energy all have a relatively large amplitude.

Fig. 9 demonstrates the long-term trend of policy uncertainty, fossil fuel energy, and global ESG investment. The long-term trend of Chinese and US EPU declined to a low point in 2017 and 2022 and continued to increase in 2023. Furthermore, the US MPU has exhibited a slow upward trend since falling to a low point in 2019; however, the US CPU has been on a downward trend since 2015. In addition, long-term fossil fuel energy trends continued to decline after reaching high points in 2017 and 2022. Furthermore, the long-term trend of global ESG investment continued to decline after reaching a high point in 2020.

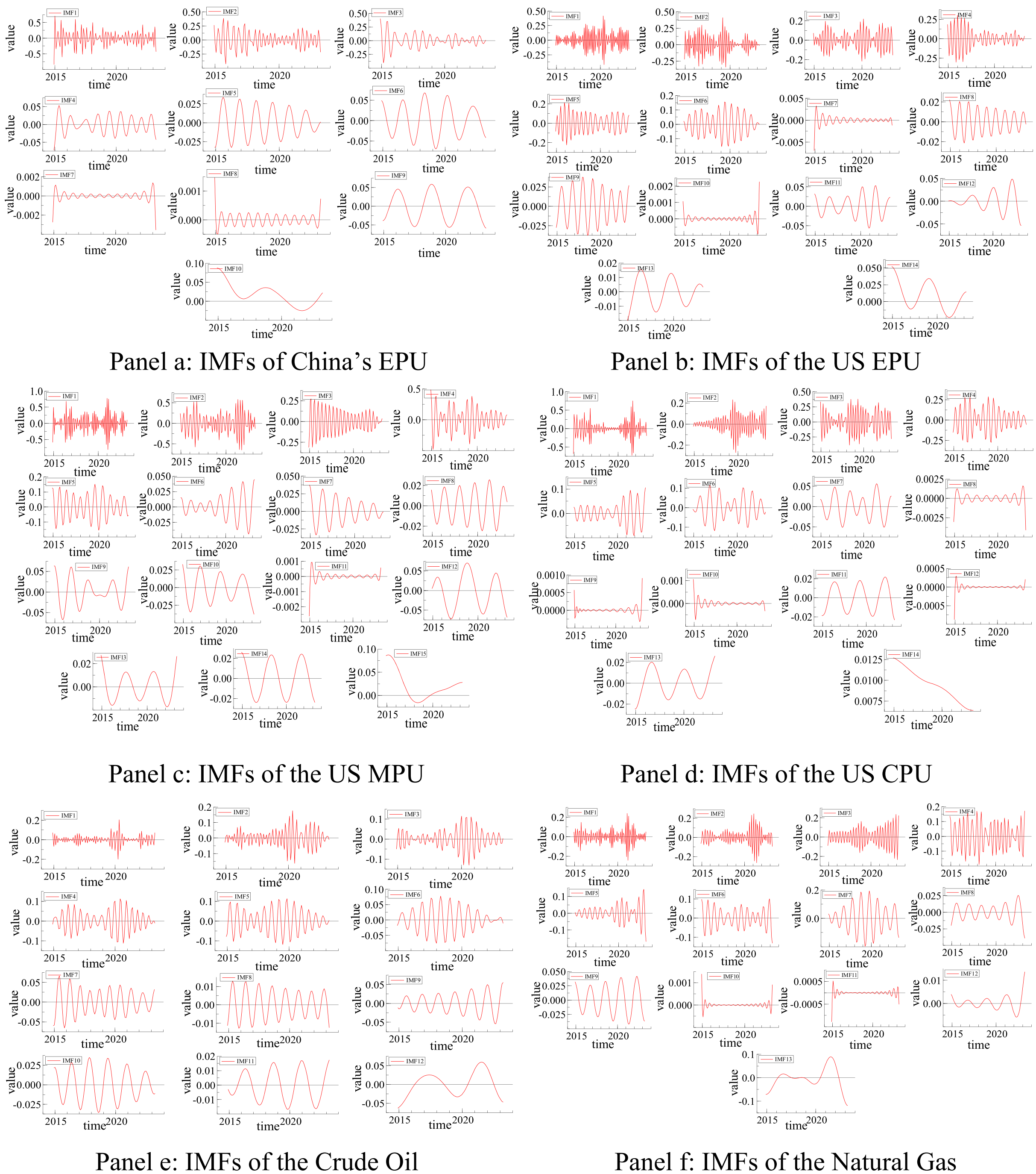


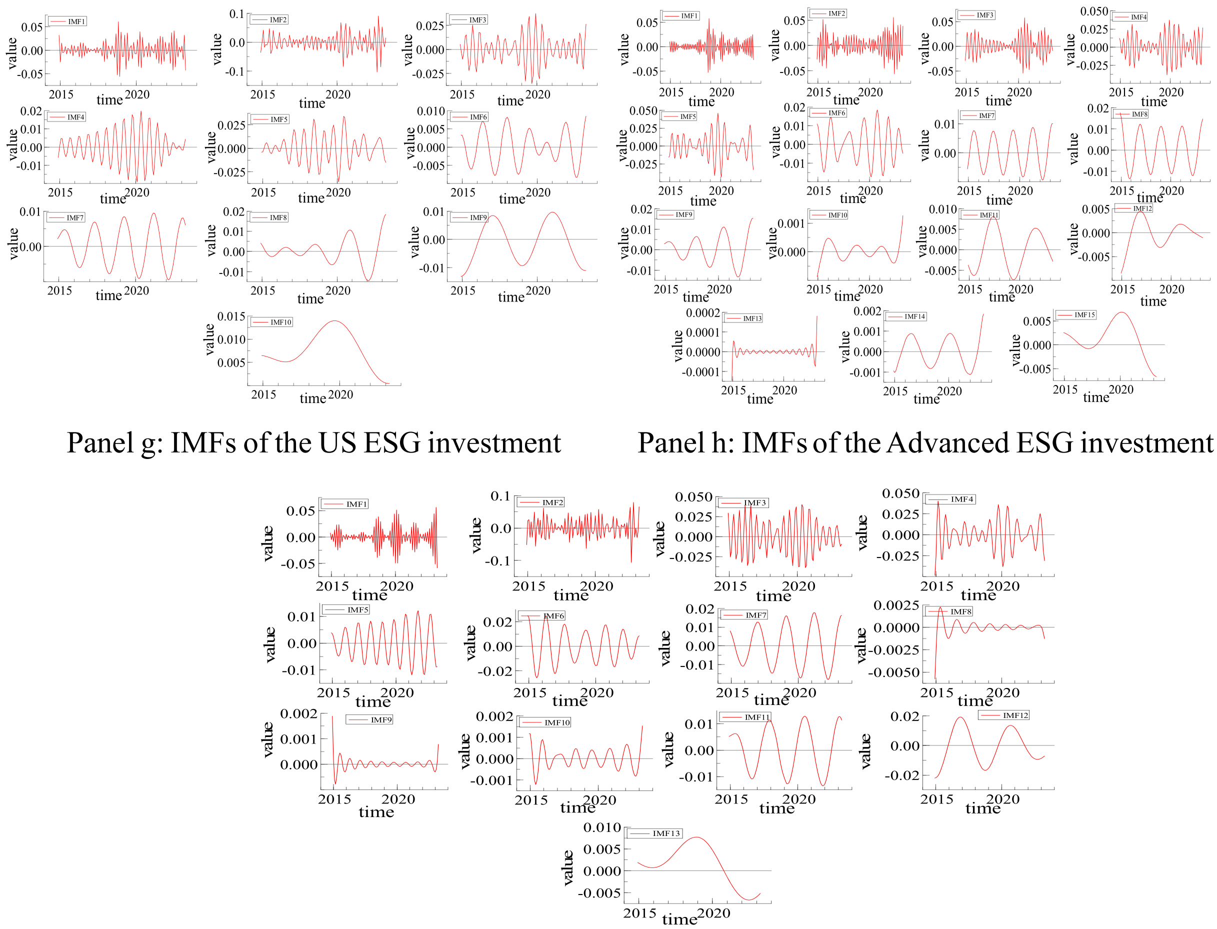
Fig. 5. Policy uncertainty, fossil energy, and global ESG investment's IMFs.

5.2. *Time-frequency risk spillover from a periodic perspective*

Based on high- and low-frequency time states, we reveal prominent periodic risk spillovers between policy uncertainty, fossil fuel energy, and global ESG investment. Therefore, this study employs the Markov switching autoregressive model combined with long-term memory and asymmetrical GARCH to describe periodic risk spillovers.

Table 2 demonstrates the high-frequency components of policy uncertainty under MS-VAR-FIAPARCH parameter estimation. US EPU, MPU, and CPU exhibited positive and negative mean spillovers to China's EPU in a low-volatility state, whereas positive mean spillovers occurred in almost all high-volatility states. China's EPU, US MPU, and US CPU all correlated with the emergence of a low-volatility regime of negative and positive mean spillovers to the US EPU. However, mean spillovers were positive in almost all high-volatility states. China's EPU, US EPU, and US CPU all generated alternate negative and positive mean spillovers in the two-volatility state. Furthermore, China's EPU and US EPU produced negative and positive mean spillovers to the US CPU in a low-volatility state. Finally, positive mean spillovers were produced in all high-volatility states.

Table 3 demonstrates the high-frequency components of fossil fuel energy under MS-VAR-FIAPARCH parameter estimation. Mean spillovers from the crude oil market to the natural gas market alternated positively and negatively under the two-volatility state. The natural gas market had negative mean spillovers to the crude oil market in the high-volatility state. Table 3 demonstrates the high-frequency components of



Panel g: IMFs of the US ESG investment

Panel h: IMFs of the Advanced ESG investment

Panel i: IMFs of the Emerging ESG investment

Fig. 5. (*continued*).

global ESG investment under MS-VAR-FIAPARCH parameter estimation. Negative dominated mean spillovers appeared to be more easily generated in the low-volatility state, and positive and negative changes formed in the high-volatility state.

Tables 4–6 present the low-frequency components of policy uncertainty, fossil fuel energy, and global ESG investment under MS-VAR-FIAPARCH parameter estimation, revealing that policy uncertainties had mutually positive and negative mean spillovers with two states of volatility. The crude oil market exhibited positive and negative changes in mean spillovers to the natural gas market under the two-volatility state. At the same time, the natural gas market caused negative mean spillovers to the crude oil market in the high-volatility state. Furthermore, global ESG investment exhibited alternate positive and negative mean spillovers in the low-volatility state, demonstrating heterogeneous mean spillovers in the high-volatility state.

Fig. 10 depicts the high-frequency components of risk spillovers from other variables with a two-state Markov chain. The risk of policy uncertainty with a two-state Markov chain stems from other variables, revealing a downward trend from 2015 to 2019, with an upward risk trend in 2020, after which market volatility risk characteristics persisted between 2021 and 2023. Notably, opposite positions (downward and upward) of the risk of crude oil with a two-state Markov chain occurred between 2015 and 2019, and the risk trend sharply rose in 2020, then gradually declined between 2021 and 2023, with a relatively significant risk of a downward trend in the high-volatility state. The risk of natural gas presented small fluctuations between 2015 and 2019 in the low-volatility state, which surged in 2020 and significantly decreased since then, exhibiting a continuously declining risk trend in the high-volatility state between 2015 and 2022, which increased rapidly in 2023. Moreover, the risk of global ESG investment in the low-volatility state exhibited a decreasing trend between 2015 and 2019, the risk rose sharply toward a high point in 2020 and then decreased until 2023. The risk of global ESG investment in the high-volatility state decreased rapidly between 2015 and 2022; however, US ESG investment exhibited an upward trend between 2022 and 2023.

The findings indicate that since 2015, insufficient global economic momentum has generated a declining trend of aggregate demand. In response, governments worldwide have introduced corresponding policies for economic stimulation. However, based on the total debt scale of some emerging and developed economies, investor sentiment has intensified since, which has exacerbated the volatility in financial markets. In addition, the Federal Reserve's quantitative easing policies have further increased global inflation and reduced investment, coupled with the multiple, short-term black swan events (such as natural disasters, trade disputes, the pandemic, and regional turbulence), global policy uncertainty continues to rise. Against the backdrop of a dual decline in global consumption and investment, the uneven fossil fuel energy supply and demand caused market price fluctuations, but the long-term risk is controllable overall. In addition, the mounting risk of global policy uncertainty will also influence the smooth implementation of ESG low-carbon energy conservation and environmental protection.

Fig. 11 presents the low-frequency risk spillovers from other variables with a two-state Markov chain. The risk of policy uncertainty (China's EPU, US EPU, and US MPU) in the low-volatility state maintained a downward trend between 2015 and 2023, and a similar trend can also be found in the high-volatility state between 2015 and 2019.

