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Assessing energy sector resilience to adverse shocks: A scenario-based QVAR approach[☆]

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ABSTRACT

Global energy sectors face heightened uncertainty due to effects of major global events, volatile energy prices, and geopolitical risks. To better understand how these factors affect energy sectors, this paper examines 14 key energy sectors worldwide, analyzing their resilience to shocks from oil, natural gas, and coal prices over the sample period from January 2006 to August 2024. Specifically, we propose a scenario-based approach based on QVAR model to measure time-varying resilience from the perspectives of intensity and duration. Additionally, we explore how economic policy uncertainty (EPU), geopolitical risks (GPR) and market volatility (VIX) influence energy sectors' resilience. Results show that the resilience indices effectively capture the energy sector's ability to withstand extreme shocks. Major events like Russia–Ukraine conflict and COVID-19 pandemic significantly alter both intensity and duration of resilience. Influence factor analysis reveals that increases in EPU, GPR, and VIX weaken resilience by reducing intensity and increasing duration, with the most pronounced impact observed in the sharp price fluctuations of oil and gas driven by rising GPR. The findings provide timely insights for policy adjustments to stabilize energy markets and guide investment strategies to mitigate potential risks.

1. Introduction

Global energy sectors are currently navigating a period of significant uncertainty. The lingering effects of COVID-19 on inflation, employment, and supply chains have yet to subside (Lin and Su, 2021; Gong et al., 2022; Sun et al., 2023). Regional conflicts like the Russia–Ukraine war have further exacerbated the situation (Lin and Ullah, 2024; Zheng et al., 2024b). Additionally, rapid shifts in international relations and fluctuations in the supply of critical energy resources, such as crude oil, natural gas, and coal, have had a profound impact on the energy sectors of many countries (Lin et al., 2024; Xu et al., 2024; Wang et al., 2020; Liu and Li, 2018). Moreover, the increase in geopolitical risks (GPR) and economic policy uncertainty (EPU) has posed significant challenges to the stability of the energy sector (Lin and Zhao, 2023; Khan et al., 2023; Zheng et al., 2024a). In this context, assessing the impact of adverse shocks on the energy sector has become a critical issue that demands immediate attention. Such analysis not only facilitate the identification of systemic vulnerabilities but also provides policymakers with empirically validated frameworks to enhance macroeconomic resilience.

Against this backdrop, the escalating impacts of geopolitical risks, economic policy uncertainty, and market volatility (VIX) on energy sector stability have become a pressing concern. Specifically, (Soybilgen et al., 2019) argued geopolitical tensions may disrupt the energy supply chain, distorting the market. Banna et al. (2023) showed political unrest, like that from territorial disputes, could have long-term energy market effects. Yilmazkuday (2024) found rising global geopolitical risks raise long-term energy uncertainties. Regarding economic policy uncertainty, scholars revealed its significant link to carbon emissions (Adams et al., 2020; Anser et al., 2021; Adedoyin et al., 2021). Wei et al. (2021) indicated stationarity and cointegration between EPU and energy production, while Erzurumlu and Gozgor (2022) showed EPU impacts per capita final energy consumption. For market

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volatility, Shaikh (2022) noted investors in the energy market are more volatile during tail events. Past research showed the U.S. VIX affects crude oil price swings (Liu et al., 2023; Dutta et al., 2021), and Bianconi and Yoshino (2014) found VIX key in explaining energy firm earnings changes. Clearly, these factors significantly influence the energy sector, and thus studying how their fluctuations affect energy sector risks is of great practical and academic value.

While these studies have established robust correlations between macro-risk factors and energy markets, a critical gap remains in understanding the nonlinear dynamics of extreme shock propagation. Specifically, the extant literature leaves two questions unanswered: *to what extent* and *for how long* will the energy sector be affected by *extreme adverse shocks*? To address this, a comprehensive quantitative framework is required, along with one or more robust indicators. A closely related concept is "*resilience*", which originates from physics, engineering, and materials science, and aims to capture both the severity and duration of a sector's response to adverse shocks. In recent years, particularly after 2010, the concept of resilience has gradually been applied to the field of economics. Resilience is assessed by the capacity of an economy to recover from exogenous shocks, reflecting its potential for adaptation and adjustment in the face of unforeseen disturbances (Martin and Sunley, 2015, 2020). Researchers have used this framework to model economic systems, in order to assess the impact of various shocks on different economic variables within the system, including the regional (Sensier et al., 2016) and country-level economic growth (Diop et al., 2021), energy sector (Dong et al., 2021), urban-rural income gap (Lin and Wang, 2024), and firm performance (Sun et al., 2024).

However, after reviewing the existing literature, we identify at least three limitations that make it difficult to address the aforementioned question. First, most current studies focus primarily on the impact of carbon emissions on the resilience of the energy sector (Dong et al., 2021; Nepal et al., 2024), with few examining the shocks on the supply and demand sides, such as the effects of crude oil and natural gas shocks on energy resilience. In fact, these short-term and sharp fluctuations may pose even greater challenges to the resilience of the energy system. This paper focuses on 14 key energy sectors globally, specifically examining their resilience in response to shocks originate from the crude oil, natural gas, and coal prices.

Moreover, existing studies primarily examine relationships between variables at their conditional means within economic systems. However, mean-based analyses often overlook the heterogeneous and asymmetric responses that emerge during major events (Adrian et al., 2019; Zheng et al., 2023a; Lv et al., 2024). When assessing energy resilience, it is crucial to capture how different sectors withstand extreme shocks and to evaluate the impacts across the entire distribution, particularly in the tails. To address these challenges, we employ a quantile vector autoregression (QVAR) model to construct a high-dimensional system encompassing energy sectors and major energy prices, including crude oil, natural gas, and coal. The choice of QVAR is motivated by its ability to model the full conditional distribution of responses rather than focusing solely on the mean. As emphasized by Ando et al. (2022), QVAR effectively identifies asymmetric and heterogeneous effects often missed by traditional approaches. Given our focus on extreme conditions and tail risks, QVAR offers a more nuanced and comprehensive framework for analyzing how energy sector resilience differs across various extreme conditions.

Furthermore, the relationships between economic variables within an economic system often undergo structural changes (Gong et al., 2022; Zheng et al., 2023b; Zhang et al., 2024). These relationships can vary significantly during major events, such as COVID-19 and the Russia–Ukraine conflict. Failing to account for these differences in time may lead to an overestimation of the resilience of energy sectors. Therefore, it is essential to thoroughly examine these variations over time. This paper identifies different scenarios faced by energy sectors at various time points by positioning them within different conditional quantiles. This allows us to thoroughly examine how the resilience of energy sectors changes across different scenarios.

The main contributions of this paper lies in three aspects: model specification, indicator measurement, and empirical analysis. In terms of model specification, we build on the ideas of Chavleishvili and Manganelli (2024) and Yang et al. (2024) by incorporating 14 energy sectors, along with crude oil, natural gas, and coal commodities, into a QVAR system. The QVAR model captures their contemporaneous and intertemporal dependencies across different quantiles, particularly in extreme scenarios. Given the established role of the 1% quantile in assessing extreme tail risks within the Value-at-Risk (VaR) framework (Wu and Yan, 2019; Taylor, 2008), this study emphasizes the 1% quantile to more precisely evaluate the extreme risks associated with potential 'black swan' events in nonlinear systems. Based on this, We propose a simulation-based method for calculating impulse response functions. These impulse response functions effectively capture the reactions of different conditional quantiles of various energy sectors to extreme idiosyncratic shocks, such as supply-side or demand-side disruptions in crude oil, natural gas and coal.

The second contribution of this paper lies in the development of a scenario-based approach to measure the time-varying resilience of energy sectors. Inspired by Ando et al. (2024), we derive the scenario for the system's economic variables at a given time point by identifying the specific quantiles for each energy sector and the shock-originating variables. Based on this, we examine the impulse response functions of the shock variables and energy sectors across various quantiles, selecting the most extreme cases, then derive time-varying resilience indicators for energy sectors. Focusing on two dimensions: intensity and duration, results demonstrate that the estimated resilience indicators for energy sectors can accurately and promptly capture shifts in the resilience during major events.

The third major contribution of this paper stems from our empirical findings. Building on the previously discussed methodology and indicator construction, we thoroughly examine the resilience of energy sectors under extreme shocks in crude oil, natural gas, and coal prices. Furthermore, we conduct panel regressions to investigate the effects of factors such as economic policy uncertainty, geopolitical risks, and market volatility on the resilience of energy sectors. The results of the resilience measurement indicate that the scenario-based time-varying metric effectively captures the energy sector's capacity to resist extreme events in a timely and precise manner. Under major shocks such as the Russia–Ukraine conflict and the COVID-19 pandemic, resilience across different energy sectors weakened, manifesting as reduced intensity and prolonged duration. During the Russia–Ukraine conflict, the most affected energy sectors concentrated in countries with generally lower resilience, while the impact of the COVID-19 pandemic was more widespread, leading to a broader, more generalized weakening of resilience across energy sectors. Moreover, the influencing factor analysis demonstrates that rising in EPU, GPR, and VIX also have a negative impact on resilience of energy sectors.

Measuring and analyzing the resilience of energy sectors during extreme scenarios is valuable for both policymakers and investors. For policymakers, having accurate and timely insights into the resilience of energy sectors enables targeted policy adjustments that can help prevent severe energy market volatility from triggering systemic economic risks. For investors, being able to detect shifts in energy sector resilience allows them to adjust their investment strategies accordingly, making it more effective to anticipate and mitigate potential risks in the energy market.

The remainder of this paper is organized as follows: Section 2 provides a literature review, covering the concept of resilience, its measurement methods, and influencing factors. Section 3 presents descriptive statistics of the data, and further substantiate the motivation through quantile Granger causality tests. Section 4 introduces the proposed methodology, focusing on the measurement of simulation-based quantile impulse response and scenario-based time-varying resilience. Section 5 discusses the empirical findings, analyzing the model estimates, resilience measurement results, and the factors affecting resilience. Section 7 offers concluding remarks.

2. Literature review

This section first reviews the relevant literature to clarify the theoretical concept of resilience. We then examine existing studies on methodologies for measuring resilience, and finally, summarizes the literature on the influencing factors of resilience.

2.1. Theoretical foundation of resilience

Resilience is generally defined as the ability of an entity or system to respond to and adapt in the face of external shocks and disturbances. However, its interpretation varies across disciplines, with its meaning shifting depending on the specific context (Evans and Karecha, 2014). As a result, resilience theory has evolved into a complex framework encompassing various attributes, interpretations, and methodologies.

Resilience theory originally emerged in the fields of physics, engineering, and materials science. In physics, resilience refers to the maximum energy a solid material can absorb while undergoing plastic deformation under external stress. It typically denotes a system or material's capacity to withstand external disturbances and return to its initial or equilibrium state (Berkes and Folke, 1998). Over time, resilience theory expanded into ecology and psychology. In ecology, resilience refers to an ecosystem's ability to recover from disturbances, focusing on its capacity to absorb, adapt to, and respond to external shocks. This concept describes an ecosystem's resistance and recovery potential when facing human-induced or natural disasters (Hopkins, 2008; Olsson et al., 2015; Meyer et al., 2018).

