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Shifting roles of renewable and fossil energy in the ENTSO-E countries: Evidence from a novel war-induced energy intensity index

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ABSTRACT

The Russia-Ukraine war, escalating in February 2022, severely disrupted European energy markets. This conflict significantly increases energy security concerns and drives costs to unprecedented levels. This study investigates the evolving roles of renewable and fossil energy in mitigating this insecurity. We introduce a novel War-Induced Energy Intensity (WEI) index, constructed from over 507,574 news reports and tweets using large language models (LLMs). Our employed LLMs enable us to apply a scoring framework that precisely captures the intensity of fossil energy induced by the war. Validation tests across 24 European countries confirm that our WEI outperforms existing geopolitical risk indices in explaining wholesale electricity market dynamics. A structural break test identifies a significant market shift in early 2022, coinciding with the conflict's outbreak. This provides a statistical basis for our pre- and post-conflict analysis, which reveals a reversal of roles. Before 2022, fossil fuels played a stabilizing role in electricity markets. After the conflict began, their supply disruptions exacerbated market risks. In contrast, renewable energy sources – particularly wind, solar, and hydropower – emerged as key stabilizers, significantly reducing market instability. These findings underscore the growing importance of renewables in ensuring energy security during geopolitical crises.

1. Introduction

The Russia-Ukraine conflict has profoundly disrupted the European electricity market by fracturing global supply chains for critical raw materials and fossil fuels, exposing the region's deep structural reliance on Russian energy (Maneejuk et al., 2024; Wang et al., 2024; Yang et al., 2025; Liu and Lee, 2025; Sassi, 2025). These logistical disruptions triggered cascading effects on grid stability (Yang and Fu, 2025) and led to unprecedented price surges, intensified market volatility (Akadiri and Ozkan, 2025), and shock transmission (Do et al., 2024). Consequently, policymakers were compelled to pursue import diversification and renewable expansion (Hille and Angerpointner, 2025) alongside a temporary, stabilizing reintroduction of coal (Frost, 2022). Despite these interventions, the resulting escalation in costs with natural gas prices doubling and oil rising by roughly 60 % during the conflict (Pereira et al., 2022; Hille and Angerpointner, 2025), has intensified energy insecurity and threatened progress toward the UN Sustainable Development Goals.

Therefore, understanding the interplay between renewable and fossil energy sources in power generation could help Europe and other nations build resilience against future geopolitical shocks. This is particularly important in addressing the risk of energy insecurity posed by the Russia–Ukraine conflict. However, a key methodological challenge lies in accurately capturing the degree and dynamics of energy insecurity risk triggered by the conflict.

The Geopolitical Risk (GPR) index developed by Caldara and Iacoviello (2022) has been widely used to quantify the effects of geopolitical events on macroeconomic and financial variables. However, it may not

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fully meet the specific analytical needs of this study for several reasons.

First, the GPR is designed as a global-level indicator that aggregates various types of geopolitical tensions – including wars, terrorist attacks, and diplomatic crises – into a single composite measure (Caldara and Iacoviello, 2022; Alonso-Álvarez et al., 2025; Wang et al., 2025a). As such, it provides a broad, generalized view of political risk but fails to isolate the idiosyncratic effects of the Russia–Ukraine conflict on energy-related outcomes. This makes it less suitable for analyzing energy-specific disruptions that are regional in nature yet have global repercussions.

Second, the GPR relies primarily on the frequency of geopolitical keywords in major international newspapers. Consequently, it captures how often conflicts are mentioned, but not how they are portrayed. The index lacks a semantic understanding of the tone, stance, or sentiment underlying news coverage (Karagozoglu et al., 2022). This limitation restricts the index's capacity to capture the intensity of conflicts, which is better assessed through the content and tone of media reports rather than frequency alone.

Therefore, a more granular, news-based measure is required – one that can assess the specific contribution of the Russia–Ukraine conflict to public perceptions of energy market movements and energy insecurity. In other words, we need a measure that not only extracts conflict-relevant news but also quantifies the opinions, tone, and emotional intensity embedded in those texts regarding energy market disruptions. Such an approach allows for a more precise weighting of conflict developments, offering deeper insight into how war reshapes energy market expectations and perceived risks.

For this purpose, we propose a new approach to construct the War-Induced Energy Intensity (WEI) Index based on news articles and tweets. More specifically, we improve Caldara and Iacoviello's (2022) measure by employing their geopolitical dictionary. However, we apply an additional filter to extract news and tweets specifically related to the Russia-Ukraine conflict, utilizing keywords we developed based on Abakah et al. (2023). After that, we apply large language models (LLMs), including BERT and LLaMA3, with a news-scoring framework to determine the tone and emotional inclination embedded in the text regarding fossil energy price movements.

To demonstrate the incremental informational value of the WEI index, we compare it against the standard GPR as a benchmark. This comparison allows us to empirically assess whether a sentiment-quantified, conflict-specific approach offers stronger explanatory power for energy market volatility and electricity price dynamics during wartime (Li et al., 2025). Methodologically, we conduct comparative tests following Engle and Campos-Martins (2023), using data from wholesale electricity markets across 24 key ENTSO-E (European Network of Transmission System Operators for Electricity) countries. The results demonstrate that our proposed WEI Index exhibits significantly higher explanatory power for electricity price changes and volatility compared to both the global and European GPRs.

Next, we capture the risk of energy insecurity induced by the war in one of the 24 key ENTSO-E countries as the risk transmitted from the dynamics of the WEI and electricity markets in other countries, influenced by the WEI. We construct this measure using Generalized Forecast Error Variance Decomposition within the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model. This analysis also examines how the conflict influences electricity prices through market mechanisms and provides insights into systemic risk in the European electricity market, and thus, the energy security issue in the region.

The significance of studying the 24 key countries in the European electricity grid lies in the fact that these countries represent the core of the European electricity market, with a high degree of interconnection within the grid. They are crucial for understanding systemic risks in the entire European grid. As energy markets become increasingly globalized and interdependent, the stability of the European grid is not only vital for individual countries but also essential for the region's economic and social well-being. By analyzing the electricity prices and market responses of these countries, we can better understand the vulnerabilities and resilience of transnational electricity supply chains in the context of geopolitical conflict. This finding allows us to offer strategic recommendations for enhancing grid resilience and ensuring energy supply security.

To further analyze the roles of renewable and fossil energy in addressing the risk of energy insecurity in Europe, we employ the Quantile Autoregressive Distributed Lag (QARDL) model. This method is particularly suitable for our study due to its ability to simultaneously capture short-term and long-term dynamics as well as nonlinear and asymmetric relationships across different market conditions. Unlike conventional ARDL or OLS approaches that focus on the conditional mean, the QARDL framework enables the estimation of heterogeneous effects across the entire conditional distribution of the dependent variable, which is the energy insecurity risk proxy. This feature is crucial in the context of the European electricity market, where the impacts of renewable and fossil energy shares on energy insecurity may vary considerably under stable versus turbulent market regimes. For example, the effect of renewable penetration on market stability may be more pronounced during high-volatility periods, while fossil energy dependence may have asymmetric effects depending on the quantile of risk. By modelling these relationships at different quantile levels, QARDL allows for a more comprehensive understanding of how the structural composition of energy sources contributes to both resilience and vulnerability under varying conditions. Specifically, we regress the previously defined energy insecurity risk proxy on the proportions of different energy sources contributing to the power generation structure in the electricity market before and after the full-scale war, using monthly data from January 2015 to December 2023.

Our empirical analyses mentioned above are underpinned by the following research hypothesis: the Russia–Ukraine conflict triggers a fundamental shift in the functional roles of renewable and fossil energy regarding electricity market stability. Specifically, we test whether fossil fuels, which acted as stabilizers prior to 2022, became sources of risk amplification following the conflict, while renewables evolved from secondary to primary stabilizers. Consequently, our core research question asks: How and to what extent did the war reshape the relative contributions of renewable and fossil energy to energy security across European electricity markets?

Fig. 1 shows the conceptual mechanism linking the Russia–Ukraine conflict, energy structure adjustment, and electricity market risk. The conflict disrupts fossil fuel supply and prices, increasing market risk, while renewable energy expansion helps mitigate volatility and enhance stability.

Our analysis considers not only renewable and fossil energy sources as a whole but also differentiates among specific energy types such as biomass, solar, wind, hydro, and other renewables, as well as coal, natural gas, and other fossil fuels. This detailed categorization captures the dynamic effects of different energy types under various market conditions and time periods. Such a refined analysis helps more accurately understand and predict the impact of external shocks, like geopolitical risks, on electricity market prices, while revealing the specific contributions of various energy types to market stability. We summarize the flow of our research process in Fig. 2.

Our findings reveal that the Russia-Ukraine war has significantly impacted the stability of the European electricity market, with renewable and fossil energies playing complex and differing roles. Before the full-scale conflict, the European electricity market was relatively stable, primarily due to the steady supply of fossil fuels. During this period, although the global energy market was gradually transitioning to renewable sources to address long-term environmental and economic challenges, oil, natural gas, and coal still held indispensable positions in electricity generation. These fossil fuels, with their mature and extensive supply chains, were less affected by geopolitical events, providing a certain degree of price and supply stability to the electricity market.

After the outbreak of the conflict, the global energy market –

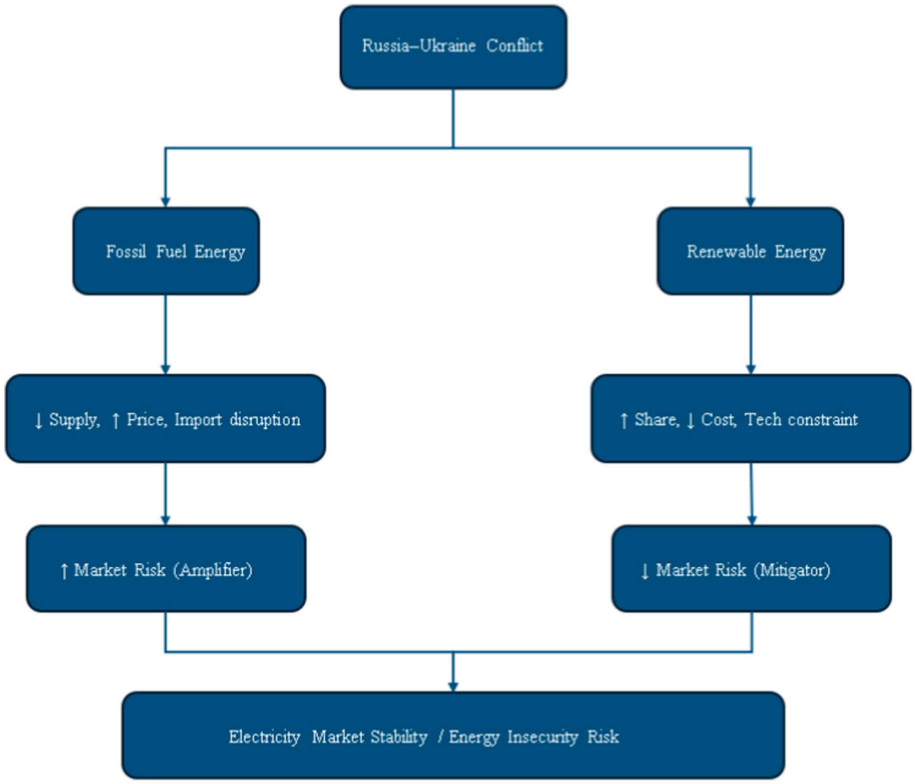

Fig. 1. Dual-path mechanism of fossil and renewable energy in market risk transmission.

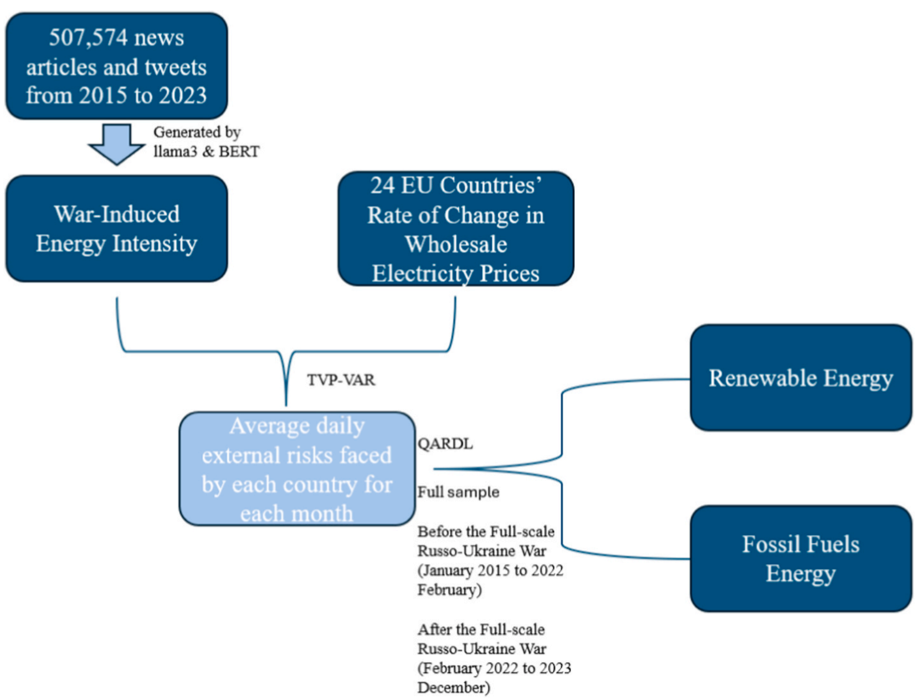

Fig. 2. Flowchart of the research process.

particularly the supply of fossil fuels – faced significant turmoil. As Russia is a major global supplier of natural gas, the conflict directly affected its energy exports to Europe and other regions, leading to shortages, soaring prices, increased market dependency, and heightened risks. Simultaneously, due to the relatively stable supply of renewable energies such as wind, solar, and hydroelectric power, and their lower sensitivity to geopolitical events, they became key factors in mitigating energy supply instability during the conflict. These renewable sources, not reliant on complex international supply chains, were able to maintain supply continuity and price stability more effectively.