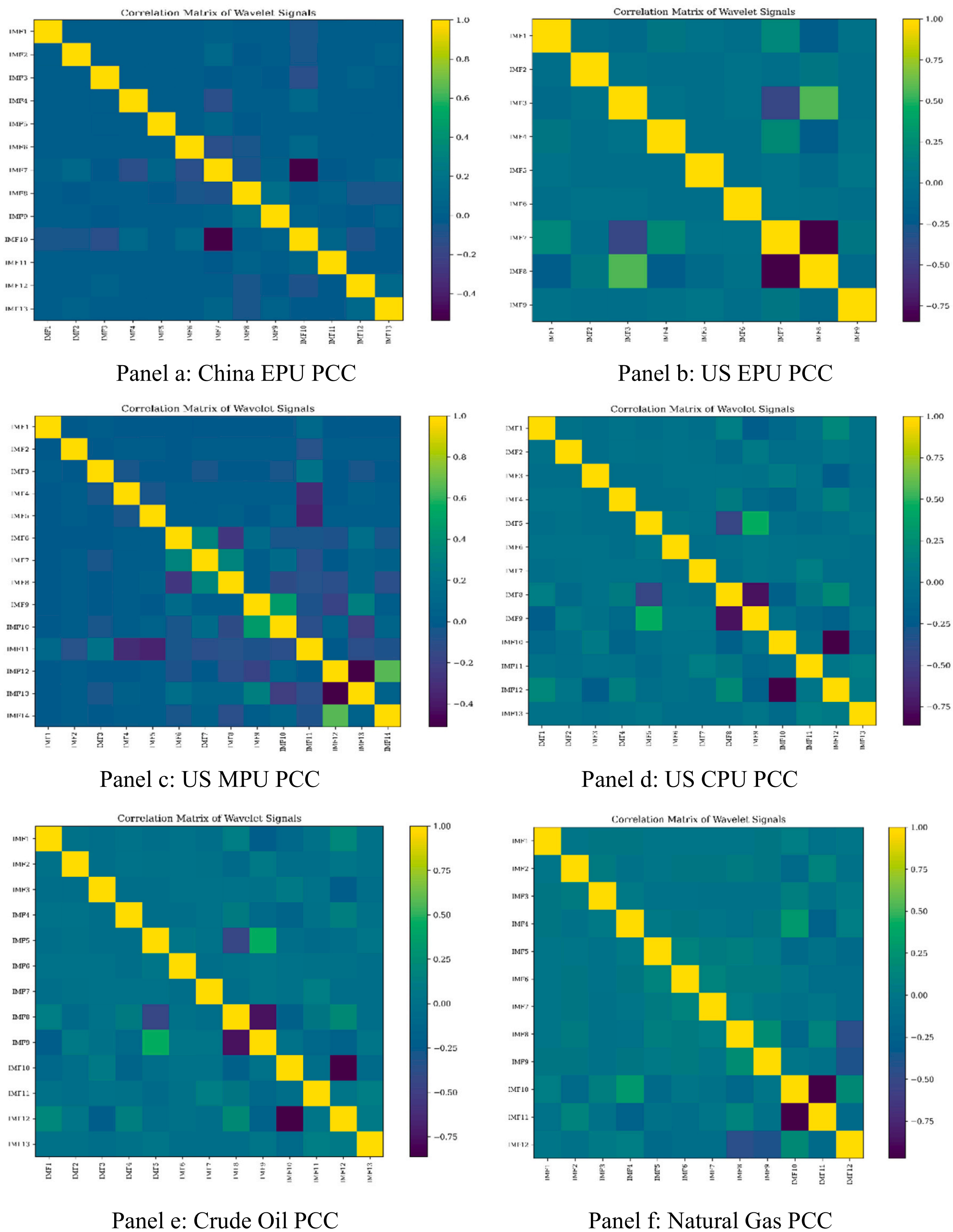
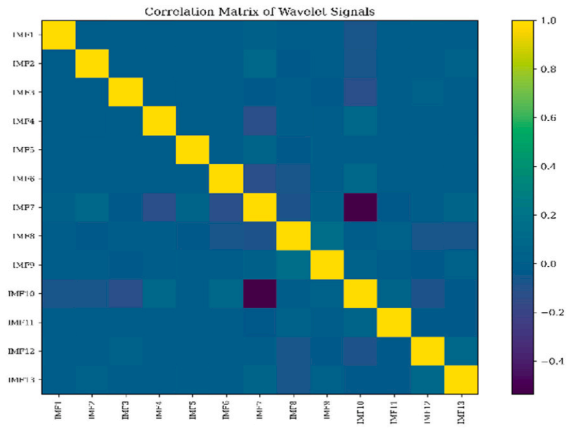


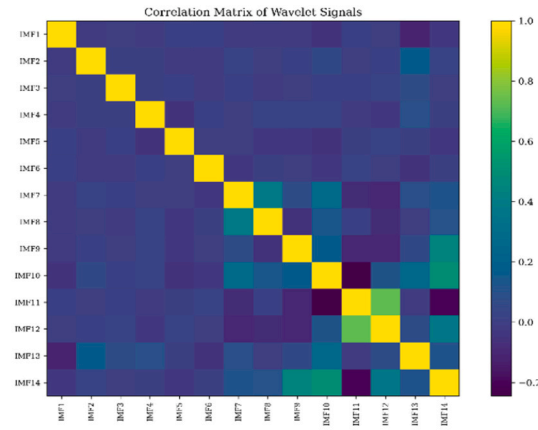
Fig. 6. Policy uncertainty, fossil energy, and global ESG investment's PCC.

However, the downward trend reversed between 2020 and 2023. Furthermore, the increasing trend of US CPU risk from other variables occurred in the low-volatility state, and a U-shaped risk trend appeared in the high-volatility state. Furthermore, decreased fossil fuel energy and ESG investment risks (US and emerging ESG) from other variables occurred in the low-volatility state between 2015 and 2022. Nevertheless, a continuous U-shaped risk from other variables appeared in the advanced ESG investment, and a similar finding occurred in the high-volatility state of fossil fuel energy markets and global ESG investment.

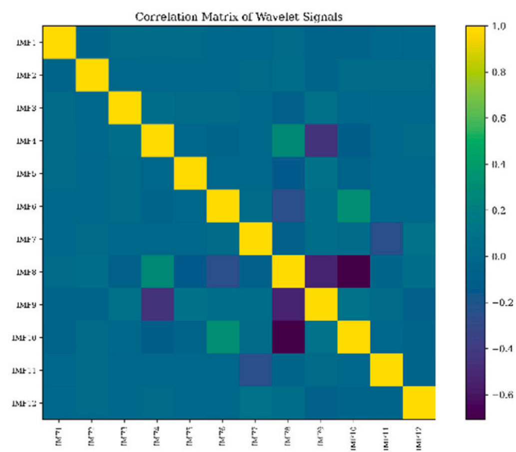
The phenomena indicate that the advent of the COVID-19 pandemic globally in 2020 caused an acute global economic crisis. To address the potential depression, developed economies like the US applied massive demand stimulus policies, which generated supply contraction and demand expansion and ultimately led to inflationary pressure. However, emerging economies like China did not adopt quantitative easing policies to stimulate demand but relied on expanding investment to stabilize growth. Due to the unsustainability of expanding investment and sustained lockdown policies that sapped investor and consumer



Panel g: US ESG PCC



Panel h: Advanced ESG PCC



Panel i: Emerging ESG PCC

Fig. 6. (*continued*).

confidence, deflation and downward pressure on the economy emerged in China. Therefore, global policy uncertainty risks have steadily increased since 2020, triggering large fluctuations in fossil fuel energy markets and significantly impacting global ESG investment.

Fig. 12 demonstrates the high-frequency risk spillovers to other variables with a two-state Markov chain, revealing a continuous downward trend between 2015 and 2021 that continued in the high-volatility state between 2022 and 2023. In contrast, a reversed trend occurred in the low-volatility state. Furthermore, the risk from the crude oil market to other variables operated at low points with a two-state Markov chain between 2015 and 2019, and rapidly reached the maximum value in 2020, decreasing sharply between 2021 and 2023. Similar patterns are also evident for global ESG investment in the low-volatility state. Moreover, a U-shaped risk trend from the natural gas market to other variables in the low-volatility state occurred between 2015 and mid-June 2021, after which the trend of the risk declined rapidly. However, the inverted U-type risk spillover in the high-volatility state is presented throughout the sample period. Moreover, global ESG investment maintained an upward trend of risk spillover between 2022 and 2023.

The rationale for this phenomenon is as follows. Affected by a series of irregular events since 2015, global enterprises reduced production capacity because of weak consumer demand, which was exacerbated by increased uncertainty in future geopolitical circumstances, weak productivity growth, and an increasingly challenging financial environment. The total fixed capital formation and industrial output of developed economies significantly slowed or contracted, dragging down international trade and manufacturing in emerging markets, which triggered further weakness in the global economy. In response, global policy uncertainty intensified, the demand for fossil fuel energy further weakened, and the motivation to advance green production, energy savings, and emissions reduction likely declined. Therefore, an increased risk spillover from reduced global ESG investment occurred.

Fig. 13 demonstrates the low-frequency risk spillovers to other variables with a two-state Markov chain. The risk from China's EPU to other variables with a two-state Markov chain remains high and volatile; however, the risk of US EPU to other variables in the low-volatility state continuously decreased between 2015 and 2023. A similar occurrence is also found in the high-volatility state, except for 2016 and 2020. An increased trend of US MPU risk to other variables in the low-volatility state occurred between 2016 and 2021, quickly declining between 2022 and 2023. Furthermore, U-shaped risk spillover is demonstrated in the high-volatility state. However, the trend of the irregular U-shaped risk from fossil fuel energy to other variables occurred in the two-state Markov chain. Nevertheless, U-shaped and inverted U-shaped risk spillover from global ESG investment to other variables emerged continuously in the two-state Markov chain.

The findings indicate that the world economy has been in an era of serious recession. Although the impact of COVID-19 on the macroeconomy has eased since 2020, the escalation of GPR between Russia and Ukraine combined with the withdrawal of major global central banks from loose monetary policies has triggered soaring commodity prices, crowding out the effect of inflationary pressure on the economy, and higher corporate credit financing costs, pushing major global

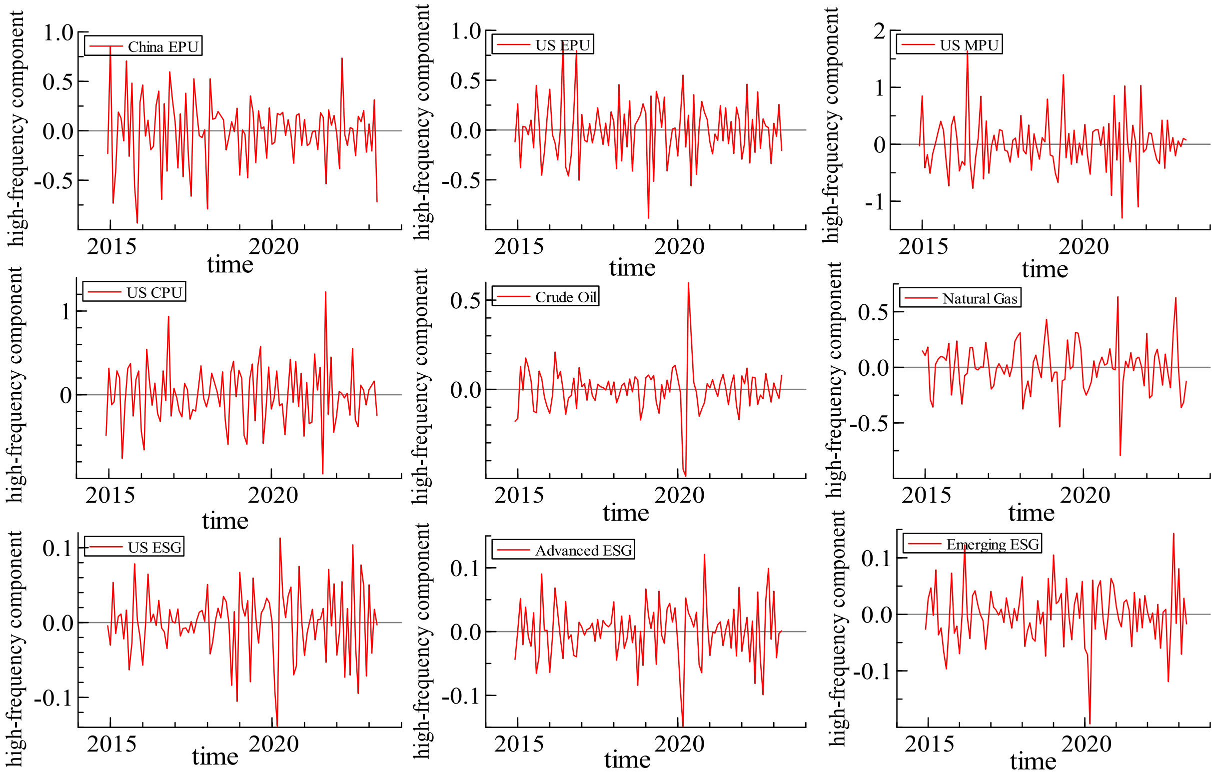


Fig. 7. Policy uncertainty, fossil energy, and ESG investment's high-frequency component.

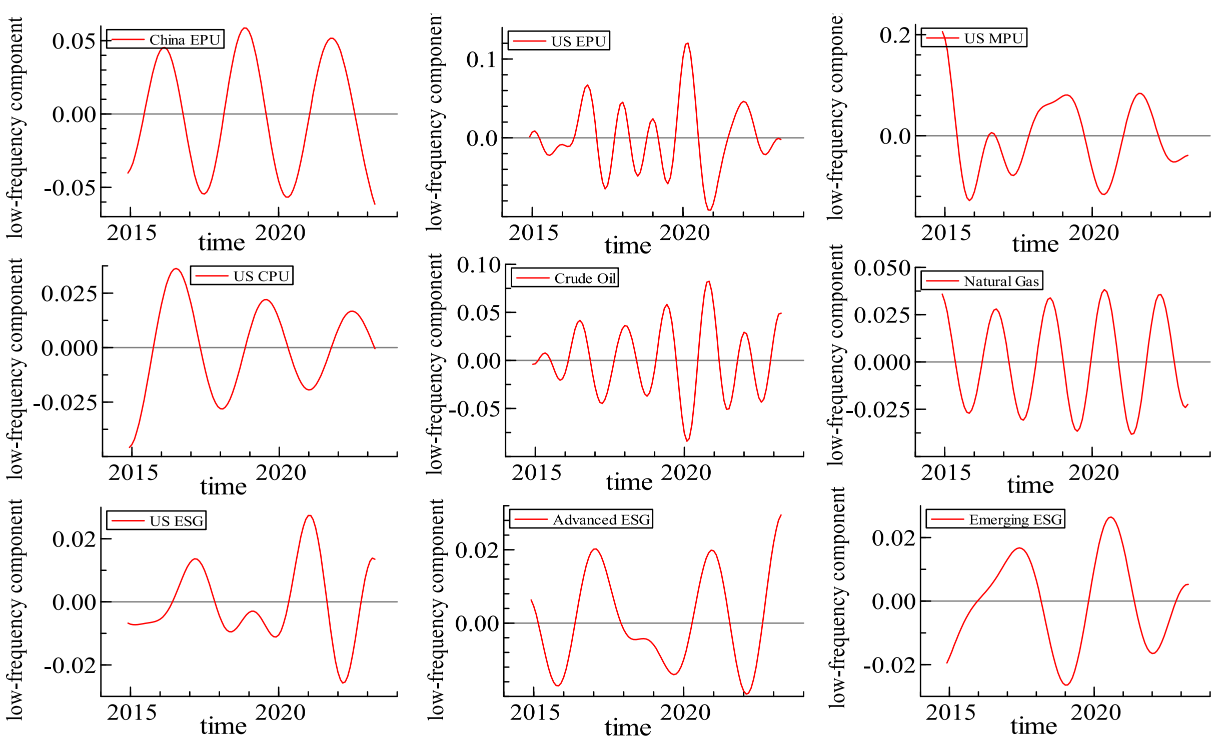


Fig. 8. Policy uncertainty, traditional energy, and ESG investment's low-frequency component.

economies back to the brink of economic recession. Therefore, global EPU and MPU significantly increased policy risks, aggravating fossil fuel energy fluctuations and resulting in persistently increased risk to global ESG investment.