While the concept of resilience is well-established in the aforementioned disciplines, its application in economics emerged relatively late. Before 2010, economic resilience remained in the conceptual stage, with no unified understanding in the field. Definitions at the time primarily borrowed from engineering and ecology, describing an economic system's ability to withstand shocks and return to equilibrium post-shock (Briguglio, 2004). Since 2010, although a comprehensive theoretical framework for economic resilience has yet to fully develop, significant progress has been made. Many scholars now argue that economic resilience refers to an economy's ability to recover swiftly from shocks, reallocate resources, adjust its industrial structure, and continue transforming and upgrading (Capello et al., 2015; Martin and Sunley, 2015; Sensier et al., 2016). In regional economics, Boschma (2015) defines economic resilience as a region's capacity to withstand external shocks. Building on this, Wang et al. (2022) emphasize that regions differ in their ability to endure and recover from shocks, indicating significant variation in economic resilience across regions.

Energy is critical for economic growth, social stability, and national defense, making it essential for industrialization and urbanization (Zhao et al., 2020; Alam et al., 2024). As a result, the concept of resilience has been increasingly applied to the energy sector. He et al. (2017) defines energy economic resilience as the minimum level of external recovery investment needed to restore production and limit total economic impact within a specified period. Gatto and Drago (2020) expands on this, describing energy resilience as a multidimensional concept that assesses the stability of energy systems when faced with economic, social, environmental, and institutional shocks, as well as their capacity to recover or improve. Dong et al. (2021) further interprets energy resilience as the ability of energy systems to respond to and recover from external disturbances, including societal, environmental, and public health challenges.

2.2. Measurement of resilience

As discussed earlier, resilience reflects a sector's ability to respond to adverse shocks. Thus, measuring and improving the resilience of the energy system has become a critical concern (Dong et al., 2021). As a physical concept, resilience has attracted significant attention, making the development of systematic measurement methods crucial for risk monitoring. Current approaches to studying economic resilience can be grouped into three categories: case studies, indicator system construction, and economic and statistical modeling.

First, case studies have been widely used to assess economic resilience. Cowell (2013) examines two deindustrializing regions, using historical documents and expert interviews to evaluate their resilience across different economic stages. Similarly, Evans and Karecha (2014) combines historical analysis with a detailed study of urban innovation clusters and technology sectors to explore Munich's resilience to economic shocks, attributing it to the complex interplay of Germany's political history and federal system.

Second, many studies have assessed economic resilience by constructing index systems. Briguglio et al. (2014) was one of the first to measure resilience through policy performance in four areas: macroeconomic stability, microeconomic efficiency, governance, and social development. Using data from 150 countries, Diop et al. (2021) developed the COVID-19 Economic Resilience Index to evaluate regional recovery from the pandemic. Cui et al. (2023) also created a multidimensional index to measure China's Rural Economic Resilience, assessing the system's capacity to respond to external shocks.

Finally, econometric modeling has gained traction in studying economic resilience. Han and Goetz (2015) developed a dynamic model of economic variables and used impulse response analysis to examine the "absorption" and "rebound" capacities of regional economies in response to shocks, proposing a new method for measuring resilience in U.S. counties during the Great Recession. Di Pietro et al. (2021) applied a spatial general equilibrium model to assess the recovery capacity of EU regions under different types of recessionary shocks and explored recovery paths for economic systems.

Despite various definitions of energy resilience, quantifying it remains challenging. Most studies rely on constructing indicator systems, where researchers select indicators based on theoretical frameworks and aggregate them into composite indices (Molyneaux et al., 2012; Banerjee et al., 2017; Gatto and Drago, 2020). However, these methods are inherently subjective. More importantly, given the interconnectedness of energy-economic systems, many sectors may be impacted by energy shocks simultaneously. To better capture these dynamics, we introduce a QVAR model to describe the relationships between energy sectors and shock variables across different quantiles. We then calculate quantile-based impulse response functions to quantify the performance of energy sectors under extreme shocks. Based on this, we propose a scenario-based resilience measurement method for timely and accurate assessment of energy sector resilience.

2.3. Influence factors

With growing interest in resilience and the refinement of its measurement methods, recent research has increasingly focused on quantifying resilience and exploring its underlying factors. These studies not only expand the theoretical framework of resilience but also provide a foundation for empirical analysis. Given the central role of energy in socio-economic development, with energy demand rising alongside economic growth (McLellan et al., 2012), we now focus on economic and energy resilience, systematically reviewing the literature about their influencing factors.

Research on the drivers of economic resilience highlights the significant influence of real economy factors. Martin (2012) notes that technological disruptions, shifts in competitive dynamics, plant closures, and changes in government policies can challenge regional resilience. Christopherson et al. (2010) emphasize the strong link between market size and resilience. From an innovation perspective, Bristow and Healy (2018) found that regions with stronger innovation capacity tend to be more resilient during economic crises. Similarly, studies by Storper and Scott (2009) and Di Caro (2017) show that human capital levels significantly impact resilience. Regional characteristics also play a role. Di Pietro et al. (2021) found that responses to shocks vary by region and depend on factors such as resource mobility, economic diversity, and financial constraints. Some scholars have examined the impact of exogenous events like COVID-19. Wang et al. (2022) used a panel vector autoregression model to show that pandemic severity had a negative effect on resilience, though timely lockdowns mitigated some of this impact.

Regarding the factors influencing energy resilience, Gatto and Drago (2020) highlight the link between renewable energy use and economic growth, suggesting a broad correlation between energy resilience and GDP. McLellan et al. (2012) emphasize the relationship between sustainability and energy resilience, identifying six key indicators: continuous, robust, independent, controllable, non-hazardous, and matched to demand. These indicators help energy systems maintain normal operations during extreme events. He et al. (2017) used an input–output model to show that China's energy resilience is closely tied to coal production, with coal recovery directly affecting the resilience of the energy sector. This suggests that energy resilience depends on the interconnectivity and recovery performance of different energy sectors when faced with shocks.

3. Data and motivating evidence

In measuring the resilience of the energy sector under shocks from energy commodity prices, we focus on two categories of variables. First, in terms of shock variables, we use the spot prices of three international energy commodities from Thomson Reuters: Brent Crude Oil Spot Price (CO), MLCX Natural Gas Spot Price (NG), and Newcastle Coal Spot Price (CL). Second, in terms of the energy sector, we collect MSCI Energy Equity Indices of 14 countries from Bloomberg, with reference to their energy import and export dependence. This allows us to capture how the energy sectors of different nations respond to shocks. To address the issue of trading day mismatches arising from time zone differences across international markets and to reduce computational complexity, we compute monthly log returns using the formula $r_{it} = (\log(P_{i,t}) - \log(P_{i,t-1})) \times 100$, where $P_{i,t}$ represents the monthly closing price of the ith energy spot price or energy equity index. Considering that the integrity of the Indonesian energy equity index starts from 2005, we set the sample period from January 2006 to August 2024.

Appendix Table A.1 presents the descriptive statistics for energy commodity and energy equity returns. We can observe that the majority of energy equity indices exhibit negative skewness. In terms of kurtosis, only Russian energy sector is greater than 3, indicating leptokurtic behavior. In addition, as confirmed by the ADF test, all series are found to be stationary at the 1% significance level. However, some series exhibit non-normality and volatility clustering, indicating limitations in traditional linear models based on conditional mean. This observation motivates the introduction of a scenario-based quantile approach in this paper, providing a more comprehensive view of the dynamics in the presence of extreme shocks and varying distributional behaviors.

To further illustrate the necessity of introducing the scenario-based quantile method in estimating impulse response functions, we conduct quantile Granger causality tests on the energy commodity and energy equity returns. The primary objective is to examine whether energy commodity returns have significant predictive power over energy equity returns across different quantiles. Specifically, for each pair of energy commodity and energy sector, we perform the Granger causality test across 99 quantiles, from the 1st to the 99th, with a maximum lag of 12 periods (representing one year in monthly data), and obtain the p-values with the Wald test statistic.

Fig. 1 displays the distribution of the p-values for all asset pairs and quantiles by scatter points, with the color representing the energy commodity (crude oil, natural gas or coal). For each energy commodity, the average p-value across all energy sectors is calculated at each quantile, and a curve is fitted accordingly. Additionally, the black horizontal line at 10% marks the significance threshold. The scatter plot in Fig. 1 shows that points falling within the 0%–10% significance range are concentrated around the lower and upper quantiles. And the p-values tend to approach 1 around the median. Additionally, the three average p-value curves only enter the 0%–10% interval at extreme quantiles, suggesting that energy commodities serve as significant Granger causes for global energy sectors only at these extreme quantiles. For further distribution of significant quantiles for different energy sectors, please refer to Appendix A.1 and Figure A.2.

In summary, the results indicate the Granger causality between energy commodity and energy sectors, particularly at the extreme quantiles. This reinforces our motivation to examine the response of energy sectors to shocks, from the perspective of extreme quantiles. However, the quantile Granger causality test also has its limitation, primarily due to the quantile regression framework it employs. This framework only incorporates the quantile information of the impacted variable (energy sector) and cannot account for that of the shock variable (energy commodity). In empirical research, such as the international energy market considered here, extreme conditions often lead to high volatility in both energy commodities and energy equities. Therefore, both of them are likely to be at extreme quantiles. In such cases, capturing the interaction and predictive relationship between extreme quantiles is highly imperative.

In light of this, we introduce a scenario-based quantile approach. It not only allows for flexible selection of quantiles for the shock variable, but also enables the adjustment of the corresponding quantiles for other variables in the system, based on the scenarios observed in actual financial markets. By fully utilizing information from all quantiles, this approach provides a more realistic and adaptable framework to simulate energy market responses under various shocks. Through tens of thousands of simulations, it helps to deduce the potential impact of extreme shocks on the energy market, thus offering a valuable measure of the resilience and recovery capacity under extreme conditions.

4. Methodology

We now introduce the scenario-based time-varying resilience measurements of the energy sectors proposed in this paper. We will first introduce a simulation-based quantile impulse response function under different quantiles. Then, we will discuss how, through billions of simulations, the scenario-based time-varying resilience of various energy sectors is characterized.