Our study makes two important contributions to literature. First, we propose a novel news-based comprehensive index tailored to capture level of public perceptions regarding the potential impacts of Russian-Ukraine war on fossil energy prices. Existing GPR indices rely on counting relevant keywords, which may not fully capture the severity and intensity of the Russia-Ukraine war. Meanwhile, our newly proposed index not only accounts for the frequency of relevant keywords but also uses advanced language processing techniques to quantify the content of news articles, thereby better reflecting the severity of the war. Therefore, our index provides more valuable information about the conflict and compared to the traditional GPR, offers better predictions of the energy market's dynamics, as confirmed by validation tests. It also offers insights into energy security issues, especially in Europe, where energy supplies have been severely affected by the Russia-Ukraine war, providing useful policy recommendations. Even though we specifically focus on Russia-Ukraine war in this study, our approach can be straightforwardly applied to other types of specific conflict. *Second*, our empirical analyses contribute comprehensive findings on how (and to what extent) the roles of renewable and fossil energies have evolved in European countries in coping with the risk of energy insecurity induced by the most significant geopolitical conflict in the region. We further provide insights into how these roles shift over the short-term versus long-term horizon and how their changes are subject to the market conditions.

The remainder of this study is organized as follows. Section 2 discusses the methodological framework for constructing the WEI index, together with the validation tests. This section also introduces the econometric models employed in the analysis: the TVP-VAR model is used to construct a proxy for country-specific energy insecurity risk induced by the war. In Section 3, we describe the QARDL model, which is applied to examine the heterogeneous short- and long-run impacts of renewable and fossil energy, and a rolling-window Bai–Perron structural break test is conducted to detect potential regime shifts over time. Section 4 presents the data and empirical results, while Section 5 concludes the paper and discusses policy implications.

2. Construction of the WEI index

2.1. The construction of the WEI

To construct a WEI for the Russia–Ukraine War, we utilize both the BERT method and a language model based on LLaMA3 to analyze a dataset comprising 507,574 news articles and tweets sourced from Factiva and Twitter. The Factiva database provides comprehensive coverage of leading international and regional media outlets, including Dow Jones, The Wall Street Journal, Reuters, Associated Press, Financial Times, Bloomberg, and other major news agencies, with materials published in multiple languages. This ensures that our dataset encompasses mainstream media reports across the globe, thereby capturing a broad spectrum of narratives and sentiments related to the conflict. The dataset spans from January 1, 2015, to December 31, 2023, and includes information from global regions.

As illustrated in Fig. 3, our analysis of Russia-Ukraine War related news is divided into two main sections. The first section involves utilizing the BERT model to analyze the sentiment expressed in news articles. This analysis focuses on detecting the tone and emotional inclination embedded in the text, that is, whether the text shows inclination to appreciation in energy prices, depreciation in energy prices, or neutral (complex emotions with both possibilities). BERT, as a language processing tool, excels at understanding linguistic subtleties, allowing it to identify nuanced emotional expressions based on word arrangement and choice (Devlin et al., 2018). Before fine-tuning for specific tasks, BERT undergoes pre-training on extensive text corpora, endowing it with a broad comprehension of language that enhances its effectiveness in specialized tasks like sentiment analysis. This approach not only improves the accuracy of emotion detection but also reduces the time and resources needed to develop task-specific models.

The second part of the analysis employs large language models to examine news content. Unlike the strictly text-based approach in the first part, this method primarily simulates real human behavior to analyze news and tweets (Chowdhery et al., 2023). Furthermore, the analysis of news and tweets focuses on capturing the public's genuine emotions and perceptions of these contents. In contrast, content analysis using methods aims for a broader understanding of the news by considering all elements within the material. Traditional geopolitical risk indices, on the other hand, often rely on news text analysis by constructing keyword dictionaries (including terms related to war, military threats, terrorism, etc.), automatically identifying and analyzing articles from historical newspapers, and calculating the proportion of articles mentioning geopolitical events to construct a time series index reflecting geopolitical risk (Caldara and Iacoviello, 2022). Compared to traditional methods, using large language models allows for a more comprehensive understanding and interpretation of textual information, capturing complex contexts and emotions, and simulating human reactions in various situations (Zhu et al., 2024), thereby providing more precise and dynamic assessments and analyses. Additionally, we also incorporated the traditional keyword dictionary approach used in geopolitical risk indices. Before analyzing these news articles and tweets with the locally deployed LLaMA3 large language model, we provided the model with common geopolitical risk keywords. Therefore, combining these analyses offers a more thorough understanding of how news about the Russia-Ukraine war is presented in the media, contributing to deeper insights into the market and its potential impact on public behavior.

While existing research has extensively explored the impacts of geopolitical conflicts on the energy market, focusing particularly on price volatility, market connectivity, and dependency and response strategies, these studies have highlighted the interactions between different countries and energy types during crises and their effects on energy market dynamics. However, they often use traditional methods to measure the impacts of the Russia-Ukraine conflict and other geopolitical events, which may not accurately reflect the true impact of geopolitical shocks. Additionally, there is a lack of in-depth analysis of the European electricity market, with most research only touching on superficial price fluctuations and market connectivity. Moreover, the literature has not sufficiently examined the specific impacts of fossil and renewable energies on systemic grid risks under geopolitical shocks, and the sample countries and time periods included in the research need further restructuring. Our news and tweets focus solely on issues related to the Russia-Ukraine War, which is highly relevant to our study of the wholesale electricity markets in 24 European countries. Furthermore, compared to the Geopolitical Risk Index (GPR) that addresses all geopolitical news, our specialized analysis of news and tweets related to the Russia-Ukraine War and its linkage with the wholesale electricity markets of the 24 main ENTSO-E participating countries provides greater accuracy (Details in Appendix A). The Russia-Ukraine War has a direct and profound impact on the energy supply chain, particularly the European electricity markets. This is not only because Russia is a major supplier of natural gas and oil to Europe, but also because the political and economic consequences of the war, such as sanctions and supply disruptions, can trigger a domino effect globally. A standalone Russian or Ukrainian GPR may not fully capture the market impact of this specific conflict. By focusing specifically on news and tweets related to the Russia-Ukraine War, we can more accurately capture the conflict's actual impact on the energy market, especially the electricity market. Compared to the broader GPR, this focus avoids the noise of unrelated events (such as domestic political disputes or terrorist activities), making the analysis more precise. The impact of the Russia-Ukraine War extends beyond Russia and Ukraine, affecting the whole of Europe.

To quantify war-related sentiment and content dynamics, we construct a War-Induced Energy Intensity (WEI) index that captures both the emotional tone and substantive content of daily news and tweets concerning the Russia–Ukraine conflict. The index combines two dimensions: (i) the emotional polarity of each article, estimated using a

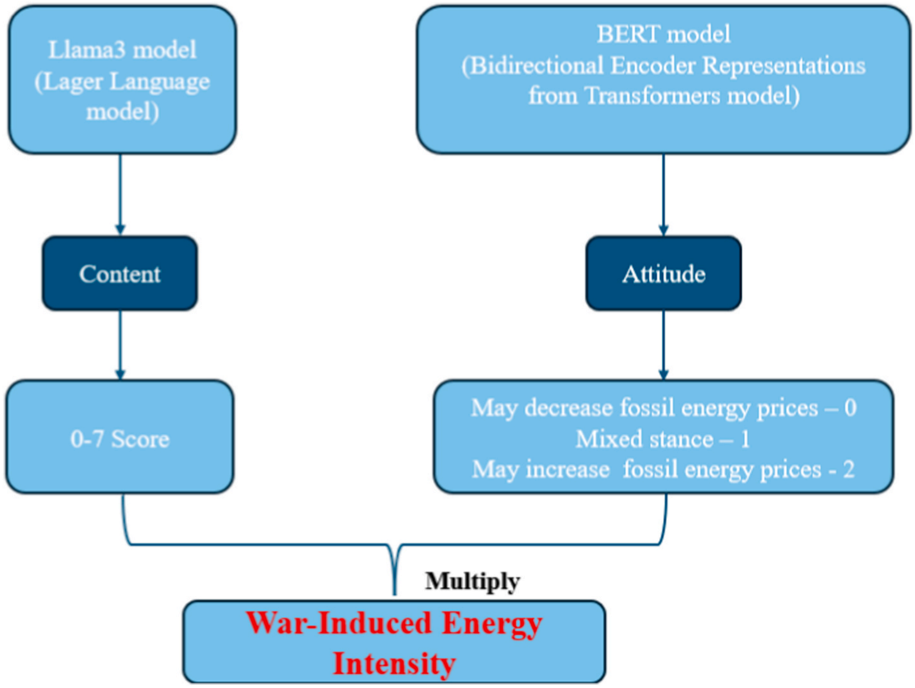

Fig. 3. Flowchart of daily index building.

BERT-based classifier with SemEval reference markers, and (ii) the content inclination score, derived from large language model (LLaMA3) assessments following the scoring framework of Lopez-Lira and Tang (2023) and Wang et al. (2025a). These two dimensions are aggregated into a daily composite measure representing the overall war-induced intensity perceived in the energy domain. Detailed calculation steps, probability weighting, and formula specifications are provided in Appendix 1.

2.2. Comparison with measures of geopolitical risk

Fig. 4 shows that compared to the global and European geopolitical conflict indices constructed by Dario Caldara and Matteo Iacoviello, our index more accurately identifies the events of the Russia-Ukraine War fossil energy tension index from 2015 to 2023. Furthermore, the overall trend demonstrates a shift from tension to relative easing, followed by a return to increased tension.

A After Russia's annexation of Crimea and its support for separatist forces in Eastern Ukraine, the region experienced continued conflict and armed tensions. The situation remained strained until it began to gradually subside following the conclusion of the Battle of Svitlodarsk.

B Following the end of the Battle of Svitlodarsk, both sides remained in a deadlock, which led to a reduction in the tension surrounding fossil energy. This continued until the outbreak of the Kerch Strait conflict on November 25, 2018.

C After the resolution of the Kerch Strait conflict, Russia and Ukraine entered a prolonged phase of standoff, during which no severe conflicts occurred.

D Starting in 2021, there were consistent reports of Russia deploying additional troops to the Russia-Ukraine border. By the end of 2021 and the beginning of 2022, NATO began discussing the possibility of a full-scale Russian invasion of Ukraine, and initiated evacuations in January 2022.

E On February 24, 2022, the Russia-Ukraine war broke out in full force. However, during the initial stages of the war, Russia did not immediately halt the transportation of natural gas and other fossil fuels used for power generation to Europe. It was not until September 2022 that Russia fully cut off these supplies, leading to an unprecedented spike in energy tensions.

Additionally, to further compare the explanatory power of our Russia-Ukraine War Index with other geopolitical risk indicators in analyzing risks to the European power grid, we follow the regression methods of Engle and Campos-Martins (2023) and present the results of explanatory power of the geopolitical indices on electricity price changes and volatilities in Tables 1 and 2, respectively. First, we calculated the demand-weighted average of daily wholesale electricity prices for 24 key member countries of the European Network of Transmission System Operators for Electricity (ENTSO-E). This gave us the demand-weighted average daily wholesale electricity price for these 24 countries. Subsequently, we processed the weighted average prices, calculating the monthly percentage changes and monthly volatilities. Next, we conducted regression analyses on the monthly percentage changes and volatilities of electricity prices for these 24 countries using the variables “Rate of Change in War Index (Fossil Energy Intensity) (%)”, “Global GPR Rate of Change (%)” (Caldara and Iacoviello, 2022), and “European GPR Rate of Change (%)” (Caldara and Iacoviello, 2022). According to the regression results in Table 1, the “Rate of Change in War Index (Fossil Energy Intensity) (%)” proved to be the most significant explanatory variable. Specifically, an increase in the Russia-Ukraine War Index is associated with an increase in the rate of change in the weighted average wholesale electricity prices for these 24 countries. Conversely, when the global and European GPR rates of change rise, the rate of change in the weighted average electricity prices for these countries tends to decrease, though these results are not statistically significant. Generally, as the war escalates and geopolitical tensions intensify, electricity prices in European countries dependent on natural gas and coal imports tend to rise. However, the results show that, from simple to multiple regression models, the “Rate of Change in War Index (Fossil Energy Intensity) (%)” is the only globally significant and positively correlated variable.

Volatility is another common characteristic. When tensions in the Russia-Ukraine War rise or the global geopolitical tension increases, the wholesale electricity prices for European countries that rely on fossil

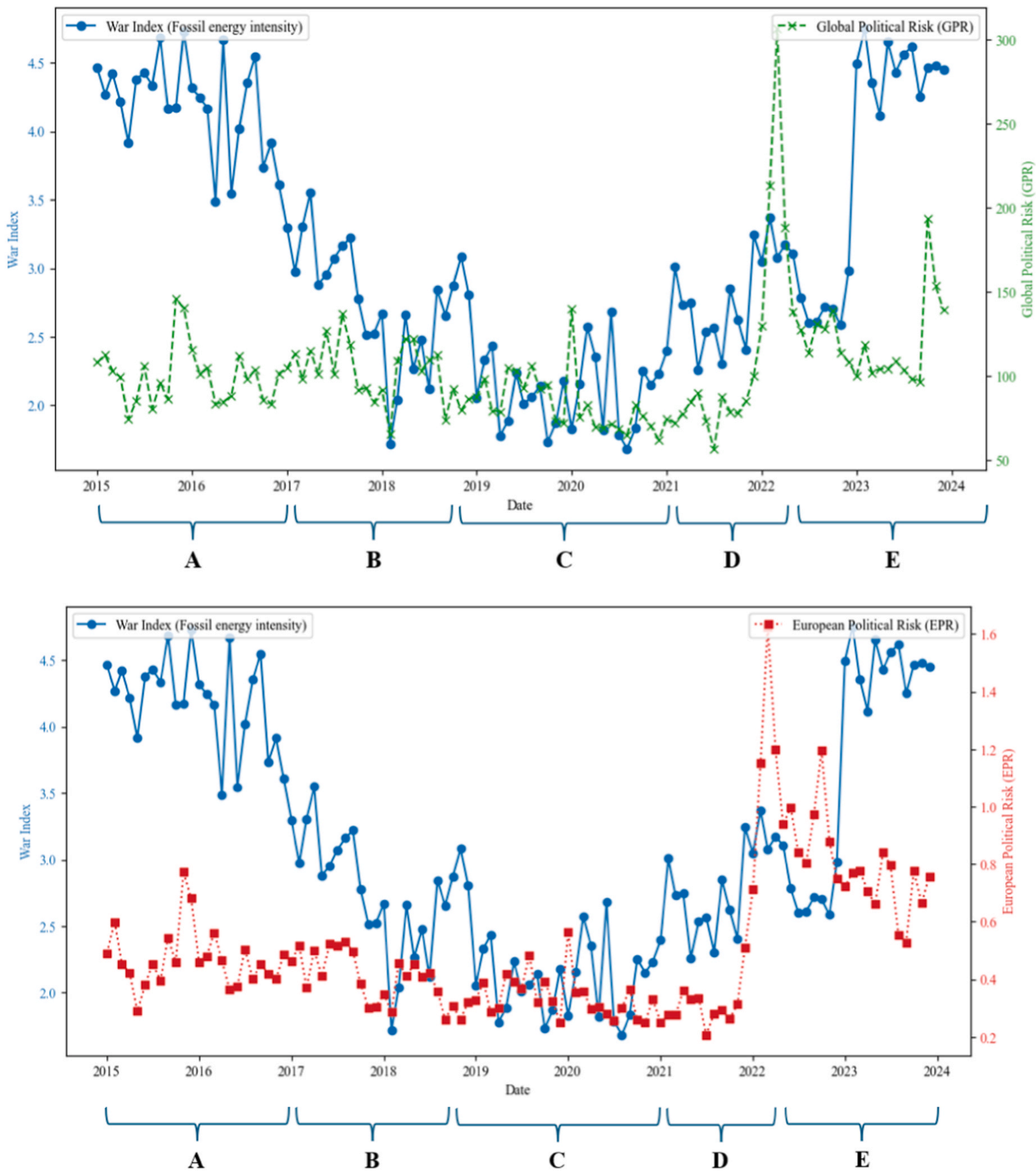

Fig. 4. The War Index, reflecting fossil energy intensity, is compared with the monthly Global Geopolitical Risk (GPR) index and the monthly European Geopolitical Risk (EPR) index, both developed following Caldara and Iacoviello (2022).

fuels for electricity generation tend to remain high, especially during the full outbreak of the Russia-Ukraine War. During these periods, wholesale electricity prices typically exhibit lower volatility because prices remain high for extended periods due to a lack of mitigation avenues. This is primarily because war or political tensions disrupt the supply chain for fossil fuels like natural gas and coal and increase import costs, thus raising electricity production costs. The limited availability of supplies and alternative energies reduces the range of price fluctuations. From Tables 2 and it is evident that whether from simple to multiple regression, only the 'War Index (Fossil energy intensity) Change Rate (%)' shows a significant negative correlation.