Fig. 14 demonstrates the high-frequency net spillovers with a two-state Markov chain. In the low-volatility state, net spillovers of policy uncertainty exhibit an overall negative trend from 2020 to 2023. In the high-volatility state, changes in positive and negative net spillovers of China's EPU occurred between 2015 and 2023, while overall negative net spillovers of US EPU appeared between 2016 and 2023. However, US

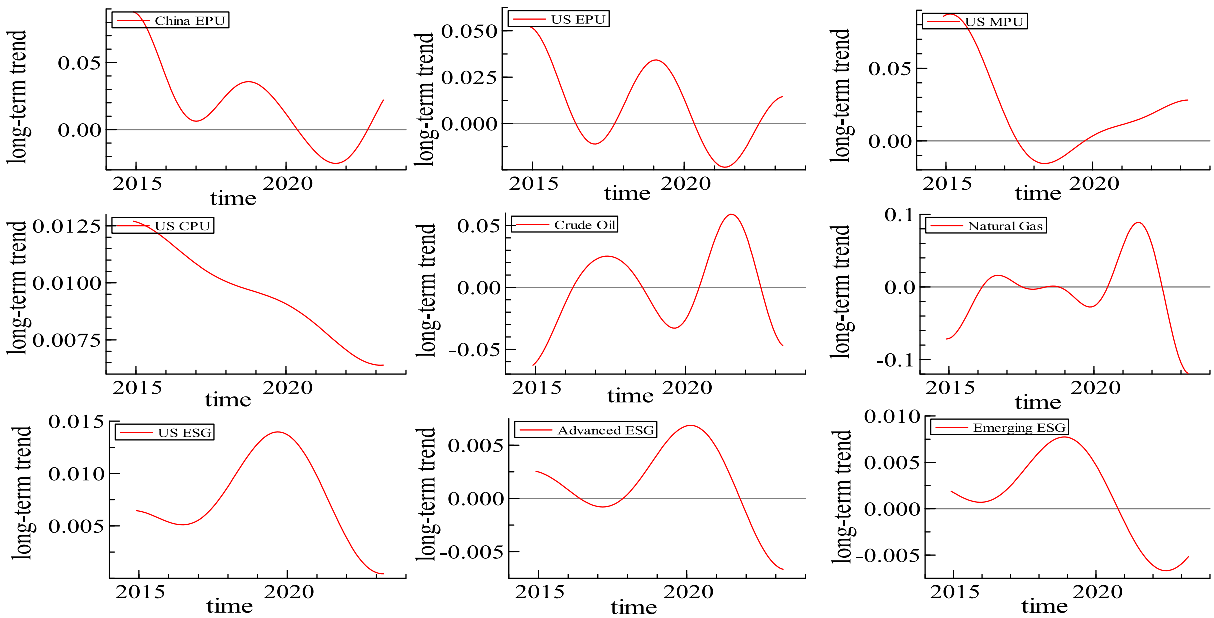


Fig. 9. Policy Uncertainty, fossil energy, and ESG investment's long-term Trend.

Table 2
The high-frequency components of policy uncertainty under MS-VAR-FIAPARCH parameter estimation.

	low volatility state				high volatility state			
Mean process	China EPU	US EPU	US MPU	US CPU	China EPU	US EPU	US MPU	US CPU
China EPU (−1)	−0.45***	−0.06	0.03	−0.15	0.08	0.06	-0.10	0.03
	(0.00)	(0.52)	(0.78)	(0.15)	(0.70)	(0.81)	(1.00)	(1.00)
China EPU (−2)	−0.24*	−0.14**	−0.11	−0.09	−0.08	−0.02	0.17	0.20
	(0.08)	(0.02)	(0.29)	(0.44)	(1.00)	(1.00)	(0.78)	(0.38)
US EPU (−1)	0.41**	−0.64***	−0.09	0.09	0.19	0.15	0.69	0.09
	(0.02)	(0.00)	(0.65)	(0.55)	(1.00)	(1.00)	(0.26)	(0.65)
US EPU (−2)	0.52***	−0.07	0.48**	0.24	-1.01***	−0.19	-0.77	−0.47
	(0.00)	(0.60)	(0.01)	(0.11)	(0.01)	(0.25)	(0.30)	(0.23)
US MPU (−1)	−0.07	0.12	−0.12	−0.08	−0.04	0.01	-0.77**	0.04
	(0.55)	(0.15)	(0.32)	(0.47)	(1.00)	(1.00)	(0.01)	(0.80)
US MPU (−2)	−0.11	0.03	−0.16	0.02	0.13	0.02	-0.29	0.04
	(0.40)	(0.70)	(0.17)	(0.81)	(0.24)	(0.90)	(0.36)	(0.84)
US CPU (−1)	−0.36***	−0.11	−0.29**	−0.18**	0.32***	0.15	0.12	−0.40
	(0.00)	(0.22)	(0.01)	(0.03)	(0.00)	(0.56)	(0.68)	(0.00)
US CPU (−2)	−0.26**	0.02	0.07	−0.48***	0.19	0.07	−0.05	0.41**
	(0.04)	(0.80)	(0.52)	(0.00)	(0.19)	(0.75)	(0.84)	(0.04)
Variance process								
Constant	0.66**	0.87	1.00***	1.00***	0.18**	0.10	1.00***	0.77**
	(2.22)	(0.40)	(468.8)	(1107.0)	(2.48)	(1.01)	(320.9)	(2.06)
d-Figarch	0.31	0.27**	0.30	0.10	0.10	0.10	0.03	0.01
	(1.55)	(1.99)	(0.40)	(0.65)	(1.31)	(1.22)	(0.41)	(0.07)
ARCH	0.40	0.10	0.40	0.26	0.40*	0.24	0.37	0.50
	(0.40)	(0.03)	(0.09)	(0.39)	(1.81)	(1.37)	(1.17)	(0.76)
GARCH	0.43	0.38	0.52	0.20	0.46**	0.10	0.46	0.40
	(0.44)	(0.13)	(0.16)	(0.36)	(2.25)	(0.38)	(1.08)	(0.64)
APARCH (γ)	−0.30	−0.23	−0.03	0.21	0.74	−0.30	1.00***	0.81
	(−0.81)	(−0.38)	(−0.02)	(0.44)	(1.12)	(−1.44)	(117.4)	(0.48)
APARCH (δ)	0.78*	0.19	0.0007**	0.0010	1.84***	2.09***	0.005*	0.36
	(1.85)	(0.06)	(2.36)	(1.63)	(5.25)	(2.73)	(1.74)	(0.55)

Notes: The values in parentheses for the mean and variance processes represent *p*-values and t-values, respectively. *, ** and *** represent the significance at the 10%, 5% and 1% level.

MPU and CPU had positive net spillovers between 2018 and 2023. In the low-volatility state, the crude oil and natural gas markets exhibited overall negative and positive net spillovers between 2015 and 2023, respectively, and alternating positive and negative net spillovers in the high-volatility state occurred between 2015 and 2023. Furthermore, overall positive net spillovers of global ESG investment are evident between 2020 and 2023. Moreover, overall negative net spillovers occurred in the US and advanced ESG investment in the high-volatility state, with negative and positive net spillovers presented in the emerging ESG investment.

Fig. 15 presents the low-frequency net risk spillovers with a two-state Markov chain. Chinese and US EPU demonstrate overall net positive risk spillovers with a two-state Markov chain, while US MPU exhibited positive and negative net spillovers with a two-state Markov chain, which is also found in global ESG investment. However, the US CPU and the crude oil market exhibited negative net spillovers in the low-

Table 3
The high-frequency components of global ESG investment under MS-VAR-FIAPARCH parameter estimation.

Mean process	low volatility state			high volatility state		
	US ESG	Advanced ESG	Emerging ESG	US ESG	Advanced ESG	Emerging ESG
US ESG (−1)	−0.63***	-0.49***	-0.62***	0.69	1.41***	1.63***
	(0.00)	(0.00)	(0.00)	(0.17)	(0.01)	(0.01)
US ESG (−2)	−0.21	−0.14	0.01	−0.35	−0.02	−0.01
	(0.23)	(0.37)	(0.96)	(0.41)	(0.95)	(0.98)
Advanced ESG (−1)	0.05	-0.40**	−0.05	0.16	0.10	−0.11
	(0.81)	(0.05)	(0.86)	(0.75)	(0.84)	(0.87)
Advanced ESG (−2)	−0.10	−0.18	−0.18	0.74	0.86	1.06***
	(0.61)	(0.33)	(0.46)	(0.19)	(0.18)	(0.00)
Emerging ESG (−1)	0.01	0.45***	0.27*	−0.03	−0.26	0.03
	(0.96)	(0.00)	(0.06)	(1.00)	(0.20)	(1.00)
Emerging ESG (−2)	−0.11	−0.02	−0.04	0.03	−0.47	−0.76
	(0.40)	(0.85)	(0.80)	(0.92)	(1.00)	(1.00)
Variance process						
Constant	18.17	0.82	100.00	2.89	0.006	0.007
	(0.18)	(0.12)	(1.20)	(0.04)	(0.38)	(0.60)
d-Figarch	0.96***	0.02	0.10	0.21	0.48	0.52***
	(3.08)	(0.36)	(0.71)	(0.27)	(1.43)	(3.71)
ARCH	0.10	0.40*	0.20	0.10	0.10	0.10
	(0.15)	(1.82)	(0.78)	(0.04)	(0.12)	(0.66)
GARCH	0.52**	0.20	0.12	0.22	0.43	0.52***
	(2.15)	(0.70)	(0.47)	(0.18)	(1.37)	(5.29)
APARCH (γ)	−0.20	0.62*	0.89*	0.90	0.90**	0.90*
	(−0.56)	(1.70)	(1.81)	(0.99)	(2.05)	(1.83)
APARCH (δ)	2.92	2.86	1.54***	2.34	1.70**	1.71***
	(1.43)	(1.23)	(7.29)	(0.45)	(1.99)	(3.72)

Notes: The values in parentheses for the mean and variance processes represent p-values and t-values, respectively. *, ** and *** represent the significance at the 10%, 5% and 1% level.

Table 4
The low-frequency components of policy uncertainty under MS-VAR-FIAPARCH parameter estimation.

	low volatility state				high volatility state			
Mean process	China EPU	US EPU	US MPU	US CPU	China EPU	US EPU	US MPU	US CPU
China EPU (−1)	1.75***	0.35	1.44***	−0.29***	−5.03	−0.13	−1.23	0.52
	(0.00)	(0.67)	(0.00)	(0.00)	(1.00)	(1.00)	(1.00)	(1.00)
China EPU (−2)	-0.70***	−0.11	−1.70***	0.36***	0.75	0.07	2.51	−1.56
	(0.00)	(0.89)	(0.00)	(0.00)	(1.00)	(1.00)	(1.00)	(1.00)
US EPU (−1)	0.01	1.96***	−0.01	0.01	−0.02	−2.09	0.09	−0.02
	(0.21)	(0.00)	(0.84)	(0.21)	(1.00)	(1.00)	(1.00)	(1.00)
US EPU (−2)	−0.01	−0.82***	0.03	−0.01	0.01	0.82	−0.04	0.02
	(0.35)	(0.00)	(0.47)	(0.36)	(1.00)	(0.87)	(0.93)	(1.00)
US MPU (−1)	−0.00	−0.15	1.82***	0.01	0.00	0.22	−6.05	−0.01
	(0.87)	(0.46)	(0.00)	(0.53)	(1.00)	(1.00)	(1.00)	(0.95)
US MPU (−2)	−0.01	0.20	−0.81***	−0.02*	−0.03	0.06	1.59	0.03
	(0.43)	(0.31)	(0.00)	(0.08)	(1.00)	(1.00)	(1.00)	(1.00)
US CPU (−1)	-0.73***	−0.94	2.46***	1.32***	1.54	1.39	2.01	4.86
	(0.00)	(0.52)	(0.00)	(0.00)	(0.91)	(1.00)	(0.91)	(1.00)
US CPU (−2)	0.58***	1.19	−1.87***	−0.52***	−0.69	−0.30	0.95	0.71
	(0.00)	(0.45)	(0.00)	(0.00)	(1.00)	(1.00)	(1.00)	(1.00)
Variance process								
Constant	0.00	0.003	0.00	0.00	0.01*	0.001	5.80	0.008
	(0.00)	(0.13)	(0.00)	(0.00)	(1.88)	(0.43)	(1.34)	(0.41)
d-Figarch	0.92***	0.74***	0.91***	0.95***	0.95***	0.71***	0.99***	0.98***
	(27.60)	(3.58)	(39.09)	(28.61)	(65.15)	(7.84)	(86.58)	(41.90)
ARCH	0.36***	0.39***	0.32***	0.40***	0.30***	0.25	0.20	0.30
	(4.15)	(6.52)	(4.23)	(3.93)	(3.02)	(1.42)	(1.08)	(1.16)
GARCH	0.13	0.10	0.10	0.27***	0.10	0.10	0.10	0.10
	(1.45)	(0.60)	(0.94)	(4.68)	(0.81)	(0.47)	(0.56)	(0.40)
APARCH (γ)	0.02	0.10**	−0.03	−0.04	0.01	−0.03	0.008	0.02
	(0.71)	(2.20)	(−0.95)	(−1.14)	(0.51)	(−0.30)	(0.30)	(0.31)
APARCH (δ)	2.58***	3.00**	2.58***	3.00***	3.00***	2.20***	3.00***	3.00***
	(33.49)	(2.05)	(50.45)	(25.22)	(10.30)	(4.32)	(8.01)	(6.15)

Notes: The values in parentheses for the mean and variance processes represent p-values and t-values, respectively. *, ** and *** represent the significance at the 10%, 5% and 1% level.

volatility state, whereas positive net spillovers are shown for the natural gas and crude oil markets in low- and high-volatility states, respectively. Finally, the natural gas market exhibited negative net spillovers in the high-volatility state.