4.1. Simulation-based quantile impulse response function

Let $\boldsymbol{y}_t = (\boldsymbol{r}_t', \boldsymbol{x}_t')'$ denote a $N \times 1$ vector of observations at time t, where $\boldsymbol{r}_t$ are $N_r \times 1$ vector of log return of energy markets, and $\boldsymbol{x}_t$ denote a $N_x \times 1$ log growth rate of some represents the logarithmic growth rates of several shock source variables, including crude oil prices, coal prices, and natural gas prices. Moreover, let $\boldsymbol{\tau} = (\tau_1, \dots, \tau_N)'$ be a $N \times 1$ vector of quantiles, where $\tau_i \in (0,1), i = 1, \dots, N$. Our first goal is to estimate the conditional τ_i-th quantile of each variable $y_{i,t}$, given path information $\mathcal{F}_{t-1}$, by assuming a vector autoregressive (VAR) process:

$$\mathcal{Q}_{\boldsymbol{\tau}}\left(\boldsymbol{y}_t | \mathcal{F}_{t-1}\right) = \boldsymbol{c}(\boldsymbol{\tau}) + \sum_{i=1}^{p} \boldsymbol{B}_i(\boldsymbol{\tau}) \boldsymbol{y}_{t-i}, \tag{1}$$

for $t = 1, \dots, T$, where p denotes the number of lag terms of the VAR process, $\boldsymbol{c}(\boldsymbol{\tau})$ is a $N \times 1$ quantile-specific vector of intercept, and $\boldsymbol{B}_i(\boldsymbol{\tau})$s are $N \times N$ quantile-specific coefficient matrices. On the other word, for each variable $y_{i,t}$ in $\boldsymbol{y}_t$, we assume that

$$\mathcal{Q}_{\tau_i}(y_{i,t} | \mathcal{F}_{t-1}) = c_i(\tau_i) + \sum_{i=1}^{p} \boldsymbol{\beta}_i(\tau_i)' \boldsymbol{y}_{t-i} \tag{2}$$

where $c_i(\tau_i)$ is the ith element of $\boldsymbol{c}_i(\boldsymbol{\tau})$ and $\boldsymbol{\beta}_i(\tau_i)$ are ith row of $\boldsymbol{B}_i(\boldsymbol{\tau})$ for $i = 1, \dots, N$.

Moreover, Eq. (1) is equivalent to the following QVAR(p) model:

$$\boldsymbol{y}_t = \boldsymbol{c}(\boldsymbol{\tau}) + \sum_{i=1}^{p} \boldsymbol{B}_i(\boldsymbol{\tau}) \boldsymbol{y}_{t-i} + \boldsymbol{\varepsilon}_t(\boldsymbol{\tau}), \tag{3}$$

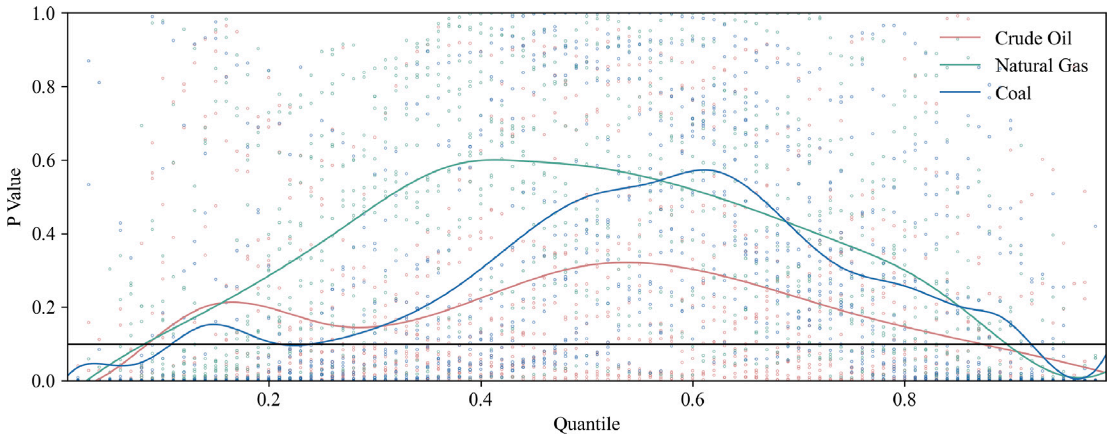


Fig. 1. p-values of quantile Granger causality tests.
Notes: The figure shows the distribution of quantile Granger causality test p-values for all asset pairs. For each energy commodity, the average p-value across all energy equity indices is calculated at each quantile, and a curve is fitted accordingly. The color of each point and fitted curve represents the corresponding energy commodity: red for crude oil, green for natural gas and blue for coal. Additionally, the black horizontal line marks the 10% significance level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

where $\boldsymbol{\varepsilon}_t = (\varepsilon_{1,t}, \dots, \varepsilon_{N,t})'$ is a $N \times 1$ vector of residuals that satisfies $Q_{\tau_i}(\varepsilon_i | \mathcal{F}_{t-1} = 0)$. The stationarity condition of the QVAR model is similar to that of the VAR model.

The above QVAR model can be estimated by minimizing the following check loss function:

$$\Pi_{\boldsymbol{\tau}}(\boldsymbol{c}(\boldsymbol{\tau}), \boldsymbol{B}(\boldsymbol{\tau})) = \sum_{t=1}^{T} \sum_{i=1}^{N} \rho_{\tau_i} \left(y_{i,t} - c_i(\tau_i) - \sum_{i=1}^{p} \boldsymbol{\beta}_i(\tau_i)' \boldsymbol{y}_{t-i} \right), \tag{4}$$

where $\boldsymbol{B}(\boldsymbol{\tau}) = [\boldsymbol{B}_1(\boldsymbol{\tau}), \dots, \boldsymbol{B}_p(\boldsymbol{\tau})]$, $\rho_\tau(\mu)$ denotes the check loss function with $\rho_\tau(\mu) = (\tau - I(\mu < 0))\mu$, where $I(\cdot)$ is the indicator function. Following Chavleishvili and Manganelli (2024) and Yang et al. (2024), we obtain the parameter estimates in the QVAR(p) model by minimizing Eq. (4) through equation-wise quantile regression. The lag term p can be determined using the BIC method.

Based on the QVAR(p) model, we are interested in estimating the τ_i-th Quantile Impulse Response Function (QIRF) of variable i based on τ_j-th quantile-specific shock from variable j:

$$\begin{aligned} QGI_{y_i}\left(H, \boldsymbol{\varepsilon}^*_{j,t}(\boldsymbol{\tau}), \mathcal{F}_{t-1}\right) &= Q_{\tau_i}\left(y_{i,t+H} \mid \boldsymbol{\varepsilon}^*_{j,t}(\boldsymbol{\tau}) = \boldsymbol{\varepsilon}_t(\boldsymbol{\tau}) + \boldsymbol{\delta}_{\tau_j}, \mathcal{F}_{t-1}\right) \\ &\quad - Q_{\tau_i}\left(y_{i,t+H} \mid \mathcal{F}_{t-1}\right) \end{aligned} \tag{5}$$

where $Q_{\tau_i}\left(y_{i,t+H} \mid \boldsymbol{\varepsilon}^*_{j,t}(\boldsymbol{\tau}) = \boldsymbol{\varepsilon}_t(\boldsymbol{\tau}) + \boldsymbol{\delta}_{\tau_j}, \mathcal{F}_{t-1}\right)$ denotes the conditional τ_i-th quantile of $y_{i,t+H}$ given past information and a τ_j-th quantile specific shock δ_j from variable j, and $Q_{\tau_i}\left(y_{i,t+H} \mid \mathcal{F}_{t-1}\right)$ is the conditional τ_i-th quantile of $y_{i,t+H}$ without shock given past information. Specifically, we choose the shock $\boldsymbol{\delta}_{\tau_j}$ to be the contemporaneous effect of one standard error of the decorrelated residuals of the variable j. That is, we set $\boldsymbol{\delta}_{\tau_j} = \boldsymbol{\Omega}(\boldsymbol{\tau})^{1/2} \boldsymbol{e}_j \tilde{\delta}_{\tau_j}$, where $\boldsymbol{\Omega}(\boldsymbol{\tau})$ is the residual correlation matrix, $\boldsymbol{e}_j$ is a vector with the jth element equals to one, and $\tilde{\delta}_{\tau_j}$ denotes the one-standard-error shock of the decorrelated residuals of the variable j.

Economically speaking, let variable i be the log return of the energy market, and variable j be the shock source variable. $QGI_{y_i}\left(H, \boldsymbol{e}^*_{j,t}(\boldsymbol{\tau}), \mathcal{F}_{t-1}\right)$ in Eq. (5) answer the following question: When there exists a strong jth variable specific shock (from the τ_j-th quantile) causes a rapid increase (or decrease) in the shock source variable j, *how and to what extent* this shock affects the tail risk of returns (at the τ_i-th quantile) of the energy market i after H periods.

Since Eq. (3) does not rely on any distribution assumptions, as suggested by Lanne and Nyberg (2016), and Yang et al. (2024), it is natural to consider a simulation-based estimation method of the QIRFs. The details of the simulation-based estimation are shown in Appendix C.

Note that our QIRF is different from the QIRF defined in Yang et al. (2024) in two aspects. First, since our QVAR model incorporates variable-specific conditional quantiles, referred to as specific *"scenarios"* in Ando et al. (2024), the QIRF captures the effects of extreme shocks from one variable on another variable's conditional quantile under these scenarios. Second, by assuming $\boldsymbol{\delta}^{(m)}_{\tau_j} = \boldsymbol{\Omega}(\boldsymbol{\tau}) \boldsymbol{e}_j \tilde{\delta}^{(m)}_{\tau_j}$, we account for the contemporaneous impact of quantile-specific positive and negative shocks.

4.2. Scenario-based time-varying resilience indices

Now we show how to estimate the scenario-based time-varying resilience indices of the energy sectors based on QIRFs in (5). For a specific energy market i and shock source variable j, we first calculate *all the potential responses* of variable i under *all possible shocks* to j, given a *time-related specific "scenario"* for the other variables. To do this, we first estimate the QVAR models under different scenarios. Specifically, we let $\boldsymbol{\tau} = \tau \boldsymbol{\ell}_N$ where $\tau \in \{0.01, 0.02, \dots, 0.99\}$ and $\boldsymbol{\ell}_N$ is a $N \times 1$ vector of ones, and estimate the model (3) at each $\boldsymbol{\tau}$. This produces:

$$\left\{ \hat{\boldsymbol{c}}(\boldsymbol{\tau}), \hat{\boldsymbol{B}}(\boldsymbol{\tau}) \mid \boldsymbol{\tau} = \tau \boldsymbol{\ell}_N;\ \tau = 0.01, \dots, 0.99 \right\}. \tag{6}$$

Since the model is estimated through equation-wise quantile regression, the set (6) is equivalent to

$$\left\{ \hat{\boldsymbol{c}}(\boldsymbol{\tau}), \hat{\boldsymbol{B}}(\boldsymbol{\tau}) \mid \boldsymbol{\tau} = (\tau_1, \dots, \tau_N)';\ \tau_i = 0.01, \dots, 0.99;\ i = 1, \dots, N \right\}. \tag{7}$$