To ensure the reliability and robustness of the analysis results, we followed the methods of Engle and Campos-Martins (2023) to conduct further robustness checks, which included removing outliers and reducing the sample size. These adjusted results are presented in Appendix 6 Tables A6.1 and A6.2. After these adjustments, we re-ran the regression analyses and found that even after removing extreme data and reducing the sample size, the regression results support the conclusions and analyses drawn in Tables 1 and 2. This finding emphasizes the stability and credibility of our original analysis, indicating that even in the face of data variations, our main findings still hold explanatory power and relevance.

Table 1
Regression results of the rate of change in War Index, Global Geopolitical Risk Index, and European Geopolitical Risk Index on the demand-weighted average wholesale electricity price change of 24 ENTSO-E countries.

	(1)	(2)	(3)	(4)
War Index (Fossil energy intensity) Change Rate (%)	0.43571*** (0.149030)			0.43530*** (0.15035)
Global GPR Change Rate (%)		−0.064496 (0.09602)		−0.04182 (0.09334)
European GPR Change Rate (%)			−0.036229 (0.04243)	−0.04133 (0.04116)
Cons	−0.74731 (1.57388)	3.73771* (2.00282)	2.74831** (1.12178)	0.12840 (2.34392)
Obs.	108	108	108	108
R-squared	0.0746	0.0042	0.0068	0.0851
Adjusted R-squared	0.0659	−0.0052	−0.0025	0.0587
Residual S.E.	124.32830	133.78474	133.43660	125.28582
F statistic	8.55***	0.45	0.73	3.22**

Note: Standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1. (monthly data from January 2015 to December 2023).

Table 2
Regression results of the rate of change in War Index, Global Geopolitical Risk Index, and European Geopolitical Risk Index on the volatility of the demand-weighted average wholesale electricity prices of 24 ENTSO-E countries.

	(1)	(2)	(3)	(4)
War Index (Fossil energy intensity) Change Rate (%)	−0.75368*** (0.25737)			−0.79530*** (0.25501)
Global GPR Change Rate (%)		−0.18715 (0.16353)		−0.22991 (0.15832)
European GPR Change Rate (%)			0.04627 (0.07267)	0.05216 (0.06981)
Cons	21.31105*** (2.66653)	18.73331*** (3.41110)	15.32293*** (1.92115)	25.43388*** (3.97562)
Obs.	108	108	108	108
R-squared	0.0764	0.0122	0.0038	0.0999
Adjusted R-squared	0.0676	0.0029	−0.0056	0.0739
Residual S.E.	362.86750	388.07028	391.36861	360.43388
F statistic	8.76***	1.31	0.41	3.85**

Note: Standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1. (monthly data from January 2015 to December 2023).

2.3. Construction of shock indicators for wholesale electricity prices in 24 European countries

To capture propagation of shocks and risks brought by the Russia-Ukraine war across European countries' electricity markets[1] at different time scales, we employ the risk spillover network model presented in Chatziantoniou et al. (2023) and Zheng et al. (2023). Initially, we constructed a TVP-VAR model using the methodology from Antonakakis et al. (2020) and Zheng et al. (2023), incorporating variance decomposition.[2] The variance-covariance matrix was estimated using a Kalman filter with a forgetting factor, thereby establishing a time-varying risk spillover network analysis framework. This model offers two main advantages: first, it overcomes the arbitrary selection of window size in traditional rolling VAR methods, which can produce unstable or flat parameters; second, the dynamic effect analysis preserves the original sample of the initial window, making it suitable for analyzing financial risk spillover effects in low-frequency, limited time series data. The p-order TVP-VAR model is represented as follows:

$$x_t = A_{1t}x_{t-1} + A_{2t}x_{t-2} + \cdots + A_{pt}x_{t-p} + u_t \; (1)$$

$$u_t \sim N(0, \Omega_t)$$

here, x_t, and u_t are $M\,x\,1$ vectors. In our context, x_t comprises electricity price changes of 24 ENTSO-E countries and the changes of the WEI. Ω_t and A_{it} (where $i = 1, 2, 3, \ldots, D$) are $M\,x\,M$ matrices, with the former representing the time-varying variance-covariance matrix and the latter representing the time-varying VAR coefficients. For simplicity, we use the $M\,x\,M$ lag polynomial matrix:

$$A(L) = \left[I_M - A_{1t}L - \cdots - A_{pt}L^p\right] \tag{2}$$

where I_M is the identity matrix. Therefore, the model can be expressed as:

$$A(L)x_t = u_t \tag{3}$$

If the TVP-VAR process is stationary, it can be written as a TVP-VMA (∞) using the Wold representation theorem:

$$x_t = B(L)u_t \tag{4}$$

where the infinite lag polynomial matrix $B(L)$ can be computed recursively through $A(L) = [B(L)]^{-1}$. However, since $B(L)$ contains an infinite number of lags, it is approximated by computing B_k for horizons $k = 1, \ldots, K$.

The Generalized Forecast Error Variance Decomposition ($\widetilde{\gamma}_{mjt}(K)$) measures the contribution of shocks to variable j to the forecast error variance of variable m, and can thus be used to interpret the risk spillovers from variable j to variable m.

$$\gamma_{mjt}(K) = (\Omega_t)_{jj}^{-1} \frac{\sum_{k=0}^{K} \left((B_k\Omega_t)_{mjt}\right)^2}{\sum_{k=0}^{K} \left((B_k\Omega_t B_k')_{mm}\right)} \tag{5}$$

$$\widetilde{\gamma}_{mjt}(K) = \frac{\gamma_{mjt}(K)}{\sum_{n=1}^{M} \gamma_{mjt}(K)} \tag{6}$$

The above two equations (5) and (6) represent the contribution of shocks to variable j to the forecast error variance of variable m over the horizon K. Since the row sums of $\widetilde{\gamma}_{mjt}(K)$ are not 1, normalization is necessary to better analyze the risk spillover effects. Through

[1] The specific countries are shown in Appendix 2.
[2] TVP-VAR model stands for the Time Varying Parameter – Vector Autoregressive model.

normalization, we obtain the following identities:

$$\sum_{m=1}^{M} \widetilde{\gamma}_{mjt}(K) = 1 \tag{7}$$

$$\sum_{j=1}^{M} \sum_{m=1}^{M} \widetilde{\gamma}_{mjt}(K) = M \tag{8}$$

Next, we calculate all connectivity measures to obtain different risk spillover indices. This paper analyzes the risk spillovers received by variable m from all other variables j, defining the risk received index for variable m from all other variables j (RiskFromOther) as follows:

$$RiskFromOther_{mt}(K) = \sum_{j=1, j\neq m}^{M} \widetilde{\gamma}_{mjt}(K) \tag{9}$$

This *RiskFromOther* indices represent the electricity price risk spillover from all other variables in the risk spillover network to the electricity market m over a specific time horizon K. This risk transmission, therefore, comprises of both direct and indirect effect (via markets other than m) emerged from the Russian-Ukraine conflict to market m.

After obtaining the daily time-varying risk exposures from the TVP-VAR model, we obtain the daily average external risk value for each month using the following formula based on the external risk faced by each country daily.

$$\text{DailyAverage}\textit{RiskFromOthers}_{\ mt} = \frac{1}{D}\sum_{d=1}^{D} \text{RiskFromOther}_{md}(K) \tag{10}$$

where D represents the number of days in a month, and $\text{RiskFromOther}_{md}(K)$ obtained from Eq. (10) represents the risk spillover value transferred to variable m from other variables at the daily level.

The resulting variable, *DailyAverageRiskFromOthers*, serves as the dependent variable in subsequent econometric analyses. In the baseline multidimensional fixed-effects model, this monthly risk measure is regressed on renewable and fossil energy shares, together with demand, trade, and macro-sentiment controls, after accounting for country-specific and time-specific effects. This integration links the dynamic risk information generated by the TVP-VAR framework with the structural characteristics of national energy systems, allowing us to assess how shifts in generation composition amplify or buffer the transmission of external geopolitical shocks across the European electricity market.

3. Econometric modelling

3.1. Benchmark model specification

This paper aims to research the relationship between the external risks faced by wholesale electricity prices in Europeans countries, due to the risk shocks from the Russia-Ukraine war, and the proportions of renewable and fossil energy in electricity generation. To eliminate the effects of entity-specific characteristics and time trends on the results, we utilize a multidimensional fixed effects model for the analysis. The specific econometric model is as follows:

$$\begin{aligned}\text{DailyAverageRiskFromOthers}_{\text{it}} &= \alpha_0 + \beta_1\,\text{Renewable}_{\text{it}} + \beta_2\,\text{Fossil}_{\text{it}} + \\ \beta_3\text{Demand}_{\text{it}} + \beta_4\text{NetImport}_{\text{it}} &+ \beta_5\text{lnGDP}_{\text{it}} + \beta_6\text{bci}_{\text{it}} + \beta_7\text{cci}_{\text{it}} + \lambda_{\text{i}} + \mu_{\text{t}} + \varepsilon_{\text{it}}\end{aligned} \tag{11}$$

The data used in this model spans from January 2015 to December 2023, with monthly frequency. DailyAverageRiskFromOthers refers to the risk each country's wholesale electricity price faces, derived from the TVP-VAR model based on the overall war index of the Russia-Ukraine war and the wholesale electricity prices of 24 key participating countries in ENTSO-E. $\text{Renewable}_{\,it}$ represents the proportion of renewable energy in the electricity grid. $\text{Fossil}_{\,it}$ denotes the proportion of fossil fuels in the electricity grid. $Demand_{it}$ is the total electricity demand of each country. $NetImport_{it}$ is the net total of electricity imports for each country. $lnGDP_{it}$ is the natural logarithm of each country's GDP. bci_{it} and cci_{it} are the Business Confidence Index and Consumer Confidence Index for each country, respectively. λ_{it} and μ_{it} represent country and month. ε_{it} is the random error term. α_0 and β_1 to β_7 are the regression coefficient. In this context, $Demand_{it}$, $NetImport_{it}$, $lnGDP_{it}$, bci_{it}, and cci_{it} have been selected as control variables. Electricity demand directly influences prices; an increase in demand usually leads to a rise in prices, whereas a decrease may cause prices to fall (de Lima and Bacchi, 2019). The net import of electricity reflects a country's dependence on international electric resources, and changes can affect price fluctuations (Jung, 2020). Moreover, the net import of electricity can also indirectly reflect the connectivity of the electric grid. Some countries are connected through interconnectors, which may affect their ability to import and export electricity, and including net electricity imports as a control variable can effectively manage the impact of this effect on the results. GDP is a comprehensive indicator of economic activity, and economic growth typically accompanies an increase in electricity demand, thereby affecting prices (de Lima and Bacchi, 2019) The Business Confidence Index reflects businesses' expectations of economic prospects, influencing their production and investment decisions, thus indirectly affecting electricity demand and prices (Liu and Gao, 2011). The Consumer Confidence Index reflects consumers' expectations of economic conditions and the future, influencing their consumption behavior, thus affecting electricity demand and prices (Qeqe et al., 2022). By controlling these variables, we can more accurately analyze how the share of renewable and fossil energy in electricity generation affects wholesale electricity prices under the impact of the Russia-Ukraine conflict. The combined effects of these variables on electricity demand and prices can be modeled to understand their impacts more accurately. Studies using vector error correction models have shown that economic growth, industrial structure, and inventory levels significantly influence electricity demand and prices.

Furthermore, to identify potential structural changes within the sample, we employed a rolling windows Bai–Perron test (Wang et al., 2025a, 2025b). This method allows us to detect multiple potential breakpoints across different subsamples, thereby capturing the dynamic evolution of the relationship between energy structure and external risk. The results confirm that March 2022 constitutes a statistically significant structural break, consistent with the onset of the Russia–Ukraine conflict, which justifies our division of the sample into pre- and post-conflict periods.