As shown in Fig. 16, in contrast to some previous research findings, concerning pairwise relationships, renewable energy is weakly associated with the green bond (Lucey and Ren [82], Lucey et al. [55]). We reveal that the natural gas market has an important role in risk spilling

Table 5
The low-frequency components of fossil energy under MS-VAR-FIAPARCH parameter estimation.

Mean process	low volatility state		high volatility state	
	Crude Oil	Natural Gas	Crude Oil	Natural Gas
Crude Oil (−1)	1.86***	−0.02	−1.78	0.06
	(0.00)	(0.41)	(0.89)	(0.74)
Crude Oil (−2)	−1.00***	0.02	−1.20	−0.08
	(0.00)	(0.35)	(1.00)	(1.00)
Natural Gas (−1)	0.00	1.91***	−0.00	−1.46
	(0.20)	(0.00)	(0.93)	(1.00)
Natural Gas (−2)	−0.00	−0.99***	−0.01	−0.28
	(0.62)	(0.00)	(0.97)	(1.00)
Variance process				
Constant	0.71	0.005***	0.0007	0.002
	(0.21)	(16.62)	(0.56)	(1.15)
d-Figarch	0.89***	0.22*	0.67***	0.92***
	(12.31)	(1.92)	(4.42)	(73.53)
ARCH	0.28***	0.86***	0.46***	0.30***
	(3.81)	(18.02)	(15.80)	(6.14)
GARCH	0.10	0.10	0.10	0.10**
	(0.54)	(0.59)	(0.66)	(2.01)
APARCH (γ)	0.03	−0.05	−0.03	0.01
	(0.45)	(−1.24)	(−0.58)	(0.32)
APARCH (δ)	2.54***	2.19***	3.00***	3.00***
	(3.59)	(52.08)	(3.36)	(12.11)

Notes: The values in parentheses for the mean and variance processes represent p-values and t-values, respectively. *, ** and *** represent the significance at the 10%, 5% and 1% level.

when the economy runs smoothly (Uddin et al., [54]). It enhances the risk spillovers of global policy uncertainty while also promoting risk overflow in ESG investment (US and emerging economies) and the crude oil market. Converging with some literature, we find that EPU can serve as a predictor across various distributions of cross-market correlations, particularly under normal market conditions [32,33] . We find that risk arising from China's EPU can influence US CPU, which indirectly transmits to emerging EGS investment and the crude oil market. Moreover, the risk from advanced ESG investment can directly spillover to emerging and US ESG venture capital investment. While a short-term dip would occur in global economic growth, the natural gas market remains the origin of risk spillovers, but the risk can only be transmitted to the ESG investment of emerging and advanced economies. At the same time, the crude oil market has a key influence in transferring the risk and can also transmit risk to global ESG investment. Furthermore, the risk from CPU can rise steadily and may produce an effect on US MPU and advanced ESG investment. Contradicting previous literature, Urom and Ndubuisi [83] indicated that the US and European green indices are net transmitters of shocks in normal times.

As shown in Fig. 17, with economic decline, EPU has an important position in risk spillovers. As found in previous research, a significant influence of economic and MPU occurs on green finance indices compared with CPU (Cepni et al., [51] , Banerjee et al., [84] , [46–48]), Wang et al., [85]). For instance, the US EPU conveys risk to China's EPU most strongly, and then the corresponding risk transfers to advanced ESG investment. Moreover, EPU risk in the US affects MPU risk, which affects advanced ESG investment and the US CPU. Furthermore, US EPU risk can be vulnerable in emerging ESG investment and impact US CPU. During the economic downturn, policy uncertainty continuously serves as the source of risk transmission. For instance, the US EPU exacerbated the risk in the natural gas market. China's EPU enhanced the US CPU and aggravated the risk in advanced ESG investment, while the risk from emerging ESG investment can directly influence advanced ESG investment. Furthermore, considerable risk from the crude oil market will have a tremendous impact on US ESG investment, which then intensifies US MPU and eventually produces a huge risk for advanced ESG investment. In contrast to some literature, CPU contributes more to total spillovers and the net total directional spillovers of other green finance markets (Lorente et al., [52] , Wu et al., [86]).

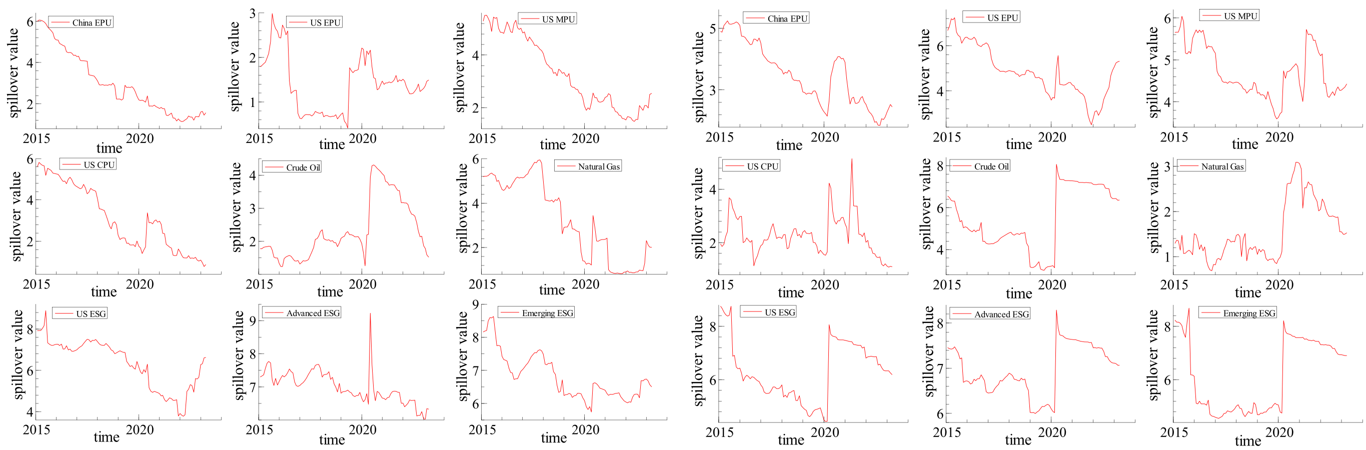
5.3. Time-frequency risk spillover from an asymmetrical perspective

In the contemporary era, economic uncertainty, particularly policy uncertainty and financial market turmoil, is greater than it has been in many years. As a result, significant asymmetrical risk spillovers between EPU, MPU, and CPU; fossil fuel energy markets (crude oil and natural

Table 6
The low-frequency components of global ESG under MS-VAR-FIAPARCH parameter estimation.

Mean process	low volatility state			high volatility state		
	US ESG	Advanced ESG	Emerging ESG	US ESG	Advanced ESG	Emerging ESG
US ESG (−1)	1.82***	0.03	−0.57***	−3.69	−0.18	0.43
	(0.00)	(0.94)	(0.00)	(1.00)	(1.00)	(0.95)
US ESG (−2)	−0.88***	−0.06	0.56***	1.74	0.09	−0.90
	(0.00)	(0.89)	(0.00)	(1.00)	(1.00)	(0.96)
Advanced ESG (−1)	0.17	1.72***	0.75	−0.10	−2.87	−1.24
	(1.00)	(0.01)	(1.00)	(0.96)	(1.00)	(0.88)
Advanced ESG (−2)	−0.18	−0.73	−0.75	0.14	1.65	−0.02
	(1.00)	(0.29)	(1.00)	(0.93)	(0.96)	(0.92)
Emerging ESG (−1)	−0.09	0.14	1.61***	0.02	−0.22	1.48
	(1.00)	(0.78)	(0.00)	(1.00)	(1.00)	(0.65)
Emerging ESG (−2)	0.11	−0.13	−0.64***	0.02	0.03	0.85
	(1.00)	(0.81)	(0.00)	(1.00)	(0.96)	(0.96)
Variance process						
Constant	0.00	0.06***	0.00	0.20	0.07	0.47
	(0.00)	(4.50)	(0.00)	(0.31)	(0.11)	(0.31)
d-Figarch	0.50	0.92***	0.86***	0.60***	0.73	0.95***
	(0.47)	(4.643e+004)	(9.63)	(3.11)	(5.19)	(26.59)
ARCH	0.62***	0.45***	0.42***	0.64***	0.55***	0.30***
	(2.97)	(52.16)	(10.55)	(7.91)	(11.49)	(2.76)
GARCH	0.10	0.10	0.10	0.10	0.05	0.10
	(0.06)	(1.40)	(0.95)	(0.32)	(0.43)	(0.73)
APARCH (γ)	0.06*	−0.11***	0.02	−0.08***	−0.02	−0.04
	(1.71)	(−3.26)	(0.51)	(−3.07)	(−0.17)	(−1.31)
APARCH (δ)	2.26***	2.54***	3.00***	3.00***	3.00	3.00***
	(3.67)	(59.98)	(5.22)	(4.54)	(1.39)	(7.56)

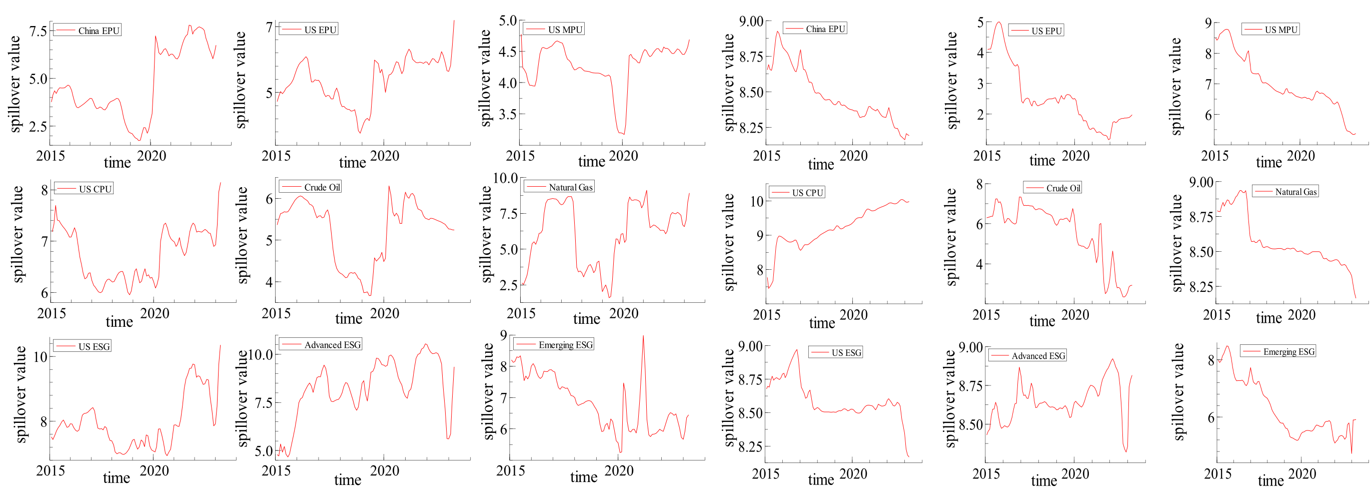
Notes: The values in parentheses for the mean and variance processes represent p-values and t-values, respectively. *, ** and *** represent the significance at the 10%, 5% and 1% level.



Panel a: risk spillovers from other variables in a high-volatility state Panel b: risk spillovers from other variables in a low-volatility state

Figure 10 Policy uncertainty, fossil energy, and ESG investment's high-frequency risk spillovers from other variables with a two-state Markov chain

Fig. 10. Policy uncertainty, fossil energy, and ESG investment's high-frequency risk spillovers from other variables with a two-state Markov chain.



Panel a: risk spillovers from other variables in a high-volatility state Panel b: risk spillovers from other variables in a low-volatility state

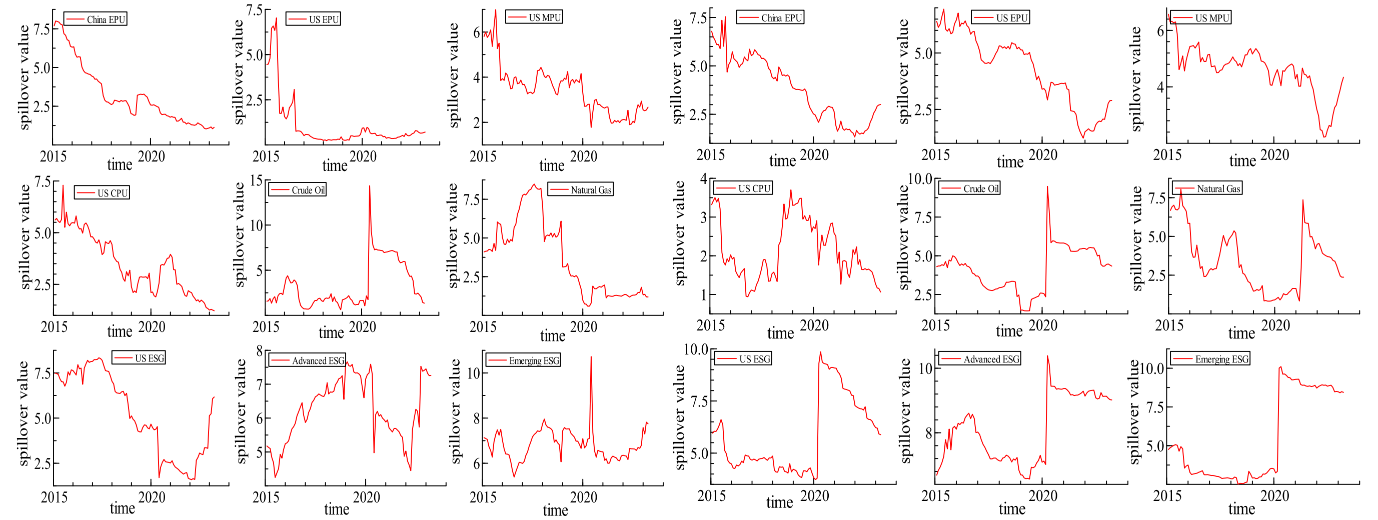
Fig. 11. Policy uncertainty, fossil energy, and ESG investment's low-frequency risk spillovers from other variables with a two-state Markov chain.

gas); and global ESG investment have been demonstrated over recent years.