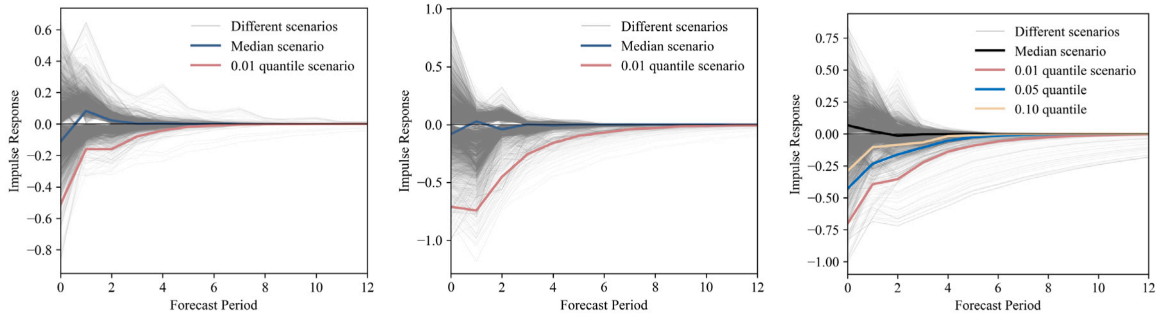
Based on (7), at each time point t, as suggested by Ando et al. (2024), for variable k other than i and j, we let $\tilde{\tau}_{k,t}$ be the percentile of $y_{k,t}$ at time t given the sample distribution of y_k. Then, given the aforementioned scenarios of all the other variables at time t, we can obtain responses of variable i at all possible quantiles given shocks from all possible quantiles of variable j:

$$\left\{ Q\hat{G}I_{y_i}\left(H, \boldsymbol{\varepsilon}^*_{j,t}(\boldsymbol{\tau}_t), \mathcal{F}_{t-1}\right) \mid \tau_{k,t} = \tilde{\tau}_{k,t};\ \tau_{i,t}, \tau_{j,t} = 0.01, \dots, 0.99 \right\}. \tag{8}$$

Given the scenario-based QIRFs for different quantiles of variable i and j from (8), we are particularly interested in the impulse response of variable i under the "worst-case" scenario. To this end, given an extremely low quantile level τ^*, we define the following time-varying response function:

$$\boldsymbol{\Phi}_{t,i\leftarrow j}\left(H, \tau^*\right) = q_{\tau^*}\left(\left\{ Q\hat{G}I_{y_i}\left(H, \boldsymbol{\varepsilon}^*_{j,t}(\boldsymbol{\tau}_t), \mathcal{F}_{t-1}\right) \right\}_{\tau_i, \tau_j = 0.01}^{0.99} \right), \tag{9}$$

where the time-variation in $\boldsymbol{\Phi}_{t,i\leftarrow j}\left(H, \tau^*\right)$ comes from the scenario path $(\tau_{1,k}, \dots, \tau_{T,k})$ of each variable k other than i and j, and the quantile level τ^* control a degree of extremity. In this paper, we choose $\tau^* =$



(a) Crude Oil (b) Natural Gas (c) Coal

Fig. 2. Quantile impulse responses of U.S. energy sector.
Notes: The figure provides an illustrative example of scenario-based quantile impulse response functions using the U.S. energy sector. It simplifies the model by fixing other variables at the median, while varying only the shock and response variables across 99 quantiles (from the 1st to the 99th) to represent different scenarios, resulting in 99 × 99 impulse response functions, as shown by the gray lines. The blue line represents the impulse response under the median scenario for both shock and response variables, while the red line connects the 1st quantile of the impulse response functions at each time point, representing the "worst-case" scenario. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

0.01, which refers to the worst 1% of cases in the H-period impulse response, out of a total of 9801 possible combinations of τ_i and τ_j.

Finally, referring to Tang et al. (2022), we assess the resilience of variable i to shocks from variable j at each time t by calculating the i's absorption intensity ($RSI^{I}_{t,i\leftarrow j}(H,\tau^*)$) and absorption duration ($RSI^{D}_{t,i\leftarrow j}(H,\tau^*)$):

$$RSI^{I}_{t,i\leftarrow j}(H,\tau^*) = \left(H\bar{h} - \sum_{h=1}^{H} |\Phi_{t,i\leftarrow j}(h,\tau^*)| \right) / H\bar{h}, \tag{10}$$

$$RSI^{D}_{t,i\leftarrow j}(H,\tau^*) = \sum_{h=1}^{H} \frac{h|\Phi_{t,i\leftarrow j}(h,\tau^*)|}{\sum_{h=1}^{H} |\Phi_{t,i\leftarrow j}(h,\tau^*)|}, \tag{11}$$

where $\bar{h} = \bar{h}(t,H,\tau^*)$ equals to the largest $|\Phi_{t,i\leftarrow j}(h,\tau^*)|$ for $h = 1,\ldots,H$.

The absorption intensity $RSI^{I}_{t,i\leftarrow j}(H,\tau^*)$ measures the "minimum surplus" of the variable i after absorbing the shock from j relative to the initial state, given the scenario at time t and all possible combinations of quantiles for the response variable i and the shock source variable j. A higher $RSI^{I}_{t,i\leftarrow j}(H,\tau^*)$ indicates that the energy market i recovers from the bottom (at $\bar{h}$) more quickly, implying stronger resilience at time t to shocks originating from the shock source variable j.

Similarly, by assigning higher weights to more distant response periods h, the absorption duration $RSI^{D}_{t,i\leftarrow j}(H,\tau^*)$ measures the "maximum duration" of the impact on variable i from shocks originating from variable j, given the scenario at time t and all possible combinations of quantiles for the response variable i and the shock source variable j. A higher $RSI^{D}_{t,i\leftarrow j}(H,\tau^*)$ indicates that the impact on the energy market i lasts longer, suggesting weaker resilience to shocks from the variable j over time t.

5. Empirical results

This section first analyzes the impulse response results based on the QVAR model, comparing the differences between impulse responses under extreme scenarios and those at the traditional median, highlighting the importance of examining responses across different quantiles. Next, we present the scenario-based time-varying resilience metrics, focusing on the intensity and duration, with a detailed analysis of resilience changes in the energy sectors during COVID-19 and the Russia–Ukraine war. We then use regression analysis to assess the impact of GPR, EPU, and VIX on the intensity and duration of resilience in energy sectors. Finally, a robustness check is provided to confirm the validity of these findings.

5.1. Quantile impulse response analysis

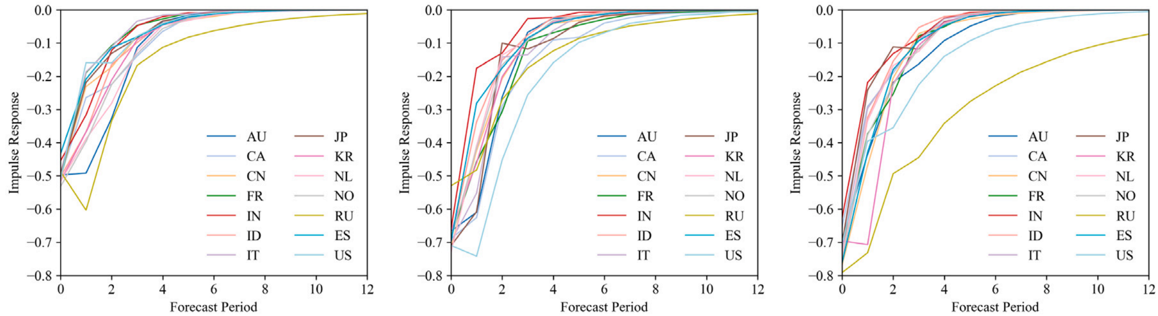
First, we provide an intuitive example and analysis of the scenario-based quantile impulse response function. To facilitate understanding, we set all other variables in the system to their median and focus on the response of the U.S. energy sector to shocks from three energy commodities, as shown in Fig. 2. For each shock, there are 99 × 99 scenarios based on the quantiles of energy commodity and energy equity returns, represented by 9801 gray lines in each subplot of Fig. 2. Additionally, the blue line indicates the impulse response function when both quantiles are set to the median, while the red line marks the lower 0.01 quantile across all impulse response functions, representing the "worst-case" scenario.

A comparison between the median and the 0.01 quantile scenario in Fig. 2 reveals that the impulse response under the median scenario (blue line) is relatively mild, fluctuating between −0.1 and 0.1, and converging within three periods. In contrast, the 0.01 quantile impulse response (red line), representing the "worst-case" scenario, shows a much stronger response, reaching a low of −0.7 and taking nearly eight periods to converge. This finding suggests that it is inadequate to analyze adverse shocks based solely on the median scenario, as the impulse response under extreme scenarios is significantly more severe in both magnitude and duration. Therefore, the resilience measure and analysis in the following subsections will be anchored to the 0.01 quantile impulse response function.[2]

Having established the focus on the 0.01 quantile, Fig. 3 illustrates the impulse response functions of energy sectors across all countries corresponding to Fig. 2. The preliminary results yield two key findings. First, regarding the heterogeneity among energy commodity shocks, the impulse responses are stronger under coal and natural gas shocks, reaching a minimum of −0.8, while the responses to crude oil shocks are weaker, with a low of −0.6. Second, concerning the heterogeneity among energy sectors, Russia (yellow line, RU) exhibits strong impulse responses to crude oil and coal shocks, with a longer response duration to natural gas; the U.S. (light blue line, US) shows a strong impulse response to natural gas and a prolonged response to coal; and Australia (dark blue line, AU) demonstrates a strong impulse response to crude oil, with a longer response duration to coal. These patterns may be associated with the significant export positions of Russia, the U.S., and Australia in the international energy market.

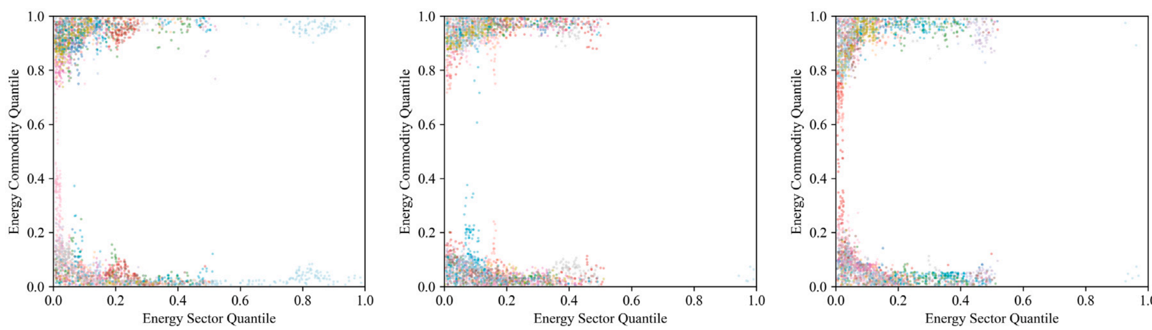
Furthermore, we relax the constraints on the scenarios, allowing other variables in the system to vary according to the actual scenarios in the market instead of being constrained to the median (Figs. 2 and 3). Specifically, in each month, we can calculate the 0.01 quantile impulse response function based on the actual quantiles of each variable within the sample distribution. This approach allows us to obtain scenario-based impulse response functions in a general sense, which vary over time based on the actual dynamic evolution of the energy market.

[2] To ensure the stability of the resilience measure, the 0.01 quantile is chosen here instead of the minimum.



(a) Crude Oil (b) Natural Gas (c) Coal

Fig. 3. Extreme impulse response of energy sectors.
Notes: The figure presents the impulse response functions of various energy sectors under the "worst-case" scenario, with each sector distinguished by color, following the approach of Fig. 2.



(a) Crude Oil (b) Natural Gas (c) Coal

Fig. 4. Scenario-based quantile realization.
Notes: In the scenario-based framework, this figure illustrates the quantile positions of energy sectors and energy commodities, shown on the horizontal and vertical axes, respectively. Treating all time points as a set, each point represents the one-period-ahead impulse response under the "worst-case" scenario for a specific month. Additionally, points are color-coded to distinguish energy sectors. Given the density of data points, the figure emphasizes the overall quantile distribution while omitting sector-specific details, which can be found in Appendix Figure B.1.