3.2. Quantile autoregressive distributed lag (QARDL) model

This study employs the Quantile Autoregressive Distributed Lag (QARDL) method (Cho et al., 2015) to conduct regression analysis using monthly data from 24 countries spanning January 2015 to December 2023. The QARDL model integrates elements of the Autoregressive Distributed Lag (ARDL) model (Pesaran and Shin, 1995) with the quantile regression approach (Koenker and Bassett, 1978). This combination allows the examination of both short-term and long-term relationships across selected quantiles. The QARDL technique, akin to the ARDL method, can be applied without considering the order of integration of the variables involved. By incorporating sufficient lags of the dependent variable, it addresses issues of endogeneity, omitted variables, and autocorrelation. Consequently, the estimators for both short-term and long-term effects are unbiased and efficient. Furthermore, QARDL has advantages over the ARDL method, which typically uses overall mean values and often fails to capture parameter variations across different quantiles within the sample period. The QARDL approach, on the other hand, provides robust results even with non-normal data generating processes and smaller sample sizes, making it superior in identifying the dynamic nature of the relationships being studied (Kaur et al., 2024).

To adapt the ARDL model explanation and the QARDL approach for panel data, we need to incorporate panel-specific terms λ_{it} and μ_{it} into the equations. These terms account for individual-specific effects and time-specific effects respectively. Here's the revised explanation and formulas with these modifications:

For the standard ARDL(p,q) process in the error correction model, we originally have:

$$\Delta Z_{it} = \theta_0 + \psi_1 Z_{it-1} + \psi_2 W_{it-1} + \sum_{i=1}^{p-1} \phi_i \Delta Z_{it-i} + \sum_{j=0}^{q-1} \kappa_j \Delta W_{it-j} + \epsilon_{it} \tag{12}$$

Now, including panel-specific terms:

$$\Delta Z_{it} = \theta_0 + \psi_1 Z_{it-1} + \psi_2 W_{it-1} + \lambda_{it} + \mu_{it} + \sum_{i=1}^{p-1} \phi_i \Delta Z_{it-i} + \sum_{j=0}^{q-1} \kappa_j \Delta W_{it-j} + \epsilon_{it} \tag{13}$$

where λ_{it} and μ_{it} are the panel-specific intercept and slope effects that could vary with individuals and time respectively.

Incorporating these terms into the QARDL model, equation (14) with error correction and projections becomes:

$$\Delta Z_{it} = \theta_0 + \psi_1 (Z_{it-1} - \beta W_{it-1}) + \lambda_{it} + \mu_{it} + \sum_{i=1}^{p-1} \phi_i \Delta Z_{it-i} + \sum_{j=0}^{q-1} \delta_j \Delta W_{it-j} + \epsilon_{it} \tag{14}$$

And the extended QARDL(p,q) model for quantile regression in the panel setting, equation (15), adapts to:

$$\Delta \mathrm{Z}_{it} = \theta_0(\tau) + \psi_1(\tau)(\mathrm{Z}_{it-1} - \beta(\tau)^{'} \mathrm{W}_{it-1}) + \lambda_{it}(\tau) + \mu_{it}(\tau) + \sum_{i=1}^{p-1} \phi_i(\tau) \Delta \mathrm{Z}_{it-i} + \sum_{j=0}^{q-1} \delta_j(\tau)^{'} \Delta \mathrm{W}_{it-j} + \epsilon_{it}(\tau) \tag{15}$$

Where $\lambda_{it}(\tau)$ and $\mu_{it}(\tau)$ are the quantile-specific panel effects which could vary across different quantiles τ. These adaptations allow the model to capture both the unique characteristics of each panel member over time and the variability across different quantiles of the distribution of the dependent variable. This approach enriches the model's capacity to handle heterogeneity and dynamic changes in panel data settings.

In the QARDL (Quantile Autoregressive Distributed Lag) model, several key parameters are pivotal: Adjustment Speed Parameter $\psi_1(\tau)$: This parameter determines how quickly the system returns to its long-term equilibrium, showcasing the economic system's capacity to recover after deviations. The adjustment speed can vary across different quantiles τ, indicating diverse rates of adjustment under various market conditions. Long-term Cointegration Parameter $\beta(\tau)^{'}$ This coefficient elucidates the enduring relationship between the dependent and explanatory variables. Within the quantile regression framework, $\beta(\tau)^{'}$ adjusts to shifts in various economic settings, reflecting the long-term elasticity and interaction dynamics under different market conditions. Short-term Dynamic Parameters $\phi_i(\tau)$ and $\delta_j(\tau)^{'}$: These parameters quantify the influence of past changes in the dependent variable and the explanatory variables on the current adjustments in ΔZ_{it}. The quantile-dependent analysis of these parameters uncovers the intricate dynamics among the variables across different economic cycles or conditions. Furthermore, the QARDL model utilizes the Akaike Information Criterion (AIC) to select the optimal lag lengths p and q, balancing the model's complexity against its ability to capture the underlying data structure without overfitting. Research by Cho et al. (2015) suggests that the parameter estimators approximate a (mixed) normal distribution in large samples, enhancing the model's statistical robustness and its practical utility in various economic applications. This adaptability makes the QARDL model an invaluable tool for analyzing and forecasting dynamic economic data shifts.

In this research, the QARDL model is formulated as per Equation (16), which is structured as follows:

$$\begin{aligned}
&\Delta \mathrm{DailyAverageRiskFromOthers}_{it} = \theta_0(\tau) + \psi_1(\tau) \\
&\left(\begin{array}{c} \mathrm{DailyAverageRiskFromOthers}_{it-1} - \beta_*^{\mathrm{Renewable}}(\tau)\mathrm{Renewable}_{t-1} - \\ \beta_*^{\mathrm{Fossil}}(\tau)\mathrm{Fossil}_{t-1} - \beta_*^{\mathrm{NetImport}}(\tau)\mathrm{NetImport}_{t-1} \\ \beta_*^{\mathrm{Demand}}(\tau)\mathrm{Demand}_{t-1} - \beta_*^{\mathrm{lnGDP}}(\tau)\mathrm{lnGDP}_{t-1} - \beta_*^{\mathrm{bci}}(\tau)\mathrm{bci}_{t-1} - \beta_*^{\mathrm{cci}}(\tau)\mathrm{cci}_{t-1} \end{array} - \right) + \\
&\sum_{j=1}^{p-1} \phi_{j*}(\tau)\Delta \mathrm{eDailyAverageRiskFromOthers}_{t-j} + \sum_{j=0}^{q-1} \delta_{j*}^{\mathrm{Renewable}}(\tau)\Delta \mathrm{Renewable}_{t-j} + \\
&\sum_{j=0}^{q-1} \delta_{j*}^{\mathrm{Fossil}}(\tau)\Delta \mathrm{Fossil}_{t-j} + \sum_{j=0}^{q-1} \delta_{j*}^{\mathrm{NetImport}}(\tau)\Delta \mathrm{NetImport}_{t-j} + \\
&\sum_{j=0}^{q-1} \delta_{j*}^{\mathrm{Demand}}(\tau)\Delta \mathrm{Demand}_{t-j} + \sum_{j=0}^{q-1} \delta_{j*}^{\mathrm{lnGDP}}(\tau)\Delta \mathrm{lnGDP}_{t-j} + \sum_{j=0}^{q-1} \delta_{j*}^{\mathrm{bci}}(\tau)\Delta\, \mathrm{bci}_{t-j} + \\
&\sum_{j=0}^{q-1} \delta_{j*}^{\mathrm{cci}}(\tau)\Delta \mathrm{cci}_{t-j} + \lambda_{it}(\tau) + \mu_{it}(\tau) + \epsilon_{it}(\tau)
\end{aligned} \tag{16}$$

Furthermore, to further explore the impact of external shocks on the electricity market due to renewable and fossil energies, we have split

Table 3
Data used and generated in TVP-VAR model.

Variables (Used)	Unit	Source
Rate of change in wholesale electricity prices	%	Ember & website of each country
Daily war index (Fossil energy intensity) score	Index	Built by LLaMA3 & BERT
Variables (Generated)	Unit	Source
Daily Risk from outside	Index	Built by TVP-VAR model
Average daily external risks faced by each country for each month	Index	Built by TVP-VAR model

*__Note:__ Ember: https://ember-climate.org/.

Table 4
Data used for regression model including the QARDL model.

Variables	Source
DailyAverageRiskFromOther (DARFO)	TVP-VAR
The texts	Factiva Twitter
Renewable	Ember
Fossil	Ember
Demand	Ember
NetImport	Ember
lnGDP	OECD Database
bci	OECD Database
cci	OECD Database
Coal	Ember
Gas	Ember
OtherFossil	Ember
Hydro	Ember
Solar	Ember
Wind	Ember
Bioenergy	Ember
OtherRenewable	Ember

*Note: Ember: https://ember-climate.org/; OECD Database: https://www.oecd.org/.

Renewable Energy and Fossil Energy. For Renewable Energy, based on the data source, we have divided it into bioenergy, solar energy, wind energy, hydro energy, and other renewable energy (primarily composed of geothermal energy). For Fossil Energy, based on the dataset, we have categorized it into coal energy, gas energy, and other fossil energy (primarily composed of petroleum).

4. Empirical results

4.1. Data and preliminary tests

To estimate the TVP-VAR model and construct the risk exposure for electricity markets in Europe (i.e., DailyAverageRiskFromOthers), we further collect the daily historical data for 24 ENTSO-E countries from January 1, 2015 to December 31, 2023. The data used in and generated from the TVP-VAR model are summarized in Table 3.

To perform the regression models including the QARDL presented in section 3, we collect additional monthly data between January 2015 and December 2023 as summarized in Table 4.

We present the summary statistics of main variables and their sources in Table 5.

We subsequently conducted panel unit root tests to confirm the stationarity of each variable. We employed three different unit root test methods: the Fisher-type and Harris-Tzavalis tests. Our findings indicate that all regression variables are stationary according to these tests (detailed results can be found in Appendix 3). Additionally, we performed a multicollinearity test, and the results indicate that there are no adverse effects impacting our regression model construction (detailed results are provided in Appendix 4). Lastly, we carried out the Breusch and Pagan (1980) LM test and the Pesaran (2004) CD test (detailed results can be found in Appendix 5). The results of both tests do not reject the null hypothesis that there is no cross-sectional dependence on the data.

4.2. Regression results

4.2.1. Benchmark results

In the full sample (Table 6) analysis from January 2015 to December 2023, the proportion of fossil fuels in the grid has a significant positive impact on the external risk index (DARFO) in both the OLS and two-way fixed effects models (coefficients of 0.00241 and 0.00251, respectively), but the significance of this impact decreases, though still significant, in the SYS-GMM model. This indicates that without accounting for potential dynamic issues, the proportion of fossil fuels in the grid significantly affects external risk; however, when controlling for dynamic effects, the significance of this impact might be influenced by other factors that were not considered. Similarly, the proportion of renewable energy in the grid has a significant positive impact on the external risk index in both the OLS and two-way fixed effects models (coefficients of 0.00226 and 0.00202, respectively), but this impact is not significant in the SYS-GMM model. This suggests that in the full sample, renewable energy has some influence on external risk, but this influence becomes insignificant when dynamic effects are controlled for. The insignificant and decreasing significance results in the full sample might be due to the counteracting effects of the periods before and after the conflict. This implies that the attributes of external risk changed due to the conflict and the subsequent changes in the international situation. Additionally, the Russia-Ukraine conflict exacerbated the global energy crisis, fundamentally impacting the international energy trade landscape (Xin and Zhang, 2023). This change in the international energy landscape likely altered the relationship between renewable and fossil fuel power generation and external risk. Therefore, dividing the sample into pre- and post-conflict periods helps to clearly identify the different impacts of fossil fuels and renewable energy on external risk.

As a subsample analysis, we divided the full sample (January 2015–December 2023) into the period before the full-scale conflict (January 2015–January 2022) and the period after the full-scale conflict (February 2022–December 2023). According to Table 7, the regression results before the full-scale conflict show that the proportion of fossil fuels in the grid has a significant positive impact on the external risk index in both the OLS and two-way fixed effects models (coefficients of

Table 5
Statistical description.

Variables	Unit	Mean	sd	min	max	Obs
DailyAverageRiskFromOther	Index	3.278	0.459	0. 476	3.990	2592
Renewable	%	43.502	24.824	4.070	99.700	2592
Fossil	%	37.586	24.586	0.000	93.420	2592
Demand	TWh	9.608	11.504	0.360	57.030	2592
NetImport	TWh	−0.001	1.616	−7.900	5.470	2592
lnGDP	Index	11.297	1.186	9.095	13.683	2592
Bci	Index	100.523	1.664	90.998	105.739	2592
Cci	Index	100.094	2.123	91.186	104.330	2592
Coal	%	13.557	19.078	0.000	91.100	2592
Gas	%	17.073	16.857	0.000	69.640	2592
OtherFossil	%	6.955	15.203	0.000	92.770	2592
Hydro	%	20.237	24.753	0.000	97.120	2592
Solar	%	4.333	5.977	0.000	50.000	2592
Wind	%	13.497	14.029	0.000	78.210	2592
Bioenergy	%	5.066	5.417	0.000	37.500	2592
OtherRenewable	%	0.368	0.802	0.000	3.980	2592

*Note: Coal, Gas, OtherFossil, Hydro, Solar, Wind, Bioenergy, and OtherRenewable represent the monthly share of electricity generation for each country in the grid.

Table 6
Benchmark results (Full sample).

	(1) OLS	(2) Two-way fixed	(3) SYS-GMM
L1. DARFO			1.01468***
			(0. 03896)
L2. DARFO			−0. 29138***
			(0. 03602)
Fossil	0. 00241***	0. 00251***	0. 00191*
	(0. 00052)	(0. 00046)	(0. 00099)
Renewable	0. 00229***	0. 00204***	0. 00071
	(0. 00052)	(0. 00049)	(0. 00093)
DemandTWh	0. 00160**	0. 00041	0. 00228
	(0. 00067)	(0. 00059)	(0. 00308)
NetImportsTWh	0. 01938***	0. 01898***	0. 01015**
	(0. 00577)	(0. 00484)	(0. 00421)
lnGDP	0. 00296***	0. 00122	0. 00131
	(0. 00766)	(0. 00681)	(0. 00260)
bci	0. 02597***	0. 01521***	−0. 00112
	(0. 00634)	(0. 00583)	(0. 00225)
cci	−0. 01338***	−0. 01271***	−0. 00228
	(0. 00503)	(0. 00439)	(0. 00296)
Cons	1.76763***	2.81964***	1.11384***
	(0. 66566)	(0. 62032)	(0. 36902)
Obs.	2592	2592	2544
R-squared	0.0238	0.2830	
AR (1)			−4. 1395***
AR (2)			−0. 93522
Sargan test			23.48513
P-value			1.0000
High Dimension Country	NO	NO	YES
Low Dimension Country	NO	YES	NO
Year	NO	YES	YES

Note: Robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
DARFO is DailyAverageRiskFromOther
High Dimension Country: Individual countries are influenced by the overall political environment.
Low Dimension Country: Whether the country is a NATO member.