As shown in Fig. 18, the high-frequency asymmetrical risk spillovers from other variables are all in decline. Specifically, the trend of asymmetrical (positive and negative) risk first increased in 2016 and then decreased in the following years; however, the positive risk of US EPU increased between 2022 and 2023. More notably, the negative risk of policy uncertainty is relatively larger, particularly risks associated with US EPU. Similar findings are also revealed for global ESG investment, and positive risk is relatively high for the traditional energy markets, particularly that of the natural gas market.

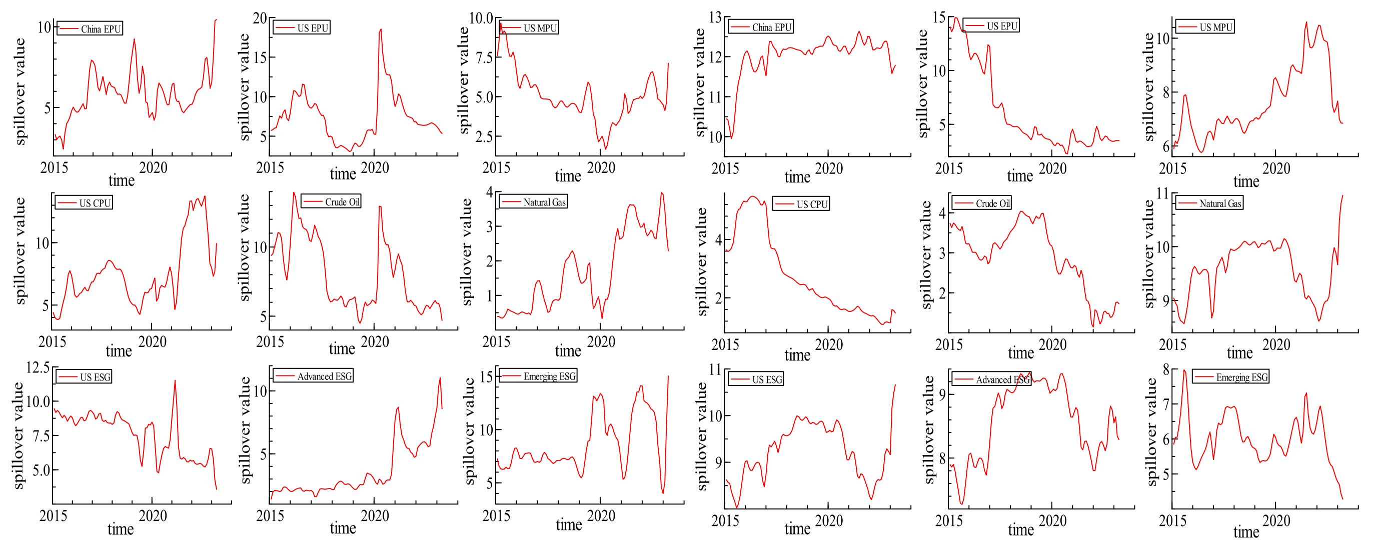
This phenomenon indicates that critical social disruptions that occur frequently such as regional turbulence, regime change, natural calamities, trade disputes, and the pandemic introduce destabilizing factors to the global economy and financial markets. These irregular events can aggravate short-term economic turmoil. However, with the rapid development of economic globalization and regional economic integration, the global economy is also entering new phases of comprehensive cooperation. Governments worldwide have achieved an unprecedented level of tangible, global economic cooperation, while also acting in unison to address the threat posed by climate change. In this regard, the risk caused by the numerous irregular events can be effectively controlled in the short and long run.

As shown in Fig. 19, low-frequency asymmetrical risk spillover has heterogeneous characteristics, wherein the negative risk of policy uncertainty is relatively higher, particularly for China's EPU. The irregular inverted U-shaped asymmetrical risks all reveal differing policy uncertainties; however, the positive risk is relatively large in fossil fuel energy markets. Furthermore, the asymmetrical risks of crude oil market fluctuations rose around 2020. Notably, the asymmetrical risks of natural gas gradually decreased to a low point in 2020, and a rapidly rising risk trend emerged between 2022 and 2023. Moreover, the positive risk of the US ESG investment gradually decreased between 2015 and 2022 and rose in 2023. The negative risk of US ESG investment was relatively stable between 2015 and 2021 and rose sharply between 2022 and 2023. In addition, the asymmetrical risks of advanced ESG investment decreased steadily between 2015 and 2023, and the positive risk of emerging ESG investment remained high between 2015 and 2023, and a



Panel a: risk spillovers to other variables in a high-volatility state Panel b: risk spillovers to other variables in a low-volatility state

Fig. 12. Policy uncertainty, fossil energy, and ESG investment's high-frequency risk spillovers to other variables with a two-state Markov chain.



Panel a: risk spillovers to other variables in a high-volatility state Panel b: risk spillovers to other variables in a low-volatility state

Fig. 13. Policy uncertainty, fossil energy, and ESG investment's low-frequency risk spillovers to other variables with a two-state Markov chain.

negative risk of emerging ESG investment was found in 2017 and 2023.

These findings indicate that the global economy has continued to decline since 2015, with a considerable impact on the global macroeconomy and financial markets. In this regard, led by the US, developed economies independently launched expansionary quantitative easing monetary policies to address economic stagnation, inflation, and employment difficulties and prevent the continued proliferation of crises. However, such policies may affect the direction and scale of the market economy and financial flow around the world, causing cyclical fluctuations in currency markets and asset prices, and inducing systemic financial risks. The COVID-19 pandemic that swept across the world in 2020 increased the probability of an economic crisis. The US Federal Reserve's subsequent continued aggressive interest rate hike policy exposes the global economy to the risk of stagflation and exposes emerging economies to the risk of currency depreciation, inflation, economic recession, and sovereign debt crisis. Therefore, systemic risk in global energy markets will become more prominent, increasing policy uncertainty in response to extreme climate change and policies for energy transformation.

As seen in Fig. 20, the high-frequency asymmetrical risk spillovers to the other variables consistently present irregular inverted U-shaped forms. The asymmetrical risks from China's EPU economic policy to other variables began to decline after 2017, while negative risk spillover was relatively higher. Furthermore, a low-stake positive risk from the US EPU to other variables has occurred since 2017; therefore, the primary risk is concentrated in negative spillovers. The asymmetrical risks from the US MPU to other variables have remained at a high level since 2017, and similar results also appeared in the asymmetrical US CPU spillovers. Moreover, positive high-risk from the crude oil market to other variables ranged from 2016 to 2019, while negative high-risk ranged from 2016 to 2022, and the positive risk from the natural gas market to other variables behaved even more remarkably. Nevertheless, asymmetrical risks from US ESG investment to other variables declined to a low position after 2020, while the positive risk from advanced ESG investment to other variables has been high since 2016. Finally, the most prominent negative spillover was that of risk in emerging ESG investment to other

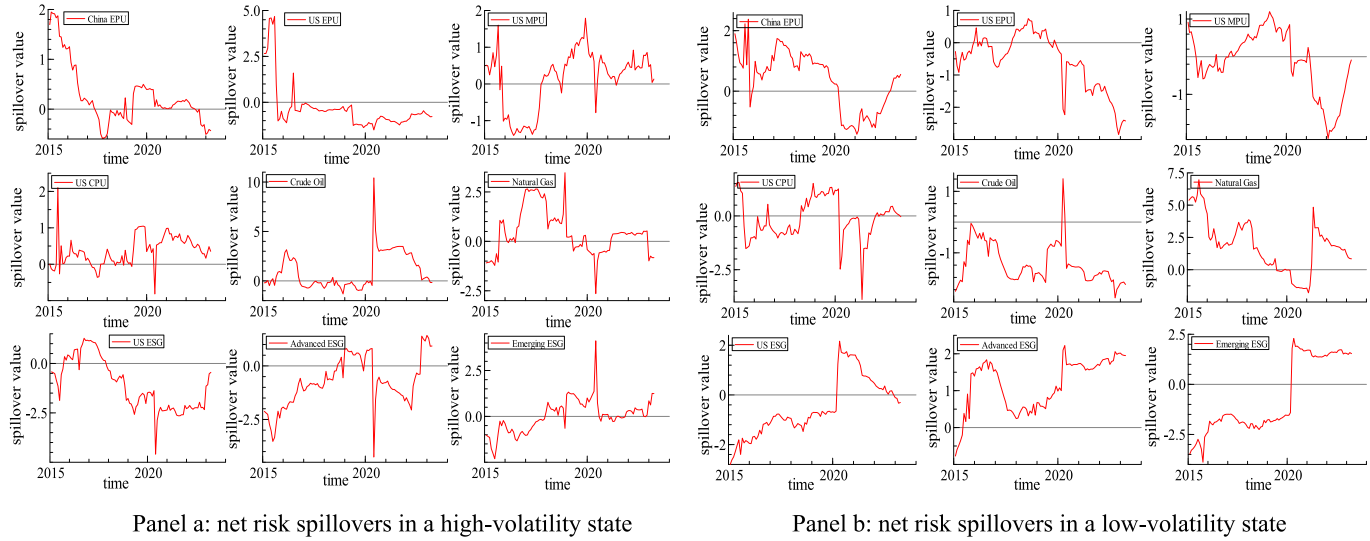


Fig. 14. Policy uncertainty, fossil energy, and ESG investment's high-frequency net risk spillovers with a two-state Markov chain.

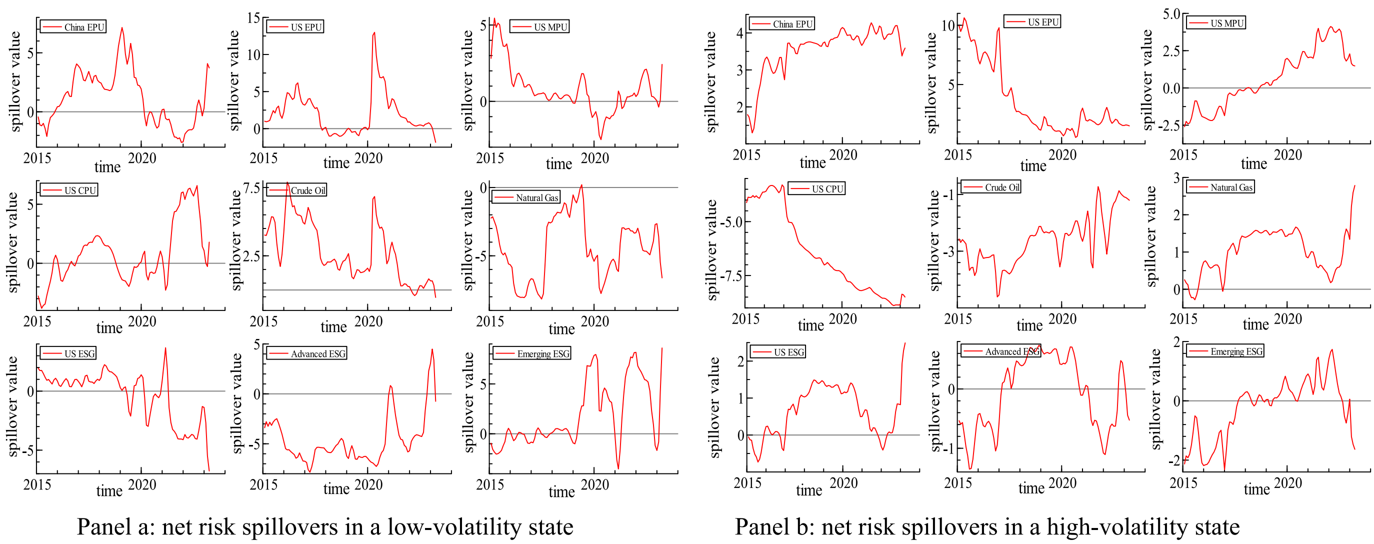


Fig. 15. Policy uncertainty, fossil energy, and ESG investment's low-frequency net risk spillovers with a two-state Markov chain.