In the scenario-based setting, Fig. 4 presents all quantile positions of the 0.01 quantile impulse response functions. The horizontal axis represents the quantiles of the energy sector, while the vertical axis represents the quantiles of energy commodities, with colors indicating different energy sectors. The forecast period for the impulse response is set to 1.[3] Emphasizing the overall distributional pattern, the results in Fig. 4 show that the 0.01 quantile impulse response predominantly corresponds to the lower quantiles of the energy sector, as evidenced by the concentration of points in the left half of the plot. Meanwhile, the quantiles of energy commodities tend to cluster at both extremes—specifically, specifically the lower 0–0.2 and the upper 0.8–1 quantiles. This suggests that extreme positive and negative shocks to energy commodity returns have a pronounced negative impact on the lower tail of the energy sector, thereby amplifying the distribution's thick tail effect.

5.2. Scenario-based resilience indices

Based on the scenario-based quantile impulse response functions, we can calculate two resilience indicators, intensity and duration, by Eqs. (10) and (11). First, we analyze intensity and duration changes of global energy sectors under adverse shocks in different scenarios, and then focus on the Russia–Ukraine conflict and COVID-19 pandemic periods to examine the heterogeneity in energy sector responses to specific adverse shocks.

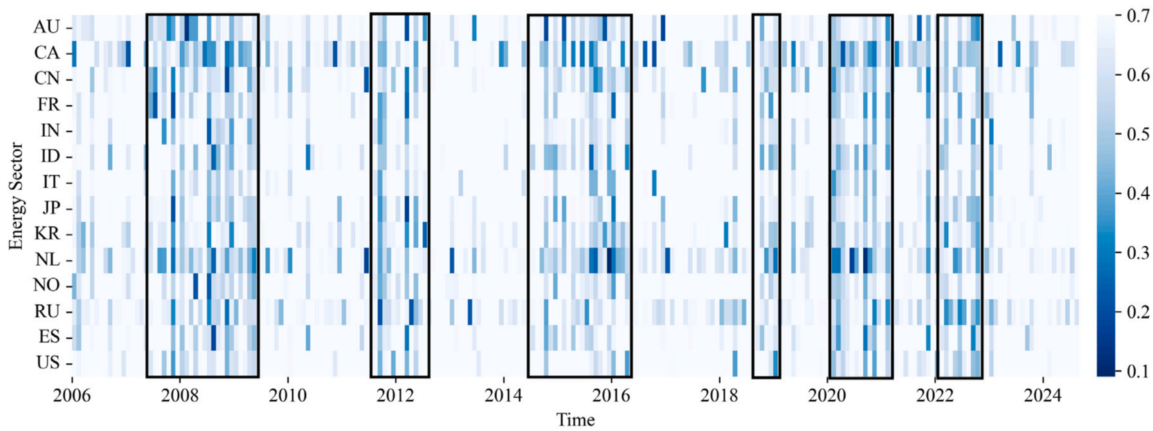
[3] The quantile positions for different forecast periods are generally consistent, see Appendix Figure B.1.

First, to examine the overall resilience dynamics of global energy sectors under energy commodity shocks, Fig. 5 presents scenario-based measurements of resilience indicators, both intensity and duration, in response to crude oil shocks.[4] Specifically, intensity measures the sectors' ability to absorb shocks, where a higher value represents stronger recovery capacity and thus greater resilience. Duration captures the time required for recovery, with lower values indicating quicker recoveries and higher resilience. These two indicators enable us to capture the dynamic, scenario-based responses of energy sectors, offering deeper insights into their resilience when facing external commodity price shocks.

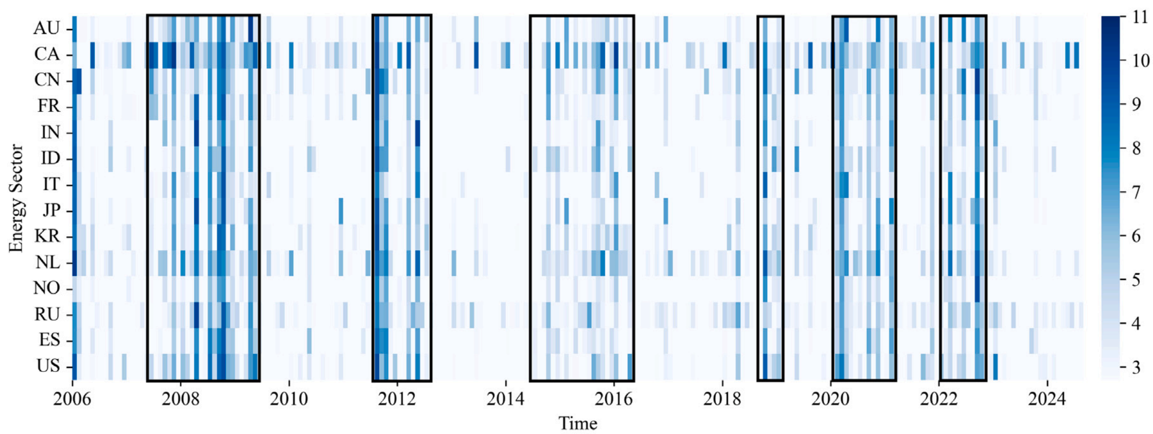
The results in Fig. 5 show that periods of weaker resilience (darker blue) in the global energy sector are concentrated within six distinct time intervals (highlighted by black boxes). These intervals align with sharp fluctuations in energy spot prices, as depicted in Fig. 6. The global energy sector experienced several periods of weakened resilience, as illustrated in Fig. 5. Specifically:

(1) From June 2007 to May 2009, the global energy sector was significantly strained by the 2008 financial crisis, leading to a sharp decline in oil demand and prices. Prior to this, in 2007, geopolitical tensions and unrest in oil-producing regions like the Middle East and

[4] For the resilience measurements under natural gas and coal shocks, see Appendix Figure B.2 and Figure B.3. Overall, the resilience indicators of global energy sectors show similar patterns across different energy commodity shocks. A more detailed analysis of the heterogeneity in response to these shocks will be presented in the event analysis.



(a) Intensity



(b) Duration

Fig. 5. Scenario-based resilience under crude oil shock.
Notes: (1) The figure presents the scenario-based resilience measures of energy markets in response to crude oil shocks, where darker colors indicate weaker resilience. (2) To capture overall trends, black-boxed sections highlight six periods of generally weaker resilience: 2007.06–2009.05, 2011.08–2012.06, 2014.07–2016.04, 2018.09–2019.01, 2020.02–2021.02, and 2022.02–2022.10. (3) For the Intensity indicator, which ranges from 0 to 1, smaller values (darker colors) reflect weaker resilience, indicating a lower capacity of the energy sector to absorb shocks. (4) For the Duration indicator, which ranges from 0 to 12, larger values (darker colors) correspond to longer recovery times after shocks, also signaling weaker resilience.

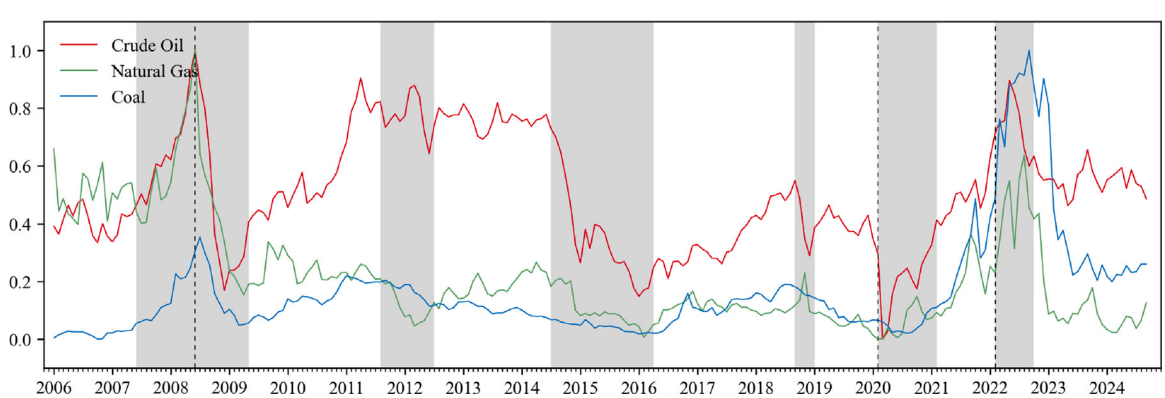


Fig. 6. Energy commodity spot price.
Notes: The figure shows the monthly spot price of crude oil, natural gas, and coal. To facilitate analysis and comparison, the data has been Min-Max normalized, scaling the values between 0 and 1. Dashed lines mark the months when energy spot prices experienced significant fluctuations: June 2008, February 2020, and February 2022. Shaded areas indicate the periods corresponding to significant declines in resilience, as shown in Fig. 5.

Table 1
Resilience of the Russia–Ukraine conflict scenario.

	Crude oil		Natural gas		Coal	
	Intensity	Duration	Intensity	Duration	Intensity	Duration
India	0.64 (−0.08*)	3.66 (1.19)	0.66 (−0.09*)	3.53 (1.27*)	0.64 (−0.11*)	3.49 (1.25*)
Norway	0.66 (−0.04)	4.05 (1.45*)	0.72 (−0.02)	3.27 (1.07)	0.70 (−0.05)	3.47 (1.16)
Indonesia	0.64 (−0.04)	3.71 (0.96)	0.68 (−0.06)	3.07 (0.81)	0.70 (−0.05)	3.15 (0.91)
Spain	0.64 (−0.07)	3.73 (0.97)	0.68 (−0.07)	3.29 (0.80)	0.66 (−0.07)	3.23 (0.79)
Italy	0.67 (−0.06)	3.82 (1.17)	0.65 (−0.05)	3.39 (0.83)	0.62 (−0.11*)	3.55 (1.05)
Japan	0.57* (−0.14*)	4.71* (2.01*)	0.63 (−0.10*)	3.82 (1.26)	0.58* (−0.15*)	4.23* (1.70*)
France	0.65 (−0.06)	4.14 (1.29)	0.64 (−0.03)	3.83 (0.86)	0.67 (−0.02)	3.87 (1.01)
Korea	0.59* (−0.08*)	4.16 (1.24)	0.63 (−0.06)	3.87 (1.07)	0.64 (−0.07)	3.50 (0.88)
U.S.	0.60 (−0.12*)	4.47 (1.33)	0.62* (−0.12*)	4.60* (1.44*)	0.56* (−0.09*)	4.27* (1.13)
Australia	0.60 (−0.07)	4.68* (1.70*)	0.59* (−0.08*)	4.20* (1.27*)	0.56* (−0.11*)	4.33* (1.31*)
China	0.64 (−0.04)	4.85* (1.67*)	0.65 (−0.02)	4.55* (1.51*)	0.69 (−0.01)	4.21 (1.32*)
Netherlands	0.57* (−0.05)	5.13* (1.61*)	0.61* (−0.07)	4.96* (1.78*)	0.59 (−0.09)	5.29* (2.09*)
Russia	0.48* (−0.16*)	4.62 (1.20)	0.54* (−0.11*)	4.11* (0.96)	0.57* (−0.07)	4.10 (0.77)
Canada	0.57* (−0.05)	4.82* (0.62)	0.59* (−0.05)	4.01(0.07)	0.55* (−0.08)	4.48* (0.43)

Notes: The table reports the mean values of scenario-based resilience indicators, intensity and duration, during the Russia–Ukraine conflict (2022 Feb to 2022 Oct), with the difference from the full sample mean shown in parentheses. For each column of indicators, we use asterisks * to highlight the five energy sectors with the weakest resilience (or the most noticeable declines). For the intensity indicator, the smallest values are highlighted, while for the duration indicator, the largest values are marked.