Table 7
Benchmark results (Before the Full-Scale Conflict between Russia and Ukraine).

	(1) OLS	(2) Two-way fixed	(3) SYS-GMM
L1. DARFO			0. 99880***
			(0. 01394)
L2. DARFO			−0. 25167***
			(0. 01514)
Fossil	0. 00214***	0. 00218***	0. 00052
	(0. 00060)	(0. 00052)	(0. 00059)
Renewable	0. 00322***	0. 00315***	0. 00137**
	(0. 00059)	(0. 00054)	(0. 00061)
DemandTWh	0. 00166**	−0. 00005	0. 00025
	(0. 00080)	(0. 00067)	(0. 00310)
NetImportsTWh	0. 01228*	0. 01350***	0. 00888
	(0. 00653)	(0. 00503)	(0. 00625)
lnGDP	0. 00525	0. 00265	0. 00313
	(0. 00862)	(0. 00730)	(0. 00255)
bci	0. 02911***	0. 01135*	−0. 00274
	(0. 00761)	(0. 00685)	(0. 00271)
cci	−0. 01394***	−0. 01507***	−0. 00563*
	(0. 00541)	(0. 00428)	(0. 00327)
Cons	1.43910*	3.38573***	1.55720***
	(0. 77470)	(0. 69148)	(0. 33741)
Obs.	2040	2040	1992
R-squared	0.0280	0.3669	
AR (1)			−4.0540***
AR (2)			−1.7376*
Sargan test			23.69319
P-value			1.0000
High Dimension Country	NO	NO	YES
Low Dimension Country	NO	YES	NO
Year	NO	YES	YES

Note: Robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
DARFO is DailyAverageRiskFromOther
High Dimension Country: Individual countries are influenced by the overall political environment.
Low Dimension Country: Whether the country is a NATO member.

0.00214 and 0.00218, respectively), but this impact is not significant in the SYS-GMM model (coefficient of 0.00052). This indicates that without considering dynamic issues, the impact of fossil fuels on external risk is significant; however, after accounting for dynamic effects, this impact becomes insignificant, although the sign of the coefficient remains positive. Before the conflict, the proportion of renewable energy in the grid significantly affects the external risk index in all models (OLS coefficient of 0.00322, two-way fixed effects coefficient of 0.00315, SYS-GMM coefficient of 0.00137). This suggests that before the conflict, renewable energy had a significant positive impact on external risk.

According to Table 8, the regression results after the full-scale conflict show that the proportion of fossil fuels in the grid continues to have a significant positive impact on the external risk index in all models (OLS coefficient of 0.00605, two-way fixed effects coefficient of 0.00582, SYS-GMM coefficient of 0.00586). This indicates that during the conflict, the impact of fossil fuels on external risk remained significant. After the conflict, the proportion of renewable energy in the grid has an insignificant impact on the external risk index in all static models, but the coefficients turned negative compared to the pre-conflict period and became significant in the dynamic model (OLS coefficient of −0.00130, two-way fixed effects coefficient of −0.00121, SYS-GMM coefficient of −0.00213).

Overall, we find that the significant impact of fossil fuels on external risk persisted after the conflict, while the impact of renewable energy, although not significant in all models, shifted from positive to negative. Based on the results in Tables 7 and 8, we observe that after the conflict, the proportion of fossil fuels in the grid may increase the external risk impact on national wholesale electricity prices. Conversely, renewable energy seems to imply a potential to reduce the external risk impact on wholesale electricity prices. This shift suggests that different types of fossil fuels (such as coal, natural gas, and oil) and renewable energy (such as solar, wind, and hydro) may have varying impacts on external risk. This might be the reason for the change in the coefficients for renewable energy before and after the conflict, despite the insignificance. Furthermore, the relationship between energy structure and external risk might be nonlinear, with different impacts at different quantiles. This implies that these energy sources may perform differently when facing varying levels of external risk. Therefore, based on the aforementioned results and analysis, this paper will use the QARDL model to further analyze the specific impacts of different categories of renewable and fossil fuels.

4.2.2. *Rolling windows results*

Fig. 5 presents the standardized rolling coefficients from two-way fixed effects regressions using a 24-month moving window. The red dashed line marks March 2022 as the structural break corresponding to the outbreak of the Russia–Ukraine conflict, while the shaded area denotes the post-conflict period. The figure illustrates the dynamic evolution of the impacts of fossil fuels, renewables, demand, net imports, and macroeconomic indicators on the external risk index.

Before conducting the regressions, we formally tested for structural changes in the time series. In addition to fixing the break at March 2022 in the figure, we applied the Bai–Perron multiple structural break test to detect potential changes within the sample period. The results confirm a statistically significant structural break around early 2022, which coincides with the conflict, thereby providing formal support for the subsequent sub-sample regressions and mechanism analysis.

In the pre-conflict period, both fossil fuels and renewables show relatively stable and positive coefficients, consistent with the

Table 8
Benchmark results (After the Full-Scale Conflict between Russia and Ukraine).

	(1) OLS	(2) Two-way fixed	(3) SYS-GMM
L1. DARFO			0.94715***
			(0.06836)
L2. DARFO			−0.45299***
			(0.04638)
Fossil	0.00605***	0. 00582***	0.00586***
	(0. 00103)	(0. 00101)	(0.00169)
Renewable	−0.00130	−0.00121	−0. 00213*
	(0. 00100)	(0. 00101)	(0. 00169)
DemandTWh	−0.00095	0.00003	0. 00123
	(0. 00124)	(0. 00128)	(0. 00120)
NetImportsTWh	0. 031170***	0.03036**	0.010836***
	(0. 01211)	(0. 01188)	(0. 00807)
lnGDP	−0. 00650	−0.00658	−0. 00413
	(0. 01529)	(0. 01527)	(0. 00350)
bci	0. 02089**	0.02505**	0. 00421
	(0. 00960)	(0. 01035)	(0. 00458)
cci	−0. 00823	−0.00539	0. 01022***
	(0. 01114)	(0. 01129)	(0. 00457)
Cons	2.01813*	1.31001	0. 20489
	(1.14984)	(1.22505)	(0. 00317)
Obs.	552	552	552
R-squared	0.1244	0.1521	
AR (1)			−3.3482***
AR (2)			0.68316
Sargan test			18.97398
P-value			1.0000
High Dimension Country	NO	NO	YES
Low Dimension Country	NO	YES	NO
Year	NO	YES	YES

Note: Robust standard errors in parentheses; ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1.
DARFO is DailyAverageRiskFromOther
High Dimension Country: Individual countries are influenced by the overall political environment.
Low Dimension Country: Whether the country is a NATO member.

benchmark full-sample results suggesting that both energy types amplified external risk. After the conflict, however, the coefficient paths diverge: fossil fuels remain positively associated with external risk, while the coefficients of renewables weaken and trend downward, even turning negative in certain windows. This graphical evidence aligns with the regression results (Tables 6–8), indicating that the conflict altered the transmission mechanism of external shocks through the energy structure. Specifically, fossil fuels consistently increase market vulnerability, while renewables gradually exhibit the potential to mitigate risk in the post-conflict period, although their statistical significance varies across models.

4.2.3. QARDL model results

As shown in Table 9 (full sample), Table 10 (before the full-scale Russia-Ukraine conflict), and Table 11 (after the full-scale Russia-Ukraine conflict), the results are based on regressions using the QARDL model, dividing power sources into renewable and fossil energies. In these tables, β represents the long-term effects, δ represents the short-term effects, and ψ_1 is the long-term equilibrium coefficient of the model (describing how variables adjust to return to their long-term equilibrium state after experiencing short-term disturbances). We summarize the meanings of the coefficient notations in Table 12.

In Tables 9 and it can be observed that for 24 major ENTSO-E member countries impacted by geopolitical conflicts, the long-term equilibrium coefficient in the wholesale electricity market shows significant positive values across all quantiles. This indicates that the Russia-Ukraine geopolitical conflict has significantly increased systemic risk in the electricity markets of these countries, reflecting the market's sensitive response to geopolitical uncertainty and supply disruptions (Serrano and Angosto-Fernández, 2022; Maneejuk et al., 2024). Furthermore, it was found that internal stability within the wholesale electricity markets of these 24 European countries is challenging to achieve solely through the power systems themselves. This suggests that relying solely on the internal mechanisms of Europe's integrated electricity system is insufficient to cope with the external shocks of geopolitical conflicts (Honkapuro et al., 2023). Therefore, policymakers and market participants need to adopt more comprehensive risk management measures, including strengthening international cooperation, enhancing energy diversification, and developing more flexible contingency plans to address the impacts of geopolitical factors on the electricity markets.

Additionally, the long-term impact of renewable energy significantly mitigates the external shock risks to the wholesale electricity markets from geopolitical conflicts at lower and medium quantiles (where risks decrease or remain stable) while significantly increasing these risks at higher quantiles (where risks rise). This indicates that the impact of renewable energy on electricity markets is nonlinear across different risk levels (Cevik and Ninomiya, 2022). In low and medium-risk scenarios, renewable energy can provide a buffering effect, reducing market

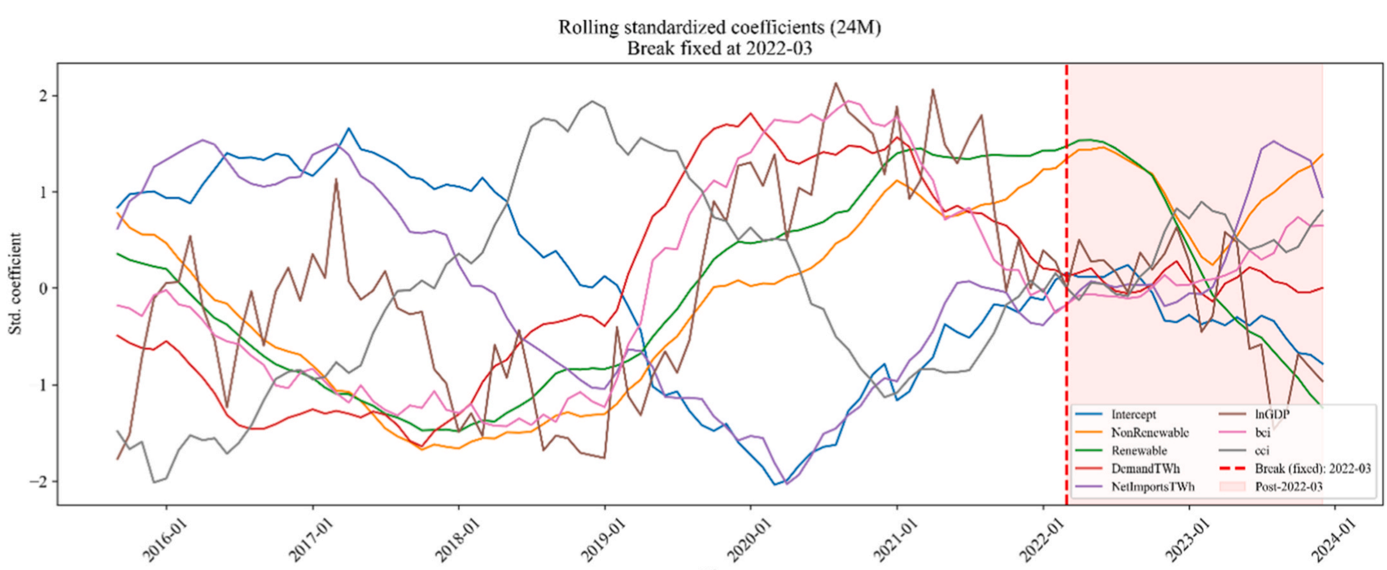

Fig. 5. Rolling Two-Way Fixed Effects Coefficients with Bai-Perron test.

Table 9
Full sample Related Parameters.

Coef	Quantile levels										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
Related parameters											
$\psi_1(\tau)$	0.62622***	0.72354***	1.01009***	1.48563***	1.42257***	1.54273***	1.38037***	1.35460***	1.13845***	1.26003***	1.11994***
	(0.00214)	(0.0370)	(0.03283)	(0.00130)	(0.00113)	(0.00738)	(0.00236)	(0.00017)	(0.00013)	(0.00057)	(0.00178)
$\beta_*^{Renewable}$	−0.00025***	−0.00003*	−0.00018***	−0.00007***	−0.00006***	−0.00006***	−0.00009***	0.00005***	0.00009***	0.00055***	0.00048***
	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00000)
β_*^{Fossil}	0.000047***	0.000016***	−0.00023***	0.00002***	−0.00001***	−0.00001***	−0.00006***	0.00001***	0.00001***	0.00050***	0.00062***
	(0.00000)	(0.00002)	(0.00002)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00001)
$\delta_{j^*}^{Renewable}$	0.00092***	−0.00025*	−0.00075***	−0.00046***	−0.00022***	−0.00030***	−0.00013***	−0.00011***	0.00000	−0.00044***	−0.00142***
	(0.00002)	(0.00015)	(0.00003)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00001)	(0.00000)	(0.00005)	(0.00002)
$\delta_{j^*}^{Fossil}$	0.00687***	0.00287***	0.00046***	0.00023***	0.00029***	−0.00004***	0.00001***	0.00014***	0.00022***	0.00133***	0.00158***
	(0.00003)	(0.00017)	(0.00003)	(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00006)	(0.00004)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The symbols ***, **, and * represent statistical significance at the levels of 1 %, 5 %, and 10 %, respectively.

Table 10
Before the full-scale war between Russia and Ukraine related parameters.

Coef	Quantile levels										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
Related parameters											
$\psi_1(\tau)$	0.96652***	0.88700***	0.85351***	1.19695***	1.79806***	1.35085***	1.41961***	1.21063***	1.12353***	1.19949***	1.16905***
	(0.00246)	(0.00820)	(0.02755)	(0.00718)	(0.00297)	(0.00290)	(0.00147)	(0.00038)	(0.00084)	(0.00459)	(0.00221)
$\beta_*^{Renewable}$	−0.00017***	−0.00025***	−0.00015***	−0.00006***	−0.00030***	0.00001***	−0.00004***	−0.00004***	0.00018***	0.00022***	0.00099***
	(0.00000)	(0.00000)	(0.00002)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00000)
β_*^{Fossil}	0.00022***	−0.00023***	−0.00027***	−0.00018***	−0.00028***	−0.00002***	−0.00003***	0.00002***	0.00029***	−0.00000	0.00073***
	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00001)
$\delta_{j^*}^{Renewable}$	0.00017***	−0.00089***	−0.00081***	−0.00044***	−0.00034***	−0.00006***	−0.00004***	0.00014***	0.00092***	0.00157***	0.00007
	(0.00004)	(0.00001)	(0.00004)	(0.00002)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00003)	(0.00005)
$\delta_{j^*}^{Fossil}$	0.00548***	0.00081***	0.00027***	−0.00005***	−0.00000	0.00011***	0.00003***	−0.00006***	0.00078***	0.00177***	0.00240***
	(0.00003)	(0.00001)	(0.00003)	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00001)	(0.00005)	(0.00006)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The symbols ***, **, and * represent statistical significance at the levels of 1 %, 5 %, and 10 %, respectively.