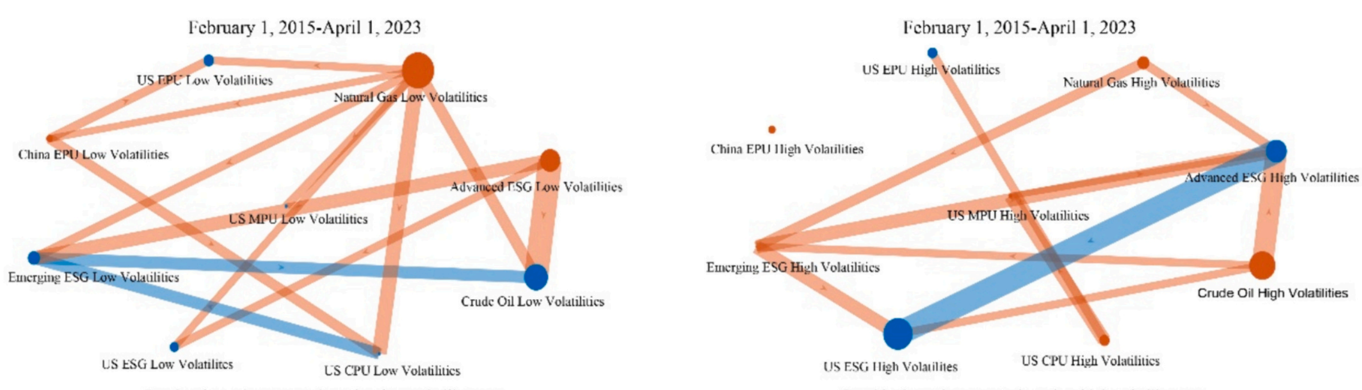


Fig. 16. Policy uncertainty, fossil energy, and ESG investment's high-frequency dynamic connectedness with a two-state Markov chain.

variables.

The findings indicate that quantitative easing policies in the US and other developed economies since 2015 have considerably increased global inflation and asset prices expanded rapidly. The interest rate hike implemented by the US Federal Reserve to curb the negative impact of inflation once again tightened the global financial environment, causing

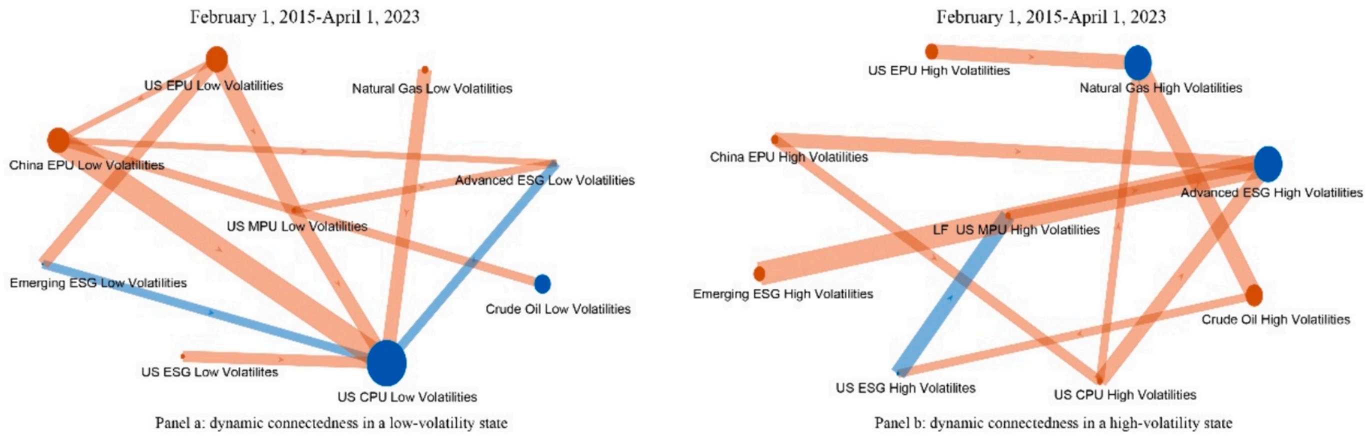


Fig. 17. Policy uncertainty, fossil energy, and ESG investment's low-frequency dynamic connectedness with a two-state Markov chain.

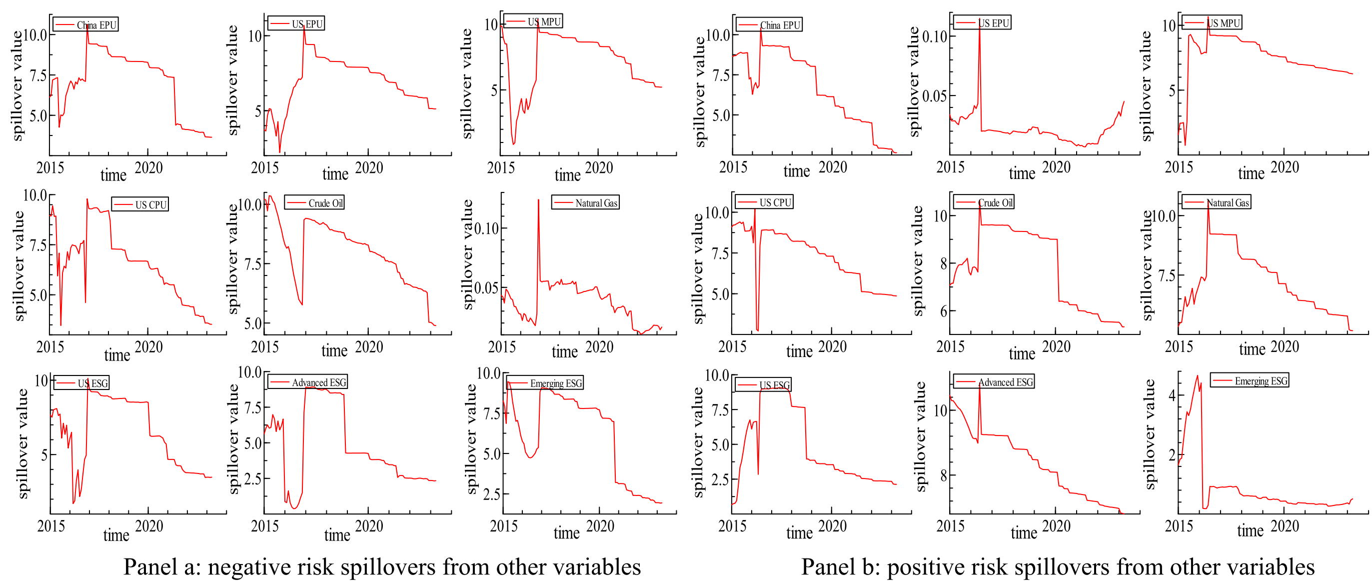


Fig. 18. Policy uncertainty, fossil energy, and ESG investment's high-frequency asymmetric risk spillovers from other variables.

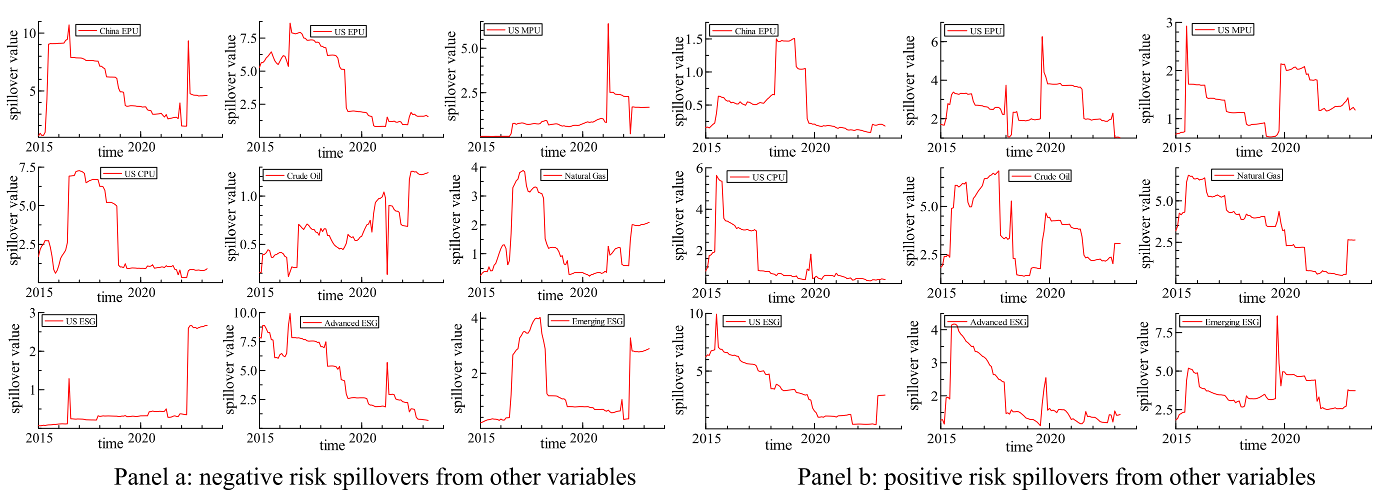


Fig. 19. Policy uncertainty, fossil energy, and ESG investment's low-frequency asymmetric risk spillovers from other variables.

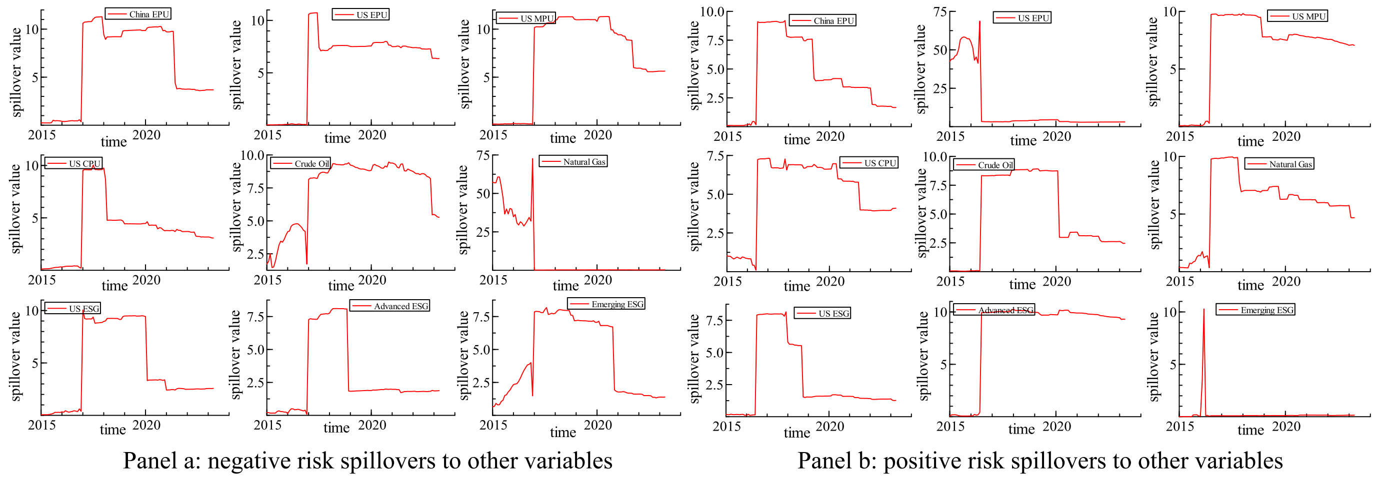


Fig. 20. Policy uncertainty, fossil energy, and ESG investment's high-frequency asymmetric risk spillovers to other variables.

short-term capital flow back to developed economies with high interest rates. However, emerging economies and high-debt countries are challenged by issues such as liquidity shortages, debt deterioration, and secondary social crises. In addition, global energy supply and demand are severely unbalanced, which may evolve into a short-term energy crisis. Hence, some countries with high debt and weak financial risk resistance may be the first to be exposed to financial risks from related economies, which may lead to regional or even global spillovers. However, with the US and Europe approaching the end of tightened monetary policy overall, volatility in developed economies has correspondingly decreased, and risk spillovers to the global economy have weakened. In an environment of global economic recovery, global energy transformation, climate governance, and cooperation are expected to improve.

As shown in Fig. 21, the low-frequency asymmetrical risk spillovers to other variables presented heterogeneous characteristics. The positive risk from China's EPU to other variables became extremely weak after 2020, while the negative risk first reduced between 2017 and 2021 and rose again between 2022 and 2023. Similarly, the risk from US EPU to other variables declined after 2020, but the positive risk remained significant. By comparison, low asymmetrical risks from the US MPU to other variables occurred, and high asymmetrical risks from the US CPU to other variables were only significant between 2016 and 2017. Moreover, asymmetrical risk spillovers from the natural gas market to other variables were generally larger than those from the crude oil market. The risk from US ESG investment was mainly concentrated in positive spillovers. The asymmetrical risk spillovers from the advanced ESG investment to other variables declined rapidly after 2017, with those from emerging ESG investment to other variables rising quickly after 2022.

The findings indicate that economic globalization has encountered a backlash since 2015, as trade protectionism and geopolitical games continued to intensify, curbing the momentum of world economic growth, and adding more uncertainty to the prospects of economic recovery worldwide. The COVID-19 pandemic prompted European and American countries to implement extraordinary stimulus policies to promote rapid economic resilience, which reduced the impact of the pandemic on enterprises and residents and the unemployment rate. However, the marginal effect of these stimulus policies is diminishing. For instance, massive quantitative easing policies resulted in excess liquidity, which generated price increases and structural labor shortages driving up wage levels, and forcing the US Federal Reserve to accelerate the pace of tightening monetary policy. If emerging economies do not respond adequately to the Federal Reserve's tightening policies and potential economic turmoil, multiple impacts such as capital outflow and increased debt burdens could occur. This may trigger a repricing of global financial assets and further increase global financial system risks. In addition, the European Central Bank announced more measures to incorporate climate change factors into the euro monetary policy framework to reduce financial risk related to climate change and green economic transformation. In addition, the European Central Bank will introduce climate change factors in corporate bond purchases, collateral

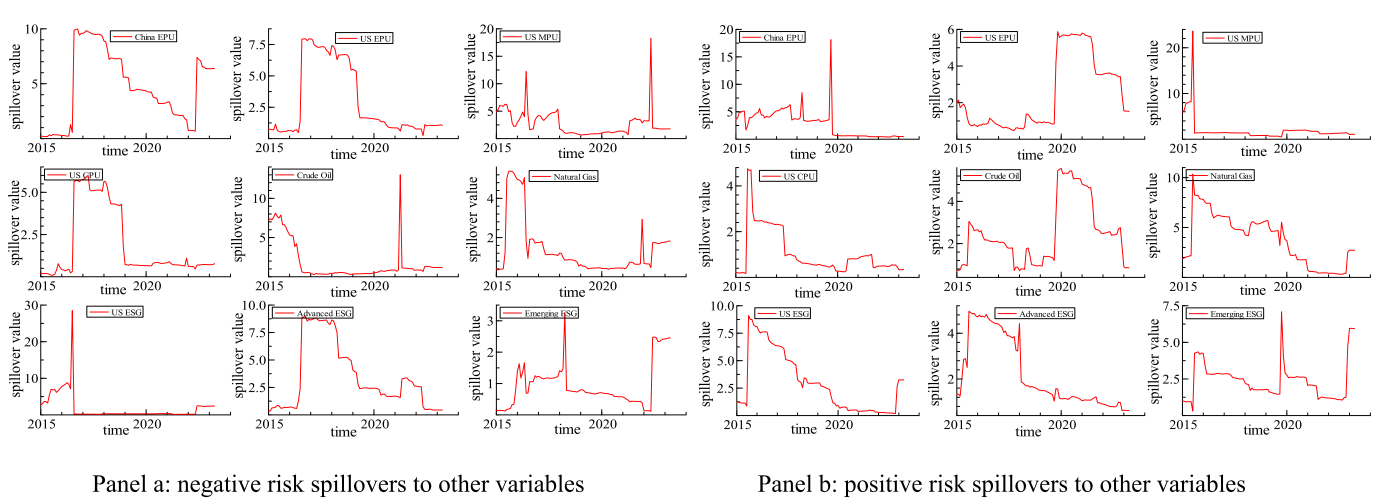


Fig. 21. Policy uncertainty, fossil energy, and ESG investment's low-frequency asymmetric risk spillovers to other variables.

frameworks, disclosure requirements, and risk management to reduce financial risks related to climate change on assets and liabilities, maintain price stability in the euro system, support green economic transformation, and promote a positive trend in the global economy.