Nigeria, combined with rising global demand, had already tightened oil supplies and increased market uncertainty.

(2) From August 2011 to June 2012, the European sovereign debt crisis and unrest from the Arab Spring, along with the sanctions on Iran, contributed to volatile energy markets.

(3) From July 2014 to April 2016, the global energy market faced a significant oversupply due to the surge in U.S. shale oil production and OPEC's refusal to cut output, aiming to pressure shale producers. This resulted in a supply–demand imbalance, with crude oil and natural gas prices falling sharply, as noted by Liu and Li (2018).

(4) From September 2018 to January 2019, sanctions on Iran were less severe than expected, and with rising U.S. crude oil exports, the global market leaned toward oversupply, leading to a sharp drop in oil prices starting in October 2018. Additionally, the escalation of the U.S.-China trade war, heightened expectations of Federal Reserve rate hikes, and significant fluctuations in global stock markets collectively weakened the resilience of the energy sector.

(5) From February 2020 to February 2021, the outbreak of Covid-19 and global lockdowns had a severe impact on the global economy and energy demand. With a sharp decline in aviation, transportation, and industrial activities, demand for oil and gas plummeted, causing oil prices to fall to near-zero levels in April 2020. Prior to the pandemic, a price war between Saudi Arabia and Russia had already led to an oversupply of oil, and the sudden drop in demand further depressed prices, undermining market balance and resilience.

(6) From February and October 2022, the Russia–Ukraine conflict triggered extreme volatility in global energy markets. As one of the world's largest energy exporters, Russia faced sanctions from Western countries, particularly targeting its oil and gas exports. This led to significant strain on global supply chains and an energy crisis in Europe. Countries competed to find alternative energy sources, resulting in sharp increases in energy prices and damaging the resilience of the energy sector.

Second, after capturing the overall trends of resilience, we focus on two recent extreme events: the COVID-19 pandemic and the Russia–Ukraine conflict, with the results displayed in Tables 1 and 2. For each event, we calculate the average resilience indicators within the period (as shown in Fig. 5) and present the deviation from the full sample average[5] in parentheses. Additionally, the weakest resilience (or the largest decline in resilience) for each indicator is highlighted in bold. The energy sectors are ordered by full-sample average resilience, with the most resilient listed first.

[5] The full sample average of each resilience indicator is provided in Appendix Table B.1.

During the Russia–Ukraine conflict, as shown in Table 1, Russia's energy sector experienced the lowest resilience intensity under crude oil and natural gas shocks (0.48 and 0.54), with significant declines compared to the averages (−0.16 and −0.11). The resilience of energy sectors in the U.S., China, Japan, the Netherlands, Canada, and Australia also saw considerable declines, with the impact on China's energy market being reflected only in the duration indicator. Additionally, aside from India and Japan, the energy sectors showing weaker resilience or notable declines (bold numbers in Table 1) are primarily concentrated in the lower half of the table. This suggests that countries facing resilience issues during the conflict were already sensitive to energy shocks throughout the entire sample period, and the Russia–Ukraine conflict further exacerbated these vulnerabilities.

For the COVID-19 pandemic, Table 2 presents the resilience of global energy sectors. The results show that the Netherlands and Canada consistently ranked at the bottom in terms of resilience indicators. China's energy sector also experienced significant deterioration, particularly in the intensity indicator for natural gas, which recorded the lowest value among all sectors. The duration indicators for the United States and Australia were relatively weak across all three energy shocks. Moreover, nearly all countries' energy sectors faced significant resilience challenges, with bold numbers appearing across almost every energy sector. This indicates that, unlike the Russia–Ukraine conflict, the impact of the COVID-19 pandemic on the global energy sector was systemic. Even energy sectors that showed strong resilience throughout the full sample period, such as those in India, Norway, Indonesia, Spain, and Italy, were also heavily impacted during this period.

5.3. Influencing factor analysis

Based on the preceding analysis, the resilience of national energy sectors to shocks from various energy commodities fluctuates considerably in response to major events. These shocks primarily arise from international conflicts, financial crises, and public health emergencies. This indicates that geopolitical risks, macroeconomic environment, and market sentiment may have a critical impact on the energy sector's ability to absorb and recover from such disruptions.

In light of these findings, the subsequent section incorporates these elements into the analysis and investigates the underlying factors influencing energy resilience through the following linear regression model:

$$Resilience_{it} = \alpha_0 + \beta_1 X_{it} + \sum_k \delta_k Controls_{iy}^k + \mu_t + \eta_i + \varepsilon_{it} \tag{12}$$

Table 2
Resilience of the COVID-19 pandemic scenario (2020 Feb to 2021 Feb).

	Crude oil		Natural gas		Coal	
	Intensity	Duration	Intensity	Duration	Intensity	Duration
India	0.65 (−0.07)	3.42 (0.95)	0.64 (−0.11*)	3.98 (1.72*)	0.64 (−0.11)	3.53 (1.29)
Norway	0.62 (−0.07)	3.71 (1.11)	0.65 (−0.10*)	3.73 (1.54)	0.64 (−0.11)	3.71 (1.40)
Indonesia	0.58* (−0.11)	3.96 (1.20)	0.62 (−0.12*)	4.20 (1.94*)	0.62 (−0.13*)	3.86 (1.62*)
Spain	0.59 (−0.12*)	4.05 (1.29*)	0.67 (−0.07)	4.18 (1.69*)	0.60 (−0.13*)	3.95 (1.52)
Italy	0.61 (−0.12*)	4.22 (1.56*)	0.58* (−0.12*)	4.03 (1.47)	0.62 (−0.12)	4.07 (1.57*)
Japan	0.64 (−0.06)	3.98 (1.27)	0.69 (−0.03)	3.96 (1.40)	0.61 (−0.12)	4.15 (1.61*)
France	0.60 (−0.11*)	3.97 (1.12)	0.59* (−0.07)	4.39* (1.43)	0.54* (−0.15*)	4.10 (1.24)
Korea	0.60 (−0.07)	4.00 (1.07)	0.60 (−0.08)	4.33 (1.53)	0.60 (−0.11)	4.03 (1.40)
U.S.	0.62 (−0.10)	4.46* (1.31*)	0.70 (−0.04)	4.57* (1.41)	0.53* (−0.12)	4.42* (1.27)
Australia	0.63 (−0.04)	4.28* (1.30*)	0.62 (−0.05)	4.48* (1.54*)	0.58* (−0.10)	4.65* (1.64*)
China	0.59* (−0.09)	4.35* (1.17)	0.56* (−0.11*)	4.31 (1.28)	0.58* (−0.11)	4.37* (1.48)
Netherlands	0.45* (−0.16*)	5.13* (1.60*)	0.60* (−0.08)	5.23* (2.05*)	0.54* (−0.14*)	4.99* (1.79*)
Russia	0.58* (−0.06)	4.07 (0.65)	0.62 (−0.03)	4.32 (1.17)	0.58* (−0.06)	4.06 (0.72)
Canada	0.49* (−0.13*)	4.86* (0.66)	0.57* (−0.07)	5.20* (1.26)	0.50* (−0.14*)	5.25* (1.20)

Notes: The table reports the mean values of scenario-based resilience indicators, intensity and duration, during the COVID-19 pandemic scenario (2020 Feb to 2021 Feb), with the difference from the full sample mean shown in parentheses. For each column of indicators, we use asterisks * to highlight the five energy sectors with the weakest resilience (or the most noticeable declines). For the intensity indicator, the smallest values are highlighted, while for the duration indicator, the largest values are marked.

Table 3
Factors influencing energy resilience.

	Intensity			Duration		
	(I) *Crude oil*	(II) *Nature gas*	(III) *Coal*	(IV) *Crude oil*	(V) *Nature gas*	(VI) *Coal*
Panel A: The influence of geopolitical uncertainty on energy resilience						
GPR_C	−0.137***	−0.140**	−0.096*	0.083*	0.105**	0.069
	(−2.725)	(−2.559)	(−1.883)	(1.898)	(2.252)	(1.523)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.422***	−0.423***	−0.443***	0.243*	0.208*	0.312**
	(−3.117)	(−3.073)	(−3.205)	(1.925)	(1.655)	(2.458)
Obs	2,640	2,640	2,640	2,640	2,640	2,640
R^2	0.221	0.222	0.227	0.264	0.251	0.259
Panel B: The influence of economic policy uncertainty on energy resilience						
EPU_C	−0.071**	−0.068**	−0.059**	0.105***	0.099***	0.095***
	(−2.430)	(−2.240)	(−2.013)	(3.720)	(3.484)	(3.330)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.449***	−0.434***	−0.469***	0.349**	0.286**	0.409***
	(−3.112)	(−2.942)	(−3.204)	(2.572)	(2.131)	(3.038)
Obs	2,195	2,195	2,195	2,195	2,195	2,195
R^2	0.224	0.201	0.212	0.267	0.238	0.252
Panel C: The influence of VIX Fear Index on energy resilience						
VIX	−0.466***	−0.471***	−0.470***	0.582***	0.555***	0.567***
	(−15.991)	(−15.868)	(−15.796)	(20.236)	(19.449)	(18.915)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.479***	−0.479***	−0.523***	0.361***	0.307***	0.434***
	(−3.709)	(−3.785)	(−4.075)	(3.080)	(2.680)	(3.749)
Obs	2,640	2,640	2,640	2,640	2,640	2,640
R^2	0.293	0.294	0.301	0.382	0.358	0.370

Notes: The table reports the results of the two-way fixed effects model, with the results for the models using GPR, EPU, and VIX as explanatory variables presented in Panel A, B, and C, respectively. The *t*-statistics for the parameter estimates are in parentheses.
*** indicate statistical significance at 1%.
** indicate statistical significance at 5%.
* indicate statistical significance at 10%.