Table 11
After the full-scale war between Russia and Ukraine related parameters.

Coef	Quantile levels										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
Related parameters											
$\psi_1(\tau)$	0.46177***	1.23950***	0.92441***	0.32561***	1.11424***	1.09939***	1.63642***	1.30753***	1.31178***	1.14964***	1.09388***
	(0.03559)	(0.02329)	(0.00830)	(0.00507)	(0.00000)	(0.01874)	(0.00191)	(0.00386)	(0.00375)	(0.00180)	(0.00299)
$\beta_*^{Renewable}$	−0.00199***	−0.00094***	−0.00005***	−0.00030***	0.00014***	−0.00012***	0.00020***	0.00024***	0.00056***	−0.00061***	0.00019***
	(0.00016)	(0.00005)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00003)
β_*^{Fossil}	0.00077***	−0.00082***	0.00031***	0.00004***	0.00018***	−0.00009***	0.00002***	0.00037***	0.00060***	0.00002***	0.00001
	(0.00015)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00003)	(0.00000)	(0.00001)	(0.00002)	(0.00001)	(0.00003)
$\delta_{j^*}^{Renewable}$	−0.00155***	−0.00103***	0.00052***	0.00004***	−0.00057***	−0.00120***	−0.00058***	−0.00073***	0.00002	−0.00448***	−0.00101***
	(0.00049)	(0.00006)	(0.00002)	(0.00001)	(0.00000)	(0.00005)	(0.00000)	(0.00005)	(0.00010)	(0.00006)	(0.00008)
$\delta_{j^*}^{Fossil}$	0.00703***	0.00471***	0.00300***	0.00205***	0.00090***	0.00014**	0.00047***	0.00108***	0.00174***	−0.00078***	0.00254***
	(0.00053)	(0.00001)	(0.00003)	(0.00001)	(0.00000)	(0.00006)	(0.00001)	(0.00003)	(0.00008)	(-0.00078)	(0.00254)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The symbols ***, **, and * represent statistical significance at the levels of 1 %, 5 %, and 10 %, respectively.

Table 12
Meaning of coefficients in QARDL model.

Symbol	Meaning
$\psi_1(\tau)$	Error Correction Coefficient
β_*^{Item}	Long-run Coefficient
$\delta_{j^*}^{item}$	Short-run Coefficient

Item represents different energy broad categories (Renewables and Fossil fuels), or their alternative sources considered in the later analyses for each category.

instability caused by external shocks. However, in high-risk scenarios, the volatility and uncertainty of renewable energy may exacerbate market risks. This result aligns with the intermittency theory of renewable generation, which posits that weather-dependent resources such as wind and solar power introduce significant supply volatility into electricity systems (Green and Vasilakos, 2010; Hirth, 2013). When reserve margins and system flexibility are insufficient to buffer these fluctuations, even minor forecast errors can lead to large price spikes and instability (Papaefthymiou and Dragoon, 2016; Milligan et al., 2010; Milligan and Kirby, 2010).

The short-term impact of renewable energy also exhibits similar nonlinear characteristics. In most cases, the short-term impacts align with the long-term impacts. However, in the 90 %–95 % quantiles, where risks rise extremely, the short-term impact of renewable energy reduces the risk posed to the grid by geopolitical conflicts. This suggests that in extreme market conditions, the flexibility and diversity of renewable energy may offer a short-term mitigation mechanism, alleviating the severe impacts of external shocks on the market (Yang et al., 2021). This short-term mitigating effect may result from the distributed and localized generation features of renewables, which can provide alternative supply sources independent of international fuel markets. Such diversification reduces reliance on geopolitically sensitive fossil-fuel imports and temporarily stabilizes market expectations.

The long-term impact of fossil fuels significantly reduces the external shock risks to the wholesale electricity market due to geopolitical conflicts at lower and medium quantiles (where risks decrease or remain stable), while significantly increasing these risks at higher quantiles (where risks rise). Specifically, at lower to medium risk levels, fossil fuels may provide a relatively stable supply source, mitigating the uncertainty brought about by geopolitical conflicts and thereby reducing the overall risk in the electricity market. This could be because certain fossil fuels, such as coal, have more mature and stable supply chains that can continue to provide reliable energy supplies during non-full-scale Russia-Ukraine conflict periods, thus reducing the volatility of other fossil fuels like natural gas (Jiang et al., 2021). However, at higher risk levels, fossil fuels, due to their own price volatility impacted by geopolitical risks, lead to increased wholesale price risks in the electricity market. This finding is consistent with prior studies showing that fossil-fuel price shocks—especially in natural gas—are rapidly transmitted to wholesale electricity prices through marginal cost pass-through and limited substitution flexibility (Borenstein, 2012; Enescu and Szeles, 2023).

The short-term impact of fossil fuels differs significantly from the long-term impact, as they significantly enhance the external shock risks to the wholesale electricity market due to geopolitical conflicts across nearly all quantiles. This indicates that in the short term, the volatility and uncertainty of fossil fuel supplies can more easily amplify the market risks brought by geopolitical conflicts. In the short term, the market's reaction to sudden supply disruptions or price fluctuations is more sensitive, leading to a sharp increase in risk.

Specifically, since the regression results in Table 9 consider the full sample, the timeline covers the period before and after the full-scale Russia-Ukraine conflict. However, the outbreak of the full-scale conflict has led to significant differences in the geopolitical impact on fossil fuels and on the grid compared to before the conflict. Before the full-

Table 13
Full sample Related Parameters (For Detailed Categories of Electricity Generation Sources).

Coef	Quantile levels										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
Long-term Related parameters											
$\psi_1(\tau)$	0.85973***	0.74049***	1.03958***	1.24181***	1.33897***	1.33537***	1.20241***	1.21775***	1.11203***	1.10622***	1.12740***
	(0.00128)	(0.00626)	(0.01433)	(0.00000)	(0.00075)	(0.00319)	(0.00045)	(0.00021)	(0.00031)	(0.00033)	(0.00207)
$\beta_*^{Bioenergy}$	−0.00170***	−0.00030***	0.00001***	−0.00001***	−0.00010***	0.00016***	−0.00002***	0.00027***	0.00094***	0.00066***	0.00145***
	(0.00000)	(0.00002)	(0.00003)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00005)
β_*^{Wind}	0.00046***	−0.00033***	−0.00040***	−0.00012***	−0.00014***	−0.00011***	−0.00007***	−0.00007***	−0.00005***	−0.00011***	−0.00050***
	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00004)
β_*^{Hydro}	−0.00022***	−0.00001***	−0.00025***	−0.00014***	−0.00009***	−0.00001***	−0.00005***	0.00001***	0.00022***	0.00076***	0.00041***
	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00002)
β_*^{Solar}	0.00001	−0.00093***	−0.00015***	−0.00043***	−0.00031***	−0.00015***	−0.00023***	−0.00028***	0.00021***	0.00197***	0.00055***
	(0.00002)	(0.00001)	(0.00002)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00005)
$\beta_*^{OtherRe}$	−0.00494***	−0.00712***	−0.00313***	0.00098***	0.00071***	0.00002	0.00213***	−0.00114***	0.00024***	0.00316***	−0.00134***
	(0.00004)	(0.00007)	(0.00016)	(0.00000)	(0.00000)	(0.00003)	(0.00001)	(0.00001)	(0.00002)	(0.00008)	(0.00034)
β_*^{Coal}	0.00044***	0.00012***	−0.00038***	−0.00001***	−0.00006***	0.00005***	−0.00004***	0.00005***	0.00027***	0.00069***	0.00054***
	(0.00001)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00003)
β_*^{Gas}	0.00017***	0.00035***	0.00000	−0.00006***	−0.00008***	0.00010***	−0.00003***	0.00013***	0.00028***	0.00102***	0.00109***
	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00004)
$\beta_*^{Otherfossil}$	−0.00494***	−0.00712***	−0.00313***	0.00098***	0.00071***	0.00002	0.00213***	−0.00114***	0.00024***	0.00316***	−0.00134***
	(0.00004)	(0.00007)	(0.00016)	(0.00000)	(0.00000)	(0.00003)	(0.00001)	(0.00001)	(0.00002)	(0.00008)	(0.00034)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The symbols ***, **, and * represent statistical significance at the levels of 1 %, 5 %, and 10 %, respectively.

scale conflict, fossil fuel supplies were relatively stable, which could somewhat mitigate the uncertainty brought about by fluctuations in electricity demand, thereby reducing the overall risk in the electricity market (Liu et al., 2023). However, after the outbreak of the full-scale conflict, the fossil fuel supply chain was severely disrupted, leading to increased fragility in the market's dependence on fossil fuels and greatly increasing supply uncertainty, which in turn significantly heightened the risk in the electricity market (Liu et al., 2023). Similarly, before the outbreak of the full-scale geopolitical conflict, the intermittent nature of renewable energy generation might have made its ability to stabilize wholesale electricity prices and reduce grid risk slightly inferior to that of fossil fuels. However, the situation changed after the outbreak. With the fossil fuel supply chain severely disrupted and market dependence on fossil fuels becoming more fragile due to increased supply uncertainty, the risks in the electricity market significantly increased. In this context, the role of renewable energy became more critical. Despite its intermittent nature, its supply is not directly affected by geopolitical conflicts, and it can provide an alternative energy source to some extent. This observation aligns with the energy diversification and resilience framework, emphasizing that geographically distributed and domestically produced renewable resources enhance energy security during external disruptions (Cherp and Jewell, 2014; Honkapuro et al., 2023).

To further investigate this situation, we also conducted regressions for the periods before and after the full-scale Russia-Ukraine conflict. In Tables 10 and 11, we find that the long-term equilibrium coefficients in the wholesale electricity market still show significant positive values across all quantiles. This further confirms that the Russia-Ukraine geopolitical conflict has significantly increased systemic risk in the electricity markets of these countries, and relying solely on the internal mechanisms of the power systems is ineffective in managing the external shock risks brought about by geopolitical conflicts. Additionally, the long-term and short-term impacts of renewable energy in Table 10 generally follow the trends in Table 9, mainly because pre-conflict samples constitute a larger proportion of the full sample. One minor difference is that the short-term impact of renewable energy in Table 10 no longer reduces risk under extreme increases in external risks. This may be due to structural changes in the electricity markets of the 24 countries before and after the full-scale Russia-Ukraine conflict. However, compared to Table 11, the situation differs somewhat. In Table 11, the short-term impact of renewable energy significantly reduces the external shock risks to the wholesale electricity market across all quantiles, especially at quantiles where external risks increase extremely. The long-term impact of renewable energy also significantly mitigates risk at the quantiles where risk increases extremely.

Further examining the long-term impact of fossil fuels in Table 11, compared to the results in Table 10, its ability to reduce the external shock risks to the wholesale electricity market due to geopolitical conflicts is only evident at lower risk quantiles. The short-term impact of fossil fuels, similar to that in Table 11, shows a significant promoting effect across all quantiles. These results indicate that after the full-scale conflict, the dynamics of the energy market have undergone significant changes. The full-scale conflict severely disrupted the fossil fuel supply chain, leading to a significant short-term enhancement of market risks (Enescu and Szeles, 2023). Meanwhile, renewable energy has shown a more active role in mitigating market risks brought about by geopolitical conflicts, reducing market uncertainty across all risk levels. This further emphasizes the importance of promoting renewable energy development and enhancing energy diversification under geopolitical tensions to ensure the resilience and ongoing stability of the electricity market. This transformation supports the view that the energy transition itself can act as a structural risk mitigation mechanism by decoupling electricity systems from fossil fuel dependency (Sovacool, 2016; Cevik and Ninomiya, 2022).

We further decompose the fossil fuels into gas, coal and other fossil fuels as well as the renewables into bioenergy, wind, hydro, solar and other renewables in order to understand the detailed impacts of each

Table 14
Full sample Related Parameters (For Detailed Categories of Electricity Generation Sources).

Coef	Quantile levels										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
Short-term Related parameters											
$\delta_{j^*}^{Bioenergy}$	0.00088***	−0.00361***	−0.00104***	−0.00051***	−0.00032***	−0.00009***	−0.00001*	−0.00051***	−0.00186***	−0.00288***	−0.00335***
	(0.00001)	(0.00004)	(0.00007)	(0.00000)	(0.00000)	(0.00002)	(0.00000)	(0.00000)	(0.00001)	(0.00003)	(0.00022)
$\delta_{j^*}^{Wind}$	0.00215***	−0.00099***	−0.00069***	−0.00045***	−0.00023***	−0.00035***	−0.00021***	−0.00030***	−0.00066***	0.00026***	−0.00135***
	(0.00001)	(0.00001)	(0.00004)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00009)
$\delta_{j^*}^{Hydro}$	0.00124***	−0.00054***	−0.00092***	−0.00063***	−0.00041***	−0.00012***	−0.00024***	−0.00009***	0.00041***	0.00093***	−0.00270***
	(0.00001)	(0.00001)	(0.00002)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00003)
$\delta_{j^*}^{Solar}$	0.00030***	−0.00312***	−0.00111***	−0.00132***	−0.00060***	−0.00031***	0.00000	0.00022***	0.00202***	0.00244***	0.00051***
	(0.00003)	(0.00002)	(0.00006)	(0.00000)	(0.00000)	(0.00002)	(0.00000)	(0.00000)	(0.00001)	(0.00002)	(0.00010)
$\delta_{j^*}^{OtherRe}$	0.07608***	0.00130***	−0.00896***	−0.00357***	0.00033***	0.00663***	0.00665***	0.00891***	0.02165***	0.04792***	−0.01174***
	(0.00018)	(0.00024)	(0.00076)	(0.00000)	(0.00003)	(0.00029)	(0.00007)	(0.00003)	(0.00006)	(0.00018)	(0.00178)
$\delta_{j^*}^{Coal}$	0.00595***	0.00365***	0.00173***	0.00045***	0.00046***	0.00024***	0.00009***	−0.00037***	−0.00024***	0.00152***	0.00256***
	(0.00001)	(0.00002)	(0.00004)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00019)
$\delta_{j^*}^{Gas}$	0.00598***	0.00180***	0.00054***	−0.00002***	0.00000***	0.00007***	0.00011***	0.00000	0.00004***	0.00187***	−0.00061***
	(0.00001)	(0.00002)	(0.00004)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00011)
$\delta_{j^*}^{Otherfossil}$	0.00537***	0.00224***	0.00080***	−0.00001***	0.00050***	0.00029***	0.00043***	0.00083***	0.00107***	0.00487***	0.00495***
	(0.00002)	(0.00004)	(0.00004)	(0.00000)	(0.00000)	(0.00002)	(0.00001)	(0.00000)	(0.00001)	(0.00002)	(0.00016)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The symbols ***, **, and * represent statistical significance at the levels of 1 %, 5 %, and 10 %, respectively.