As shown in Fig. 22, similar features are presented in the high-frequency components of asymmetrical net spillovers. The positive net spillover of natural gas and emerging ESG investment was extremely weak after 2020, while the asymmetrical net spillover of China's EPU and US CPU was approximately the same. A similar conclusion is found for the asymmetrical net spillovers of US MPU and the natural gas market. Furthermore, a higher positive net spillover of crude oil and advanced ESG investment was sustained after 2020. The negative net spillover of US EPU and crude oil rose slowly between 2018 and 2022, with similar findings from US MPU between 2017 and 2020. However, a steadily increasing trend of negative net spillover from EGS investment (US and advanced economies) emerged after 2020. Moreover, the negative net spillover of the emerging ESG investment was very weak after 2016.

As shown in Fig. 23, the low-frequency asymmetrical net spillovers demonstrate heterogeneous characteristics. More positive net spillovers of China's EPU, natural gas, and advanced ESG investment were revealed between 2015 and 2019, while noticeable negative net spillovers emerged from US EPU and the crude oil market. However, the situation reversed between 2020 and 2022. Furthermore, emerging ESG investment experienced negative net spillovers between 2015 and 2022, and a positive net spillover occurred in the US MPU in 2015, becoming extremely weak after that. Finally, a negative net spillover of the US CPU occurred between 2015 and 2023.

As shown in Fig. 24, unlike previous research findings that irregular risks in the global energy–stock system usually transform one another (Rehman et al., [87], Yang et al., [88]), the results reveal that patterns of asymmetrical dynamic connectedness from the high-frequency component are broadly similar. That is, the core positive risks all originate from US EPU. The crude oil market is the most affected variable, followed by US CPU, and ESG investment (US and advanced economies) are seriously affected, whereas China's EPU and natural gas are less affected. Furthermore, the natural gas market became the central risk for negative spillovers to other variables. The negative spillover strength of policy uncertainty (China's EPU and US CPU) and ESG investment (US and emerging ESG) were also relatively higher.

As shown in Fig. 25, complicated risk spillovers occurred between policy uncertainty, fossil fuel energy, and ESG investment, with alternating positive and negative trends throughout the low-frequency component, as shown in previous research (Pham et al., [89], Sarker et al., [90], [46–48]), Wu and Qin [91]). Low-frequency asymmetric dynamic connectedness exhibited different characteristics. The positive risk from China's EPU had a direct impact on the US EPU, and the higher risk was transferred to the emerging ESG investment. In contrast, a positive risk from China's EPU was demonstrated for the US MPU and the natural gas market. Therefore, these dual risks ultimately had a significant effect on US ESG investment. Furthermore, the accumulated positive risk transmitted from US ESG investment was directly passed to US EPU, with considerable impact. Furthermore, the negative risk from the US MPU imposed a massive amount of risk on ESG investment (emerging and advanced economies) and strengthened the risk of policy uncertainties (China's EPU, US EPU, and US CPU). In addition, negative spillover from traditional energy markets (crude oil and natural gas) simultaneously transmitted risk to the US and China's EPU. Moreover, negative spillover was transmitted directly from the US ESG investment to China's EPU and US EPU and CPU.

Fig. 26 displays the common factor of policy uncertainty, fossil fuel energy, and ESG investment's time-frequency risk spillovers from other variables with high volatility state. Affected by common nonsystematic risks, the ESG stock market has a higher overall degree of policy uncertainty and contagion of fossil energy risks during the sample period. In addition, the uncertainty of economic policies between China and the United States has seen a significant increase in risk spillovers from the fossil fuel energy market and the ESG stock market in 2020. Affected by systemic risks, the ESG stock market received a high level of risk spillovers from policy uncertainty and fossil fuel energy markets before 2018, and then it rapidly declined. After 2020, the uncertainty of US climate policy is most affected by external factors.

Fig. 27 reveals common factors of policy uncertainty, fossil fuel energy, and ESG investment's time-frequency risk spillovers to other variables with high volatility state. Affected by common non-systematic risks, the crude oil market has the greatest risk spillover to policy uncertainty and the ESG stock market. Followed by the global ESG stock market. Affected by systemic risks, The crude oil market and policy uncertainty jointly generate significant risk spillovers on the global ESG stock market.

Fig. 28 reveals the common factors of policy uncertainty, fossil fuel energy, and ESG investment's time-frequency net risk spillovers with high volatility state. Under the high-frequency component, the crude oil market and emerging ESG stock markets are both the emitters of risk. However, the crude oil market and the economic policy uncertainty are both the sender of risks under the low-frequency component.

with high volatility state.

Fig. 29 demonstrates the policy uncertainty, fossil fuel energy, and

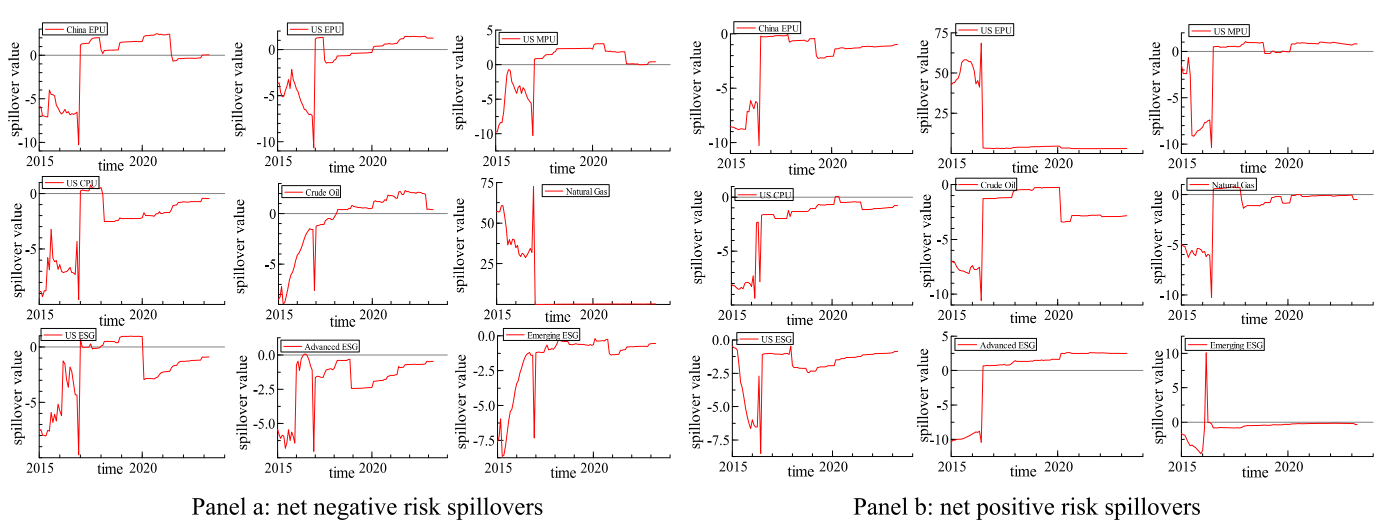
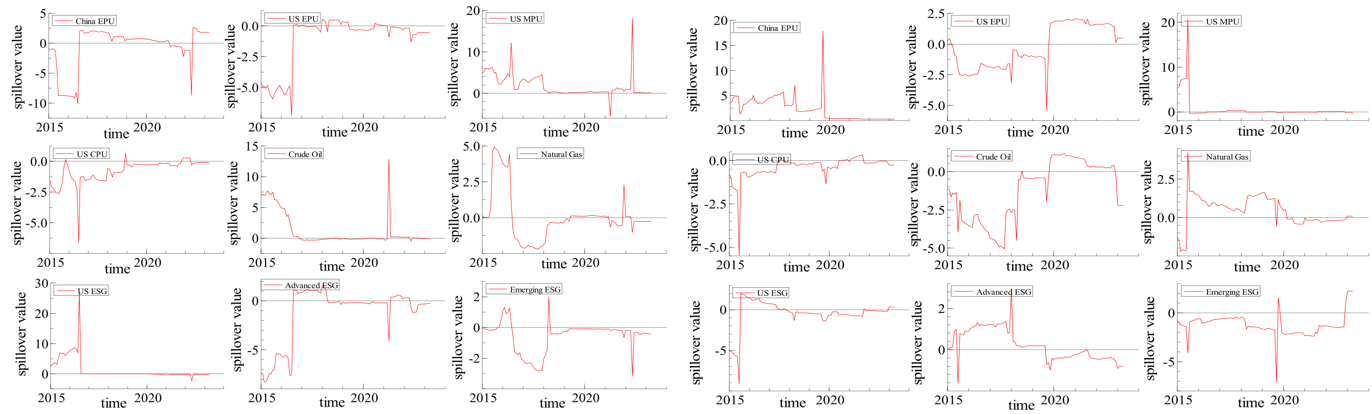


Fig. 22. Policy uncertainty, fossil energy, and ESG investment's high frequency asymmetric net risk spillovers.



Panel a: net negative risk spillovers

Panel b: net positive risk spillovers

Fig. 23. Policy uncertainty, fossil energy, and ESG investment's low frequency asymmetric net risk spillovers.

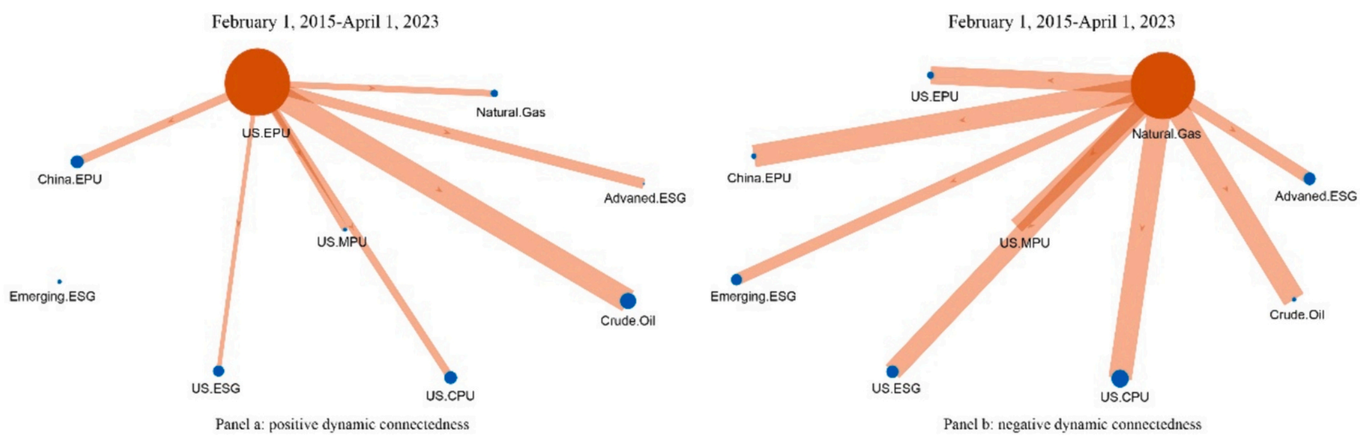


Fig. 24. Policy uncertainty, fossil energy, and ESG investment's high frequency asymmetric dynamic connectedness.

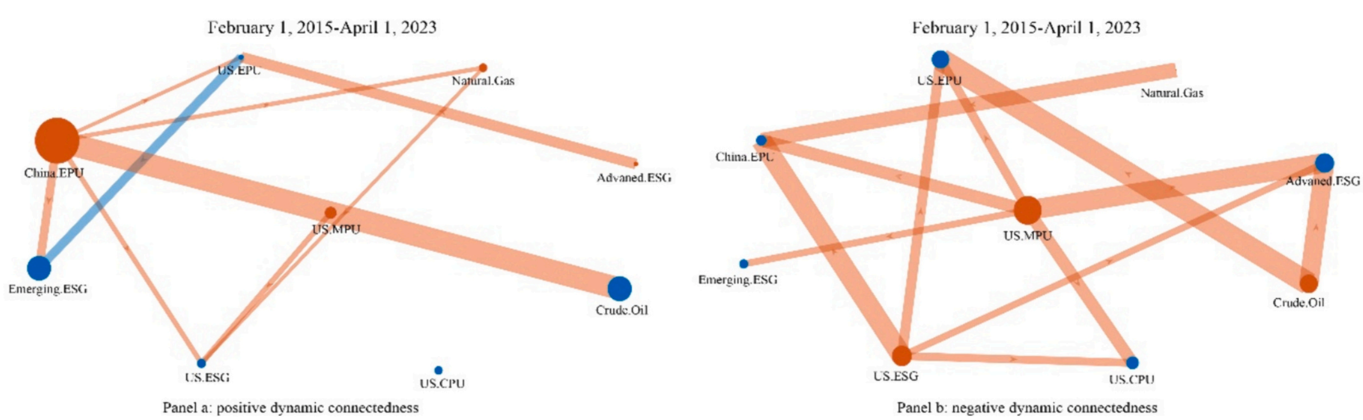


Fig. 25. Policy uncertainty, fossil energy, and ESG investment's low frequency asymmetric dynamic connectedness.