In Eq. (12), $Resilience$ refers to energy resilience, which is measured through two key indicators, $Intensity$ and $Duration$. $Intensity$ represents the energy sector's capacity to absorb shocks, with higher values indicating stronger resilience. $Duration$ measures the time required for recovery, with shorter duration indicating stronger resilience. Additionally, the explanatory variables in Eq. (12) include national geopolitical risk (GPR_C), economic policy uncertainty (EPU_C), and the S&P 500 volatility index (VIX). These variables are employed to assess the dynamics of geopolitical conditions, economic environments, and market sentiment fluctuations, respectively. The control variables ($Controls$) consist of annual macroeconomic indicators, which primarily include gross domestic product (GDP), employment rate (Lab), population

($Urban\_pop$), industrial value added (IVA), and the trade openness to GDP ratio ($Trade$). Furthermore, the model incorporates monthly time-fixed effects μ_t and country-fixed effects η_i.[6]

First, Panel A of Table 3 presents the impact of geopolitical risk (GPR_C) on energy resilience. The results in columns (I) to (III) of Panel B show that the coefficient estimates for GPR_C are all negative, indicating that as geopolitical risk increases, the ability of national energy sectors to absorb shocks from crude oil, natural gas, and coal commodities weakens, with a particularly pronounced decline in the Intensity indicator when facing shocks from crude oil and natural gas. Additionally, in columns (IV) to (VI), the coefficients of GPR_C are all positive, and the coefficients related to crude oil and natural gas are higher and statistically significant. This indicates that an increase in geopolitical risk significantly prolongs the recover time of the energy sector in response to shocks from these two commodities. The underlying rationale may lie in the fact that escalating geopolitical tensions disrupt energy supply chains and distort energy markets (Soybilgen et al., 2019), leading to supply instability and thereby impairing the sector's absorptive capacity. Additionally, as demonstrated by Banna et al. (2023), political instability exerts persistent long-term effects on energy markets, which could necessitate extended adjustment periods for the energy sector.

Second, given that a country's level of economic policy uncertainty typically reflect its economic environment through multiple dimensions such as policy uncertainty, market reactions, and growth expectations, this study further assess the impact of economic policy uncertainty (EPU_C) on energy resilience indicators, with the results presented in Panel B of Table 3. The results in columns (I) to (III) indicate that an increase in economic policy uncertainty significantly weakens the energy sector's ability to absorb commodity price shocks, with this effect most pronounced in response to crude oil shocks. In addition, the results in columns (IV) to (VI) indicate that rising economic policy uncertainty not only significantly reduces the energy sector's risk absorption capacity but also prolongs the duration of risk exposure, with the crude oil shock showing the greatest persistence. This phenomenon may stem from the challenges that heightened economic policy uncertainty poses in anticipating regulatory frameworks, which destabilizes energy production, consumption, and investment. Furthermore, such uncertainty exacerbates disruptions to energy production through price shocks and oil shortages (Adedoyin et al., 2021), thereby limiting the sector's ability to hedge against price volatility in commodities like crude oil via technological upgrades or inventory management. Additionally, as noted by Erzurumlu and Gozgor (2022), economic policy uncertainty influences per capita final energy consumption, and its fluctuations may induce demand-side instability, consequently extending recovery periods.

Finally, we selects the S&P 500 Volatility Index (VIX) as a representative measure of market panic sentiment to examine its impact on the energy sector's risk absorption and resilience capabilities. The relevant results are shown in Panel C of Table 3. In columns (I) to (III) of Panel C of Table 3, the VIX coefficients are all negative and significant at least at the 5% confidence level, indicating that the intensification of market panic sentiment significantly weakens the energy sector's ability to absorb shocks from commodities such as crude oil, natural gas, and coal. Moreover, the results in columns (IV) to (VI) show that the higher the VIX level, the longer the duration of commodity price shocks on the energy sector, further highlighting the significant negative impact of market sentiment on the resilience of the energy sector. As Shaikh (2022) demonstrates, during extreme market downturns, heightened volatility in energy market investor sentiment tends to trigger cross-asset sell-offs, substantially reducing liquidity in financialized energy commodity futures markets and thereby impeding price recovery. Additionally, Bianconi and Yoshino (2014) find that VIX fluctuations significantly affect energy firms' earnings. We thus posit that VIX volatility may prolong energy market rebalancing periods by increasing financing costs and constraining corporate investment.

Building on the aforementioned analysis, it is evident that the risk absorption capacity of a nation's energy sector in response to commodity shocks exhibits a significant negative correlation with geopolitical risk, economic policy uncertainty, and the fear index. However, when confronted with shocks from commodities such as crude oil, natural gas, and coal, the duration of the impact on the energy sector is more susceptible to the effects of economic policy uncertainty and the fear index. This indicates that as levels of economic uncertainty rise and market panic intensifies, the impact of commodity shocks becomes more persistent, making short-term recovery more difficult. Thus, enhancing the energy sector's resilience requires not only strengthening its internal structural robustness but also relying on national-level policy stability and effective market expectation management.

5.4. Robustness check

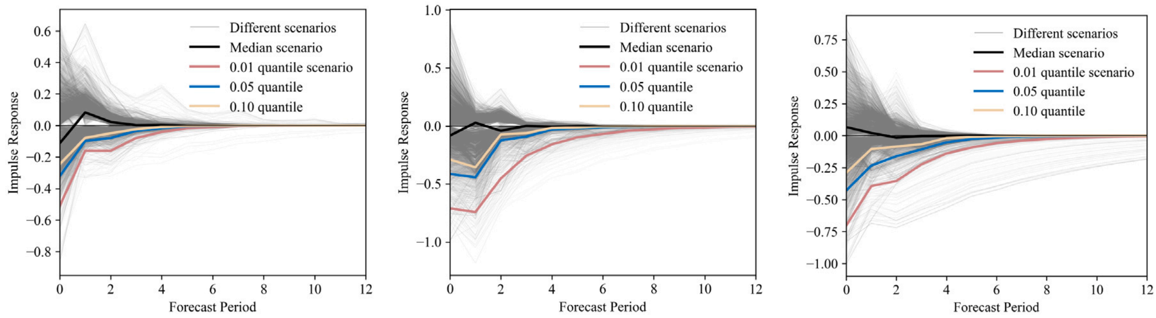
In order to check whether the selection of the "worst-case" scenario quantile impacts the conclusions of this paper, we replace the "worst-case" scenario quantile from 0.01 to 0.05 and 0.1, respectively, for robustness test.

First, regarding the quantile impulse response results, Fig. 7 compares the impulse response functions under different "worst-case" scenario quantile selections. The 0.01, 0.05, 0.1 and 0.5 quantiles are represented by red, blue, yellow and black lines, respectively. It results show that due to the differences in quantiles, the impulse response functions naturally differ in magnitude. As the quantile approaches the median, the impulse responses gradually weaken, but the overall shape of the impulse response functions remain robust. Additionally, the difference between the 0.05 and 0.1 quantile impulse response functions is relatively small, while the gap between the 0.05 and 0.01 quantiles is more pronounced. This suggests that the 0.01 quantile is more effective in capturing extreme scenarios, which is the basis for selecting it as the "worst-case" scenario in this paper.

Next, regarding the robustness of the resilience measures, Fig. 8, using the 0.05 quantile under crude oil shocks as an example, confirms the robustness of the intensity and duration resilience indicators. Additionally, the complete resilience measures for natural gas and coal shocks, as well as under the 0.1 quantile, are provided in Appendix Figure B.4 to Figure B.7, with conclusions remaining robust. In Fig. 8, black boxes highlight the same six intervals of weakened resilience as in Fig. 5. Clearly, when the quantile shifts from 0.01 to 0.05, reducing the extremity, colors in the heatmap lighten overall, indicating an improvement in resilience. Nevertheless, under major event shocks highlighted by the black boxes, the 0.05 quantile setting still captures signals of weakened resilience to some extent.

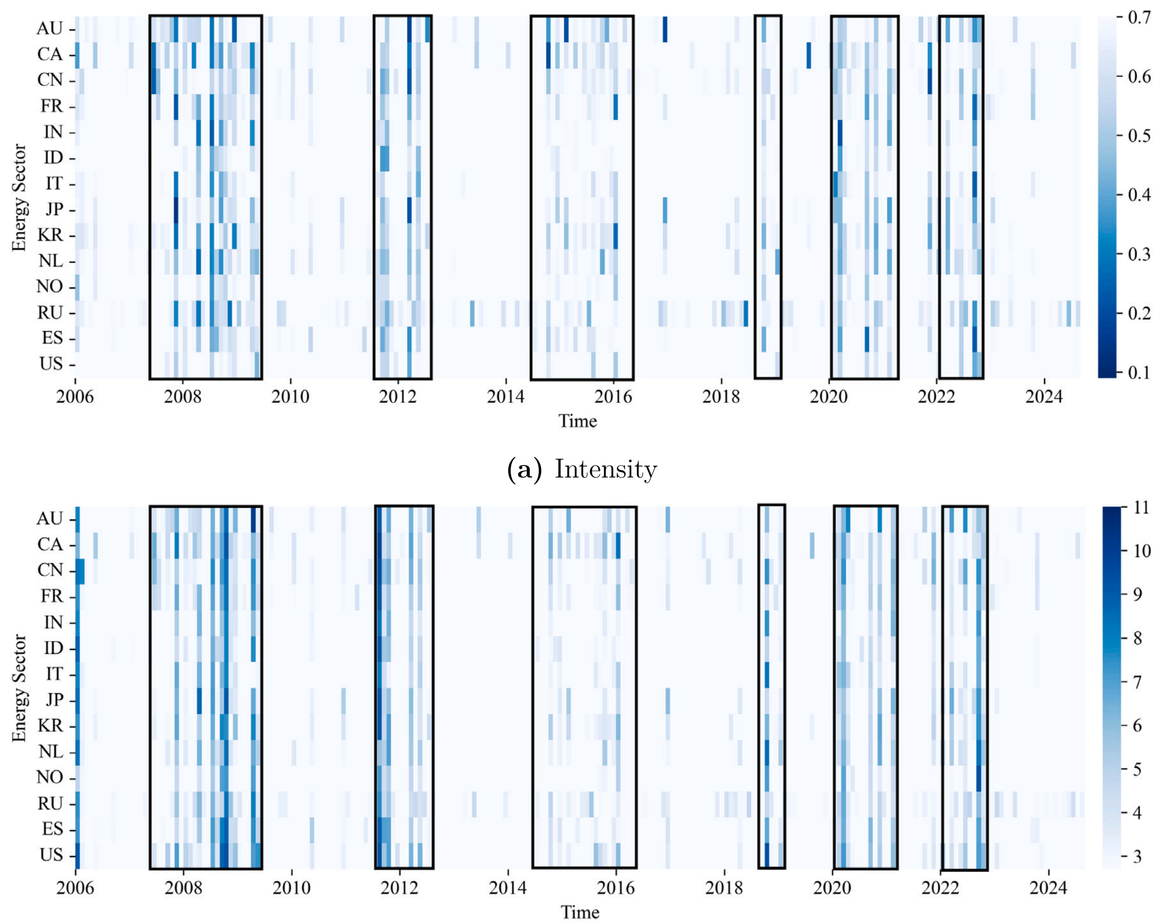
Finally, regarding the analysis of influencing factors, Table 4 presents the regression results at the 0.05 and 0.1 quantiles, respectively. Overall, the results remain robust, with GPR, EPU, and VIX still showing a significant negative relationship with the resilience of energy sectors. As previously observed, VIX continues to have the most substantial negative impact on the resilience indicators, while GPR has a relatively larger influence on the resilience of energy sectors under crude oil and natural gas shocks, consistent with the empirical findings. Additionally, comparing the results across different quantiles reveals some insightful findings. For instance, the negative impact of GPR

[6] The data sources for the variables include various authoritative databases and research findings. Firstly, the macroeconomic data is sourced from the World Development Indicators (WDI) database. Secondly, the Economic Policy Uncertainty Index is based on the index published by Baker et al. (2016), and the geopolitical risk index is derived from the geopolitical risk index constructed by Caldara and Iacoviello (2022) using newspaper word frequency analysis. Additionally, financial data is obtained from the Wind Financial Terminal. The data spans the period from January 2007 to December 2023. Notably, the Economic Policy Uncertainty Index does not include data for Norway and Indonesia.