Table 15
Before the full-scale war between Russia and Ukraine related parameters (for detailed categories of electricity generation sources).

Coef	Quantile levels										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
Long-term Related parameters											
$\psi_1(\tau)$	0.40460***	0.88717***	0.80963***	1.08722***	1.23405***	1.16362***	1.26834***	1.18807***	1.08249***	1.02861***	1.04688***
	(0.00100)	(0.00610)	(0.00893)	(0.00985)	(0.00027)	(0.00347)	(0.00023)	(0.00215)	(0.00121)	(0.00000)	(0.00074)
$\beta_*^{Bioenergy}$	−0.00158***	−0.00060***	0.00011***	−0.00020***	−0.00017***	0.00032***	0.00019***	0.00021***	0.00095***	0.00027***	0.00075***
	(0.00002)	(0.00002)	(0.00001)	(0.00003)	(0.00000)	(0.00001)	(0.00000)	(0.00002)	(0.00002)	(0.00000)	(0.00002)
β_*^{Wind}	0.00172***	−0.00016***	−0.00035***	−0.00034***	−0.00011***	−0.00012***	−0.00011***	−0.00012***	−0.00003***	0.00021***	0.00013***
	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00001)
β_*^{Hydro}	−0.00008***	−0.00005***	−0.00031***	−0.00024***	−0.00013***	0.00003***	0.00002***	−0.00003***	0.00032***	0.00046***	0.00060***
	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)
β_*^{Solar}	0.00126***	−0.00070***	−0.00045***	−0.00038***	−0.00059***	−0.00028***	−0.00034***	−0.00010***	0.00087***	0.00211***	0.00243***
	(0.00001)	(0.00002)	(0.00003)	(0.00001)	(0.00000)	(0.00001)	(0.00000)	(0.00002)	(0.00002)	(0.00000)	(0.00003)
$\beta_*^{OtherRe}$	−0.00153***	−0.00700***	−0.00442***	−0.00074***	0.00003***	−0.00127***	0.00047***	−0.00058***	0.00484***	0.00197***	−0.01467***
	(0.00006)	(0.00008)	(0.00012)	(0.00003)	(0.00001)	(0.00007)	(0.00001)	(0.00010)	(0.00015)	(0.00000)	(0.00020)
β_*^{Coal}	−0.00068***	0.00027***	−0.00036***	−0.00020***	−0.00005***	0.00011***	0.00007***	0.00008***	0.00038***	0.00068***	0.00053***
	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00001)
β_*^{Gas}	0.00062***	0.00001**	−0.00036***	−0.00004***	−0.00012***	0.00008***	0.00013***	0.00003***	0.00039***	0.00084***	0.00092***
	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00002)
$\beta_*^{Otherfossil}$	0.00033***	0.00053***	−0.00014***	−0.00009***	−0.00007***	0.00003***	0.00002***	0.00009***	0.00014***	−0.00028***	0.00042***
	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00001)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The symbols ***, **, and * represent statistical significance at the levels of 1 %, 5 %, and 10 %, respectively.

energy type. The main findings show that renewable energy sources – particularly wind, solar, and hydro – generally mitigate the geopolitical shock to the wholesale electricity market in both the short- and long-term. Their local and diversified supply chains make them less susceptible to international political tensions. Wind power was identified as the most consistent and effective hedge against geopolitical shocks. Conversely, fossil fuels, especially natural gas, were found to significantly increase market risk. This is due to their supply chains being highly concentrated in politically sensitive regions, making them vulnerable to disruptions and price volatility during conflicts. Coal presented a mixed impact; while it increases long-term risk due to environmental policies, it can serve as a crucial short-term risk mitigator by providing a stable energy backup when other supplies, like natural gas, are constrained. To sum up, the full-scale Russia-Ukraine conflict strengthened the risk-reducing capabilities of renewables. The crisis accelerated the energy transition, enhancing the role of wind, solar, and hydro in ensuring energy security. Simultaneously, the conflict exacerbated the risks associated with natural gas, cementing its position as a source of market instability.

4.2.4. *Results for different types of energy sources*

To further explore the impact of various types of energy on the wholesale electricity market's vulnerability to geopolitical conflicts, we conducted detailed QARDL model regressions as follows: Table 13 (Full Sample Long-term Effects), Table 14 (Full Sample Short-term Effects), Table 15 (Pre-full-scale Russia-Ukraine Conflict Long-term Effects), Table 16 (Pre-full-scale Russia-Ukraine Conflict Short-term Effects), Table 17 (Post-full-scale Russia-Ukraine Conflict Long-term Effects), and Table 18 (Post-full-scale Russia-Ukraine Conflict Short-term Effects). We begin by analyzing the results from the full sample. In Table 13, bioenergy shows significant negative effects on the long-term external shock risks to the wholesale electricity market at quantiles where risks decrease or remain stable, and positive effects at rising risk quantiles. When external risks are stable or declining, bioenergy, due to its renewable and environmentally friendly attributes, helps mitigate market shock risks (Elina and Fleig, 2018). However, in scenarios of rising risks, the market's dependence on traditional energy sources and the relatively high costs of bioenergy may not reduce external shock risks and may even increase them due to its own volatility.

Wind energy significantly mitigates risk across almost all quantiles in the long term. In stable and rising risk quantiles, wind energy can be seen as an effective hedge, helping the market cope with energy supply risks caused by geopolitical conflicts. The widespread deployment of wind energy can provide stable power generation capacity during geopolitical shocks, thereby reducing market volatility (Mays and Jenkins, 2023). Hydroelectric power shows significant negative effects at decreasing and stable risk quantiles and positive effects at rising risk quantiles in the long term. This is typically because hydroelectricity, as a reliable and stable energy supply, can provide continuous and predictable electricity in stable or reduced-risk scenarios, thereby reducing market fluctuations caused by uncertainty (Pereira et al., 2015). However, in high-risk environments, due to the predictability and fixity of hydro output, its effectiveness may be limited, and overall market risks might remain high or increase (Anghileri et al., 2018).

Solar energy shows significant negative effects at decreasing and stable risk quantiles, and positive effects at rising risk quantiles in the long term. Solar energy, being a clean and sustainable source, with relatively stable investment and operation, can provide a continuous energy supply when market conditions are stable (Bushnell and Novan, 2018). Furthermore, the maturation of solar technology and the reduction in costs make it more competitive in the market, helping stabilize power supply and prices, thus reducing risks caused by market fluctuations. However, the positive effects of solar energy in stable and rising risk scenarios suggest it may not be sufficient to handle market instability or increased external shocks. While solar still provides a stable energy supply, its capacity to counter risks may be limited in

Table 16
Before the full-scale war between Russia and Ukraine related parameters (for detailed categories of electricity generation sources).

Coef	Quantile levels										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
Short-term Related parameters											
$\delta_{j*}^{Bioenergy}$	−0.00614***	−0.00198***	−0.00159***	−0.00080***	−0.00078***	−0.00091***	0.00018***	0.00027***	−0.00016***	0.00125***	−0.00011***
	(0.00003)	(0.00005)	(0.00003)	(0.00004)	(0.00000)	(0.00003)	(0.00000)	(0.00004)	(0.00003)	(0.00000)	(0.00010)
δ_{j*}^{Wind}	0.00574***	0.00123***	0.00011***	−0.00017***	0.00000***	−0.00014***	−0.00001***	−0.00001	0.00059***	0.00233***	0.00076***
	(0.00002)	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00000)	(0.00002)	(0.00002)	(0.00000)	(0.00007)
δ_{j*}^{Hydro}	−0.00058***	−0.00040***	−0.00095***	−0.00055***	−0.00042***	−0.00019***	0.00008***	0.00029***	0.00168***	0.00292***	0.00073***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00003)
δ_{j*}^{Solar}	0.00169***	−0.00040***	−0.00045***	−0.00155***	−0.00082***	−0.00033***	0.00004***	0.00054***	0.00597***	0.01032***	0.01245***
	(0.00006)	(0.00003)	(0.00004)	(0.00004)	(0.00000)	(0.00002)	(0.00000)	(0.00004)	(0.00004)	(0.00000)	(0.00008)
$\delta_{j*}^{OtherRe}$	0.07046***	−0.00405***	−0.00777***	−0.00518***	−0.00390***	0.00307***	0.00468***	0.00899***	0.02448***	0.04415***	0.01433***
	(0.00006)	(0.00033)	(0.00041)	(0.00037)	(0.00002)	(0.00017)	(0.00003)	(0.00036)	(0.00037)	(0.00000)	(0.00052)
δ_{j*}^{Coal}	0.00698***	0.00370***	0.00209***	0.00045***	0.00030***	0.00008***	0.00013***	−0.00015***	0.00020***	0.00319***	0.00353***
	(0.00002)	(0.00001)	(0.00003)	(0.00001)	(0.00000)	(0.00001)	(0.00000)	(0.00003)	(0.00002)	(0.00000)	(0.00002)
δ_{j*}^{Gas}	0.00426***	0.00128***	0.00024***	−0.00019***	−0.00020***	−0.00013***	0.00001***	0.00002	0.00090***	0.00301***	0.00193***
	(0.00001)	(0.00002)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00000)	(0.00002)	(0.00002)	(0.00000)	(0.00007)
$\delta_{j*}^{Otherfossil}$	0.00035	0.00234	0.00099	0.00022	0.00009	0.00005	0.00055	0.00081	0.00172	0.00509	0.00499
	(0.00003)	(0.00002)	(0.00004)	(0.00002)	(0.00000)	(0.00001)	(0.00000)	(0.00005)	(0.00002)	(0.00000)	(0.00011)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The symbols ***, **, and * represent statistical significance at the levels of 1 %, 5 %, and 10 %, respectively.

Table 17
After the full-scale war between Russia and Ukraine related parameters (for detailed categories of electricity generation sources).

Coef	Quantile levels										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
Long-term Related parameters											
$\psi_1(\tau)$	0.33768***	0.70917***	0.36941***	0.72329***	0.89166***	1.8840***	1.27797***	1.44872***	1.18913***	0.95021***	1.00649***
	(0.00000)	(0.01283)	(0.02842)	(0.00000)	(0.00553)	(0.01364)	(0.00653)	(0.00474)	(0.00144)	(0.00042)	(0.00821)
$\beta_*^{Bioenergy}$	−0.00635***	−0.00062***	−0.00009	−0.00007***	0.00074***	0.00072***	0.00089***	0.00210***	0.00205***	0.00012***	−0.00015**
	(0.00000)	(0.00020)	(0.00012)	(0.00000)	(0.00002)	(0.00006)	(0.00004)	(0.00006)	(0.00001)	(0.00002)	(0.00008)
β_*^{Wind}	−0.00206***	−0.00326***	−0.00021***	0.00002***	−0.00012***	−0.00027***	−0.00012***	−0.00060***	−0.00023***	−0.00103***	−0.00131***
	(0.00000)	(0.00005)	(0.00003)	(0.00000)	(0.00001)	(0.00002)	(0.00001)	(0.00002)	(0.00000)	(0.00000)	(0.00003)
β_*^{Hydro}	−0.00234***	−0.00070***	−0.00017***	0.00003***	−0.00004***	0.00004***	−0.00020***	−0.00021***	−0.00035***	−0.00031***	0.00012
	(0.00000)	(0.00008)	(0.00002)	(0.00000)	(0.00000)	(0.00002)	(0.00001)	(0.00002)	(0.00001)	(0.00001)	(0.00008)
β_*^{Solar}	0.00325***	0.00102***	0.00030***	−0.00020***	−0.00018***	−0.00035***	−0.00094***	−0.00174***	−0.00107***	0.00117***	0.00246***
	(0.00000)	(0.00013)	(0.00006)	(0.00000)	(0.00001)	(0.00002)	(0.00001)	(0.00004)	(0.00001)	(0.00001)	(0.00009)
$\beta_*^{OtherRe}$	0.00422***	0.00424***	0.00801***	−0.00157***	0.00497***	−0.00272***	−0.00906***	−0.01949***	−0.02439***	0.01921***	0.03593***
	(0.00000)	(0.00067)	(0.00084)	(0.00000)	(0.00015)	(0.00030)	(0.00015)	(0.00041)	(0.00009)	(0.00022)	(0.00186)
β_*^{Coal}	−0.00003***	0.00052***	0.00073***	0.00037***	0.00018***	−0.00010***	−0.00005***	0.00013***	0.00029***	0.00025***	0.00000
	(0.00000)	(0.00006)	(0.00006)	(0.00000)	(0.00001)	(0.00001)	(0.00002)	(0.00003)	(0.00000)	(0.00001)	(0.00019)
β_*^{Gas}	−0.00139***	0.00027***	0.00015***	0.00014***	−0.00013***	0.00018***	0.00045***	0.00036***	0.00041***	0.00057***	0.00174***
	(0.00000)	(0.00005)	(0.00004)	(0.00000)	(0.00001)	(0.00003)	(0.00001)	(0.00002)	(0.00001)	(0.00001)	(0.00008)
$\beta_*^{Otherfossil}$	0.00000***	0.00070***	0.00004	−0.00038***	−0.00042***	−0.00004	0.00007***	0.00046***	0.00077***	0.00023***	−0.00020**
	(0.00000)	(0.00012)	(0.00004)	(0.00000)	(0.00001)	(0.00003)	(0.00001)	(0.00004)	(0.00001)	(0.00001)	(0.00009)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The symbols ***, **, and * represent statistical significance at the levels of 1 %, 5 %, and 10 %, respectively.