ESG investment's time-frequency common factor under high volatility state. Contrary to Umar et al., [92] findings, when considering common factors, the US economic policy uncertainty can directly transmit non-systemic risk and systemic risk to the advanced economy ESG investments. In addition, risks originating from the crude oil market can also be directly transmitted to global ESG investments (Hanif et al., [93], Malik and Umar [94], Yousaf et al., [95]).

6. Policy implication

To address the risk spillovers in macroeconomic regulation of the global economy, governments worldwide should actively enhance risk warning measures, publicize effective policy information, and strengthen the information of communication with the market to enhance the openness and predictability of policy formulation. It is also essential to coordinate the tools for regulating macroeconomic policies, establish clear control and response systems, and avoid the risk of

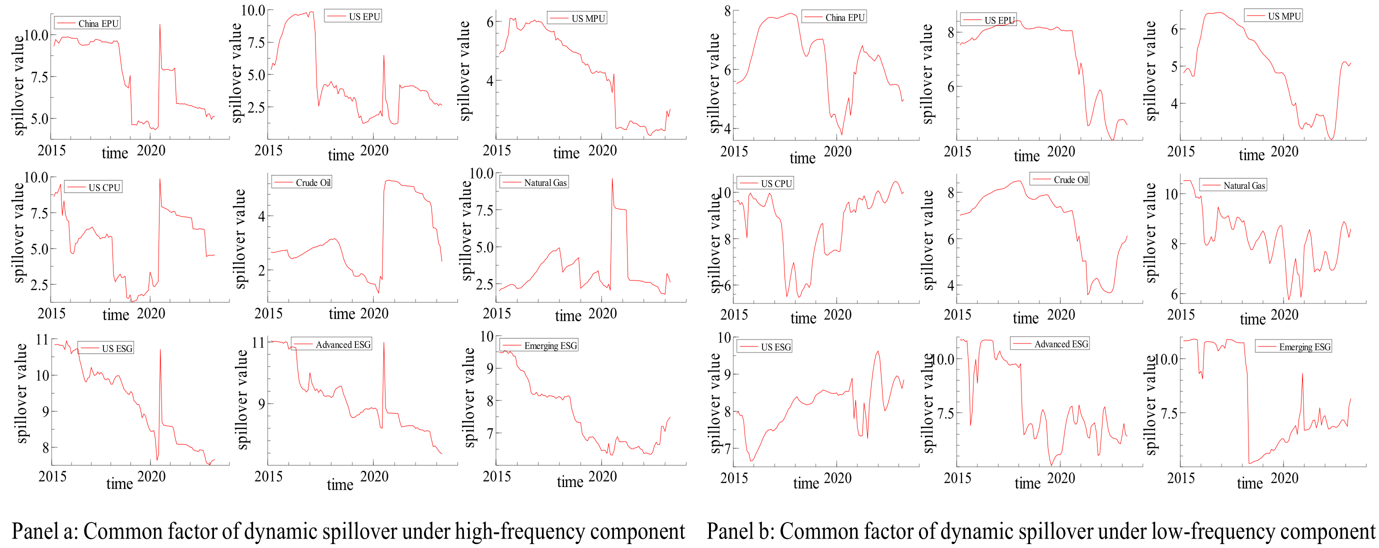


Fig. 26. Common factor of policy uncertainty, fossil energy, and ESG investment's time-frequency risk spillovers from other variables with high volatility state.

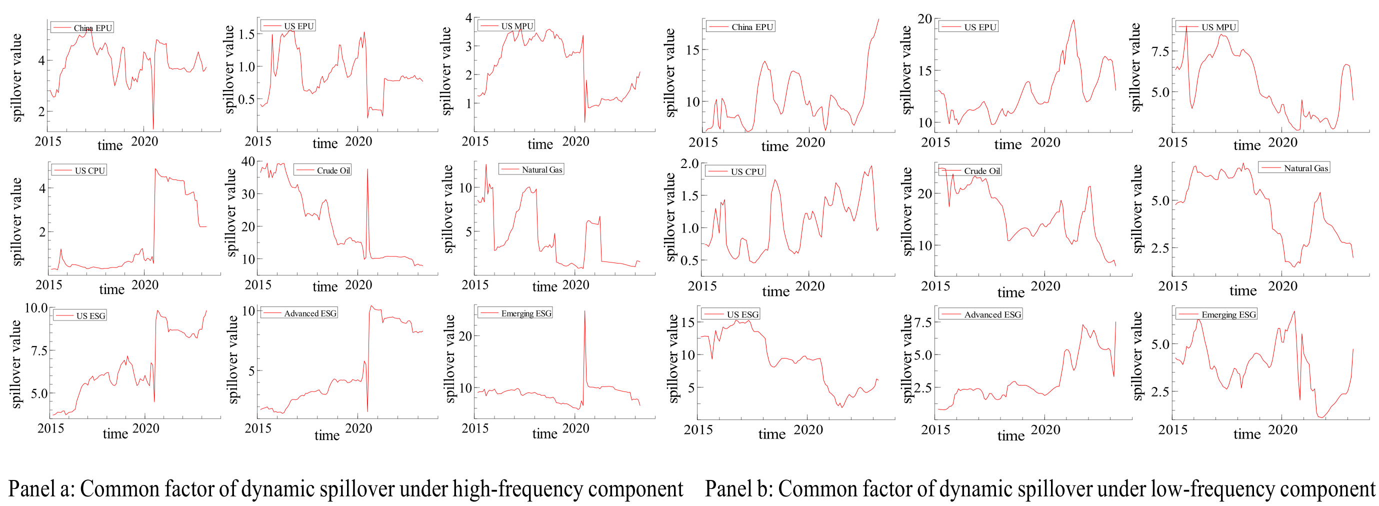


Fig. 27. Common factor of policy uncertainty, fossil energy, and ESG investment's time-frequency risk spillovers to other variables with high volatility state.

uncertainty between different policy measures. In addition, based on the characteristics of government debt and changes in fiscal pressure under multidimensional uncertainty shocks, governments should fully leverage the complementarity and coordination mechanisms among policy tools, provide time windows or buffer mechanisms for different policy implementation, and ensure continuity, stability, and sustainability of macroeconomic policies after uncertainty shocks occur.

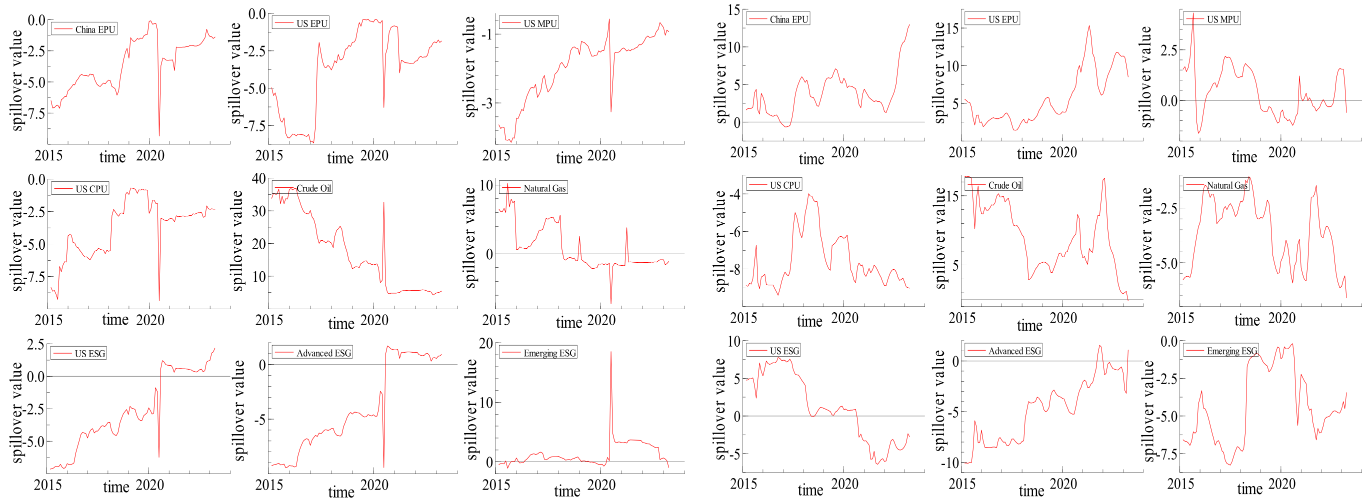
Multiple measures should be taken simultaneously to prevent risks in the world's energy supply system and promote the efficient use of global energy reserves. Such measures could include increased exploration and development efforts of oil and gas industries in various countries around the world, promoting increased oil and gas reserves and production, and accelerating oil and gas production, supply, storage, and sales systems development. Finally, nations should establish large-scale underground gas storage groups across regions to enhance and maintain oil and gas self-sufficiency.

To better prevent and navigate the emerging risks and uncertainties related to sustainable green finance, the international community must transform financing mechanisms into green models and further standardize the issuance and approval processes of green financing tools. Continuous supervision of green credit and green bonds throughout the entire cycle should be established and strengthened, and default standards must also be set for sustainable linked financing products. Financial institutions conducting credit business should also consider incorporating ESG indicators into green credit ratings and default risk warnings.

7. Conclusion

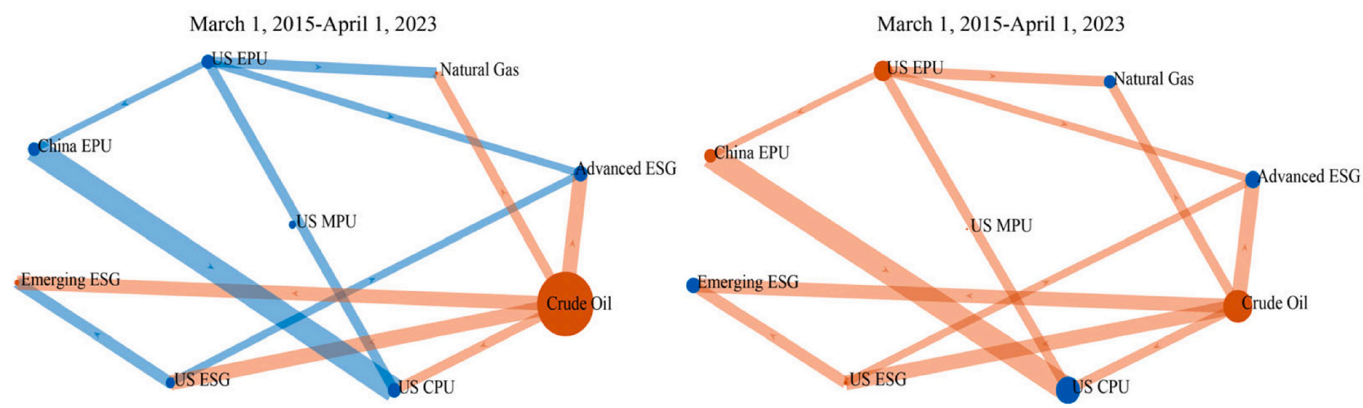
Since economic growth is full of uncertainty and risk and subject to multiple crises, the spillover effects of policy uncertainty, fossil fuel energy markets, and global ESG investment exhibit heterogeneous characteristics. Therefore, time-frequency components can be distinguished by introducing TVF-EMD and the PCC. Based on this, we combined the MS-VAR embedded with the FIAPARCH with the asymmetric TVP-VAR variance decomposition, constructing a high-dimensional network based on a VAR-CF model to accurately determine asymmetric time-frequency spillover effects. The main conclusions are fourfold.

First, when the economy runs smoothly, changes in crude oil and natural gas prices can still impose risks to global ESG investment. Second, during economic downturns, risks from US EPU can directly or indirectly intensify global ESG investment. With the global economic recession, risks from China's EPU and crude oil market can indirectly



Panel a: Common factor of dynamic spillover under high-frequency component Panel b: Common factor of dynamic spillover under low-frequency component

Fig. 28. Common factor of policy uncertainty, fossil energy, and ESG investment's time-frequency net risk spillovers with high volatility state.



Panel a: Common factor dynamic connectedness under high-frequency component Panel b: Common factor dynamic connectedness under low-frequency component

Fig. 29. Policy uncertainty, fossil energy, and ESG investment's time-frequency common factor dynamic connectedness.

cause large fluctuations in advanced economies' ESG investment. Third, when facing irregular events, US EPU can impose positive risks, and the strongest source of the negative spillover is the natural gas market. Thirdly, confronted with extreme events, positive risks from China's EPU can be indirectly delivered to emerging economies' ESG investment. Moreover, the US MPU can exert a negative spillover to global ESG investment. Finally, when facing common higher risks, the crude oil market can be considered the main source of spillover to global ESG investment.

Based on our findings, we propose prospects for navigating future policy uncertainty and risk spillovers between fossil fuel energy and ESG stock markets. First, the selection of international financial markets to be tested should be expanded. Second, the improved wavelet model can be combined with other nonlinear neural network models to accurately simulate the risk spillover of complex data features in the international financial market. Finally, the long-term asymmetric multivariate GARCH family model combined with the MS-VAR quantile autoregressive model or copula model can be further applied using extreme point theory to investigate the multiple channels and underlying causes of risk spillovers in international financial markets.

CRediT authorship contribution statement

Ling Lin: Writing – review & editing, Writing – original draft, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yong Jiang:** Supervision, Resources, Methodology, Investigation, Funding acquisition. **Zhongbao Zhou:** Supervision, Software, Methodology, Investigation.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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