(a) Crude Oil   (b) Natural Gas   (c) Coal

Fig. 7. Quantile impulse responses at different quantiles.
Notes: The figure presents a robustness test of the impulse response function for energy sectors (using the U.S. as an example) under different quantile scenarios, corresponding to Fig. 3 in the previous section. Specifically, other variables are held at their median, while the quantiles of the shock and response variables are varied, generating impulse response functions for 99 × 99 scenarios, shown by the gray lines. The red, blue, and yellow lines represent the impulse response functions connecting the 0.01, 0.05, and 0.1 quantiles across all scenarios at each forecast horizon, respectively.



(a) Intensity

(b) Duration

Fig. 8. Scenario-based resilience for crude oil shock at the 0.05 quantile.
Notes: The figure presents the robustness result for resilience measures of energy markets in response to crude oil shocks at the 0.05 quantile. For the intensity indicator, which ranges from 0 to 1, darker colors (smaller values) indicate weaker resilience, meaning that the energy sector's ability to absorb shocks is lower. For the Duration indicator, which ranges from 0 to 12, darker colors (larger values) represent longer recovery times after shocks, also signaling weaker resilience. The black-boxed sections represent six periods of generally weaker resilience, consistent with Fig. 5. The resilience results in response to natural gas and coal shocks at the 0.05 quantile can be found in Appendix Figure B.4 and Figure B.5, while the 0.1 and 0.5 (median) quantile results are provided in Appendix Figure B.6 to B.9.

on the resilience of energy sectors under oil and gas shocks is most pronounced at the 0.01 quantile, with stronger significance compared to other quantiles, particularly in terms of intensity. In contrast, the negative impact on resilience under coal shocks is more significant at the 0.05 and 0.1 quantiles. Furthermore, the influence of both EPU and VIX on resilience is relatively stronger at the 0.1 quantile. These results further underscore the heightened sensitivity of crude oil and natural gas to geopolitical risks, not only in terms of the size and significance

Table 4
Robustness results for influencing factor analysis.

	Intensity			Duration		
	(I) *Crude oil*	(II) *Nature gas*	(III) *Coal*	(IV) *Crude oil*	(V) *Nature gas*	(VI) *Coal*
Panel A: Factors influencing energy resilience at the 0.05 quantile						
GPR_C	−0.102**	−0.126**	−0.109**	0.086**	0.105**	0.085*
	(−2.189)	(−2.548)	(−2.145)	(2.015)	(2.317)	(1.862)
EPU_C	−0.078***	−0.086***	−0.088***	0.112***	0.126***	0.117***
	(−2.752)	(−2.949)	(−3.015)	(3.980)	(4.481)	(4.142)
VIX	−0.488***	−0.554***	−0.554***	0.565***	0.620***	0.613***
	(−16.752)	(−18.716)	(−18.332)	(18.648)	(21.437)	(20.139)
Panel B: Factors influencing energy resilience at the 0.1 quantile						
GPR_C	−0.070	−0.110**	−0.116**	0.078*	0.092**	0.081*
	(−1.599)	(−2.301)	(−2.436)	(1.877)	(2.078)	(1.850)
EPU_C	−0.090***	−0.100***	−0.113***	0.119***	0.139***	0.132***
	(−3.321)	(−3.515)	(−3.993)	(4.267)	(5.023)	(4.711)
VIX	−0.498***	−0.553***	−0.572***	0.574***	0.642***	0.630***
	(−17.358)	(−18.204)	(−18.869)	(18.587)	(21.855)	(20.683)

Notes: The table reports the robustness results of the two-way fixed effects model at the 0.05 and 0.1 quantiles, shown in Panel A and Panel B, respectively. For brevity, only the coefficient estimates of the key explanatory variables (GPR, EPU, and VIX) are presented. Full model estimation results can be found in Appendix Table B.2 and Table B.3. The *t*-statistics for the parameter estimates are in parentheses.

*** indicate statistical significance at 1%.

** indicate statistical significance at 5%.

* indicate statistical significance at 10%.

of the regression coefficients, but also in their concentration at the extreme 0.01 quantile. This reinforces and supplements the conclusions from the empirical analysis. When assessing global energy sector resilience in the face of adverse shocks, it is critical to pay closer attention to the extreme price fluctuations in oil and gas triggered by geopolitical conflicts. These extreme movements can exacerbate the weakening of resilience, making it an essential factor for policymakers and market participants to consider when evaluating potential vulnerabilities in global energy sector.

6. Policy implications

Our empirical analysis provides important insights into the dynamics of energy sector resilience under major external shocks. The scenario-based, time-varying resilience measure effectively captures sectoral responses to extreme events, revealing a significant weakening of resilience during global crises such as the Russia–Ukraine conflict and the COVID-19 pandemic. Specifically, the Russia–Ukraine conflict disproportionately affected energy sectors in countries with relatively lower baseline resilience, whereas the COVID-19 pandemic led to a more widespread and generalized erosion of resilience across the board. Moreover, panel regression results indicate that increases in economic policy uncertainty (EPU), geopolitical risk (GPR), and market volatility (VIX) systematically undermine energy sector resilience. Taken together, these results highlight the need for targeted policy interventions aimed at strengthening energy sector resilience and mitigating vulnerability to future external shocks. In light of these findings, we propose the following policy recommendations:

Establish Real-Time Monitoring of Energy Sector Resilience. Governments and international organizations should establish real-time monitoring systems to track the resilience of energy sectors. By leveraging scenario-based dynamic resilience metrics, policymakers can detect early warning signs of systemic vulnerabilities and implement timely interventions to enhance sectoral resilience and mitigate systemic risks. Such monitoring becomes particularly crucial during periods of heightened geopolitical tensions or economic instability.

Enhance Risk Absorption Capacity through Diversification. To buffer against external disruptions, energy sectors should prioritize the diversification of energy sources, supply chains, and trading partners. Policies that promote the adoption of renewable energy, encourage regional energy cooperation, and foster supply chain resilience can significantly reduce dependence on volatile fossil fuel markets and enhance overall sectoral resilience.

Strengthen Institutional Stability to Counter Policy Uncertainty, Geopolitical Risks, and Market Volatility. Policymakers should seek to reduce economic policy uncertainty by maintaining transparent, predictable, and consistent regulatory frameworks. Diplomatic initiatives aimed at de-escalating geopolitical tensions and fostering international cooperation are essential to mitigating the adverse effects of geopolitical risks on energy sector resilience. Furthermore, efforts to enhance financial market stability — such as strengthening oversight of commodity markets, promoting market transparency, and developing risk management instruments — can mitigate the adverse impact of market volatility (VIX) on energy sector resilience.

Develop Comprehensive Contingency Plans for Extreme Events. In light of the substantial disruptions caused by events such as the COVID-19 pandemic and the Russia–Ukraine conflict, governments, regulatory bodies, and energy companies should develop comprehensive contingency plans. These should include the establishment of strategic energy reserves, the design of multi-level emergency response protocols, and the strengthening of coordinated international mechanisms to stabilize global energy markets.

7. Concluding remark

This paper addresses the critical issue of energy sector resilience in the face of extreme shocks by developing a comprehensive framework that builds upon the quantile vector autoregression (QVAR) model. In a world where energy systems are increasingly vulnerable to disruptions caused by geopolitical tensions, economic instability, and natural disasters, understanding the degree to which these systems can absorb and recover from such shocks is essential. Through a detailed exploration of 14 key global energy sectors and their reactions to crude oil, natural gas, and coal price shocks, we have provided valuable insights into the dynamics of energy resilience. Specifically, our scenario-based time-varying resilience metric allows for a more nuanced and timely understanding of how energy sectors withstand and recover from shocks under varying economic conditions. This framework offers an innovative approach to assessing resilience, moving beyond traditional methods that rely on conditional means, and instead focusing on the tail risks that often arise during significant events, such as the COVID-19 pandemic and the Russia–Ukraine conflict.

The scenario-based dynamic resilience estimates reveal that during major events such as the 2008 global financial crisis, the European debt crisis, the Arab Spring, the Iran nuclear issue, U.S.-China trade tensions, the Covid-19 pandemic, and the Russia–Ukraine conflict, sharp fluctuations in international energy prices had a significant impact on energy sectors. Across 14 energy sectors, the intensity indicator decreased while the duration increased, signaling a reduced ability to absorb shocks and longer recovery times. This points to a significant deterioration in resilience across the global energy sector. Furthermore, the event analysis shows that during the Russia–Ukraine conflict, the energy sectors experiencing the most significant weakening of resilience were primarily those already exhibiting lower resilience in the full sample, such as Russia, Australia, the U.S., Canada, China, and the Netherlands. In contrast, during the Covid-19 pandemic, nearly all energy sectors saw a marked decline in resilience, reflecting a widespread synchronized shock across global markets. Additionally, the analysis of influencing factors indicates that economic policy uncertainty (EPU), geopolitical risk (GPR), and market volatility (VIX) significantly affect the resilience of energy sectors. Increases in these factors tend to reduce the intensity of resilience while extending the recovery period. Among them, VIX has the most pronounced negative impact on both the risk absorption capacity and recovery ability of energy sectors. GPR exerts a relatively strong influence on risk absorption capacity, while EPU has the weakest impact on risk absorption but still contributes negatively to recovery ability to some extent.

The implications of this study are profound for both policymakers and investors. For policymakers, understanding the resilience of energy sectors in real-time can help inform targeted interventions that stabilize energy markets and mitigate the risks of systemic economic crises. By monitoring resilience indicators, governments can enact policies that address supply chain disruptions, price volatility, and other external shocks before they trigger broader economic instability. Investors, on the other hand, can use the resilience metrics developed in this paper to adjust their portfolios in response to shifts in energy sector resilience. The ability to anticipate changes in sector performance allows for more informed investment decisions, particularly in times of heightened geopolitical or economic uncertainty. In conclusion, this paper not only advances the academic understanding of energy resilience but also provides practical tools for addressing the challenges posed by an increasingly volatile global energy landscape. Further research should explore the application of this framework across other sectors and regions, as well as investigate how resilience can be strengthened in the face of evolving global risks.

Naturally, there is room for further improvement. For example, on the sectoral side, future research could incorporate a broader set of energy-related sectors. From a methodological perspective, it would also be valuable to integrate richer information sources, such as macroeconomic big data from FRED-MD—and extend the current framework to applications like factor-augmented QVAR (QFAVAR) models. These represent promising directions for future investigation.

CRediT authorship contribution statement

Shiqi Ye: Writing – original draft, Methodology, Software, Conceptualization. **Hongyin Zhang:** Writing – original draft, Resources, Software, Data curation. **Mo Zhou:** Validation, Writing – original draft, Formal analysis. **Tingguo Zheng:** Funding acquisition, Writing – review & editing.

Declaration of competing interest

Authors declare that I have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper "Global Energy Market Connectedness and Inflation at Risk".

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2025.108733.

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