Table 18
After the full-scale war between Russia and Ukraine related parameters (for detailed categories of electricity generation sources).

Coef	Quantile levels										
	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
Short-term Related parameters											
$\delta_{j*}^{Bioenergy}$	−0.00915***	0.00362***	0.00167***	0.00192***	0.00211***	−0.00066***	−0.00108***	−0.00142***	−0.00583***	−0.00392***	−0.01459***
	(0.00000)	(0.00038)	(0.00031)	(0.00000)	(0.00004)	(0.00014)	(0.00006)	(0.00029)	(0.00006)	(0.00009)	(0.00044)
δ_{j*}^{Wind}	−0.00470***	−0.00372***	−0.00074***	0.00071***	−0.00008***	−0.00095***	−0.00004	−0.00014	−0.00241***	−0.00280***	−0.00286***
	(0.00000)	(0.00030)	(0.00013)	(0.00000)	(0.00002)	(0.00009)	(0.00007)	(0.00011)	(0.00003)	(0.00003)	(0.00015)
δ_{j*}^{Hydro}	−0.00042***	0.00223***	0.00022**	0.00043***	−0.00091***	−0.00110***	−0.00027***	0.00012**	−0.00079***	−0.00242***	−0.00358***
	(0.00000)	(0.00008)	(0.00010)	(0.00000)	(0.00002)	(0.00004)	(0.00003)	(0.00006)	(0.00002)	(0.00002)	(0.00011)
δ_{j*}^{Solar}	0.00426***	0.00229***	−0.00156***	−0.00033***	0.00025***	−0.00089***	−0.00071***	−0.00044***	−0.00080***	−0.00548***	−0.00852***
	(0.00000)	(0.00026)	(0.00018)	(0.00000)	(0.00006)	(0.00016)	(0.00006)	(0.00012)	(0.00003)	(0.00003)	(0.00033)
$\delta_{j*}^{OtherRe}$	0.13489***	−0.10082***	−0.02905**	−0.01526***	0.04514***	0.04989***	0.02867***	0.00405	0.05029***	0.17222***	0.44194***
	(0.00000)	(0.00737)	(0.01156)	(0.00000)	(0.00086)	(0.00224)	(0.00224)	(0.00456)	(0.00069)	(0.00144)	(0.01384)
δ_{j*}^{Coal}	0.00547***	0.00391***	0.00086***	0.00138***	0.00003	0.00013	−0.00025***	−0.00093***	−0.00110***	−0.00072***	0.00492***
	(0.00000)	(0.00020)	(0.00014)	(0.00000)	(0.00004)	(0.00013)	(0.00006)	(0.00012)	(0.00003)	(0.00002)	(0.00062)
δ_{j*}^{Gas}	0.00829***	0.00648***	0.00185***	0.00175***	0.00035***	0.00033***	0.00154***	0.00207***	0.00145***	0.00041***	0.00149***
	(0.00000)	(0.00024)	(0.00009)	(0.00000)	(0.00001)	(0.00007)	(0.00005)	(0.00009)	(0.00003)	(0.00002)	(0.00035)
$\delta_{j*}^{Otherfossil}$	0.00810***	0.00713***	0.00318***	0.00168***	0.00042***	0.00000	0.00198***	0.00415***	0.00563***	0.00641***	0.00302***
	(0.00000)	(0.00057)	(0.00030)	(0.00000)	(0.00004)	(0.00009)	(0.00011)	(0.00011)	(0.00003)	(0.00004)	(0.00027)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The symbols ***, **, and * represent statistical significance at the levels of 1 %, 5 %, and 10 %, respectively.

unstable environments due to high initial investment costs, long construction periods, and dependence on policies and subsidies (Mills et al., 2019).

Other renewables show significant negative effects at some decreasing and rising risk quantiles and positive effects at other quantiles in the long term. At decreasing risk quantiles, other renewable sources show significant negative effects, meaning they help reduce risks. This phenomenon is primarily due to the use of renewable energy that helps reduce dependence on geopolitically sensitive fossil fuels. For example, by increasing the share of wind and solar energy, nations or regions can reduce their dependence on imported oil and natural gas, thus decreasing reliance on the political stability of certain global regions for energy supplies. The introduction of other renewables as a response to power shortfall demands can also resist external risks at rising risk quantiles. The positive effects at other quantiles may be due to the fact that other renewable sources mostly serve as supplemental power sources during technical development and early policy implementation, associated with high costs and investment uncertainties (Mills et al., 2020). Moreover, while other renewable sources are less directly affected by geopolitical conflicts, policy instability, rapid technological changes, and market acceptance inconsistencies may increase market uncertainty and risks at these quantiles.

To further investigate this situation, we also found that coal exhibits significant negative effects at some decreasing and stable risk quantiles and significant positive effects at rising and other risk quantiles. Under normal circumstances, such as temporary natural gas shortages caused by the Russia-Ukraine conflict, the availability of coal can ensure the continuity of electricity production, thus reducing market turbulence caused by energy supply tensions. While coal can serve as an energy supplement to reduce supply risks in the short term, its long-term use, associated with high carbon emissions and environmental damage, may increase regulatory and policy pressures (Sizov, 2023). In markets sensitive to environmental policies, coal usage may raise compliance risks and incur additional carbon emission costs due to policy changes, thereby increasing overall grid price risks. Natural gas shows a significant positive effect across almost all quantiles, except for some stable risk quantiles. In the market, natural gas supply is often closely linked to specific geographic and political contexts. The European market was highly dependent on Russian natural gas supplies before and after the Russia-Ukraine conflict. The positive effect of natural gas may be related to the fact that most of Europe's gas is imported from Russia, alongside environmental policy pressures and the market's demand for sustainable energy transitions. Geopolitical trends and tensions indirectly influence the price and quantity of Russian gas exports to Europe, as in high-tension scenarios, gas export prices are higher, and supply is more limited (Ma et al., 2019). Furthermore, with the growing global focus on carbon emissions, energy markets relying on fossil fuels may face greater policy and regulatory risks. These risks could pose long-term challenges to the market positioning of natural gas. Therefore, due to the full exposure of natural gas to Russia-Ukraine geopolitical interventions, its effect on grid risk is heightened when addressing external geopolitical risks. Other fossil fuels show significant positive effects across almost all quantiles in the long term. Other fossil fuels, such as oil, are typically closely related to geopolitics. The main producing countries and supply routes for these energy resources often involve politically unstable regions or countries (Ali et al., 2018). Therefore, any geopolitical conflict or sanctions between countries can directly affect the security of supply, transportation costs, and the final prices of these fuels, thereby triggering market risks (Liu et al., 2023).

In Table 14, we find that bioenergy exhibits significant negative short-term effects on the wholesale electricity market's risk due to geopolitical conflicts across almost all quantiles. Bioenergy typically relies on local biomass resources, such as agricultural residues, forestry products, or organic waste, which are less directly affected by international geopolitical events compared to traditional fossil fuels. Therefore, due to its relatively stable supply chain, bioenergy contributes to reducing the market's sensitivity to external shocks, thereby mitigating risk fluctuations (Brutschin and Fleig, 2018). Wind energy, as a renewable resource, is generally unaffected by geopolitical conflicts, especially when wind power facilities are located in politically stable countries or regions. Therefore, across nearly all risk quantiles, wind energy can provide a stable energy supply, reducing market risks caused by unstable energy supplies (Forrest and MacGill, 2013; Quint and Dahlke, 2019). Although wind energy reduces risk in the vast majority of quantiles, it may increase risk at extreme quantiles, particularly in markets where wind technology or infrastructure is not fully mature or evenly distributed. For example, wind power generation is highly dependent on climate and weather conditions, and unstable wind can cause fluctuations in power generation, thus increasing price and supply uncertainty in the market. This may lead to intensified market fluctuations instead of mitigating them at high-risk quantiles. Hydropower shows significant negative short-term effects on risks due to geopolitical conflicts across all quantiles, except for some rising risk quantiles, where it shows significant positive effects. As a renewable energy based on water resources, hydropower operates at low costs and is unaffected by fuel price fluctuations. In most scenarios, hydropower can provide a stable and reliable electricity supply, especially when geopolitical conflicts may affect fuel supplies, as its locality and independence from global resources significantly reduce electricity market risks. Although hydropower generally helps reduce risk, its generation efficiency depends heavily on climatic conditions, particularly the availability of water resources. During droughts or when water resources are scarce, hydro output can be limited, potentially causing instability in electricity supply, especially in regions heavily reliant on hydro power (Rübbelke and Vögele, 2013). This may explain why hydropower shows increased risk effects at certain rising risk quantiles.

Solar energy shows significant negative short-term effects at decreasing and stable risk quantiles, and significant positive effects at other quantiles due to geopolitical conflicts. As a renewable resource, solar energy primarily relies on sunlight, a widely available natural resource, making it relatively independent of geopolitical factors. Therefore, at decreasing and stable risk quantiles, solar energy provides a relatively stable energy supply, reducing market risks caused by unstable traditional energy supplies. Although solar energy helps reduce risk at some quantiles, its generation instability and high dependency on weather conditions may increase risk at other quantiles (Bushnell and Novan, 2018). For instance, during cloudy or rainy seasons, unstable solar power generation may lead to supply uncertainties, especially in regions heavily dependent on solar energy as a primary power source (Joskow, 2019). Unstable solar resource endowment might cause fluctuations in power generation, thus increasing price and supply uncertainty in the market, potentially exacerbating market fluctuations at high-risk quantiles instead of mitigating them.

Other renewable energies show significant negative short-term effects at some decreasing risk quantiles while displaying significant positive effects at other quantiles due to geopolitical conflicts. At decreasing risk quantiles, other renewable sources, such as geothermal and tidal energy, due to their broad geographical distribution and relative independence from geopolitical events, may help reduce energy supply risks. These energy sources typically do not rely on imports and can be produced locally, maintaining supply stability in situations where political conflicts affect energy markets. The positive effects at other quantiles may relate to the maturity and cost-effectiveness of these energy technologies. Many other types of renewable energy technologies are relatively new and may face higher initial investment and maintenance costs, which could increase economic risks in markets where the technology has not yet been widely commercialized or cost-effectiveness has not been optimized (Chowdhury et al., 2020). Therefore, this may lead to intensified market fluctuations at high-risk quantiles instead of mitigating them.

We also found that natural gas and other fossil fuels show significant positive short-term effects on market risk across almost all quantiles due to geopolitical conflicts. The supply of these fossil fuels is highly dependent on specific geographical regions, which are often hotspots for geopolitical conflicts. This dependency means that any geopolitical conflict could directly impact the market performance of these fuels, thereby increasing market risk in the short term. The supply chain for fossil fuels involves complex international transportation, refining, and distribution processes, and any segment affected by geopolitical events can lead to supply disruptions or increased transportation costs. This vulnerability becomes particularly apparent as geopolitical tensions intensify, thus elevating market risks. In the context of geopolitical conflicts, governments may take emergency measures, such as imposing sanctions or adjusting import tariffs, which can directly affect the supply and prices of fossil fuels, further exacerbating market uncertainty (Liu and Jin, 2020; Genc and Kosempel, 2023).

Additionally, in extreme risk scenarios, coal, as a substitute for natural gas, shows negative risk effects at some non-extreme rising risk quantiles. Furthermore, with the growing global focus on climate change, fossil fuels are also facing increasing policy pressure, and this long-term policy risk may be amplified in the short term due to geopolitical conflicts.

Next, we divided the sample into two periods: before and after the full-scale Russia-Ukraine conflict, to more closely examine the relationship between different types of power generation sources and geopolitical risk in the electricity market. Comparing Tables 15 and 17 (before and after the full-scale Russia-Ukraine conflict), we observed changes in the long-term impact of bioenergy on the external shock risks to the wholesale electricity market at both rising and decreasing risk quantiles. After the full-scale conflict, bioenergy's ability to cope with extreme risk fluctuations (extreme risk increases) improved. The long-term impact of wind on the external shock risks to the wholesale electricity market showed significant changes across almost all quantiles, with its risk-reducing ability strengthened across the board. Hydropower also displayed significant changes in its long-term impact on rising risk quantiles, with enhanced risk reduction capabilities. Solar power also showed significant changes in its long-term impact on external shock risks across decreasing, stable, and rising risk quantiles, with its risk-reducing ability shifting from lower to higher risk quantiles. After the full-scale Russia-Ukraine conflict, hydropower demonstrated a significantly enhanced capability to reduce external risks at high-risk quantiles. In general, after the conflict, renewable sources such as bioenergy, wind, hydropower, and solar power showed stronger capabilities in reducing the long-term impact of external shocks due to geopolitical conflicts on the wholesale electricity market. This phenomenon is mainly due to the accelerated shift toward localization and renewable energy post-conflict, aimed at reducing dependence on fossil fuels from geopolitically sensitive regions (Chedid and Penteado, 2022; Korosteleva, 2022; Kabadayı, 2023). Strengthened policy support, technological advancements, and increased market demand for energy diversification have enabled these renewable sources to exhibit greater stability and resilience against extreme market fluctuations, thereby more effectively mitigating market risks. The long-term impact of other renewable energy sources on external shock risks to the wholesale electricity market showed almost no change across all quantiles. This may be because these energy technologies have not yet fully matured or been widely commercialized, so their supply and generation capabilities only provide additional supplementary capacity under extreme market conditions (Alsagr and Hemmen, 2021). Furthermore, due to insufficient policy support and market acceptance, combined with technological and economic uncertainties, these sources have been unable to stabilize the market as effectively as other, more mature renewable sources during geopolitical conflicts. This has led to no substantial change in their risk-reducing capabilities before and after the full-scale conflict (Sayed et al., 2020). The long-term impact of coal on external shock risks to the wholesale electricity market at rising risk quantiles showed an increase in its risk-reducing ability. This might be because, in the long term, as geopolitical conflicts exacerbate the instability of other energy supplies, especially natural gas, the market has again relied on coal as a reliable baseload energy source to ensure power supply. Despite environmental pressures and energy transition goals pushing for restrictions on coal, its supply stability and the reliability of existing infrastructure make it a key energy source for reducing market risks in extreme risk scenarios (Masoumzadeh et al., 2017; Ma et al., 2021).

The long-term impact of natural gas on external shock risks to the wholesale electricity market also changed across various quantiles. After the full-scale conflict, natural gas showed significant positive effects on external risks to the grid across nearly all quantiles. This may be because Russia's supply of natural gas to Europe decreased significantly after the full-scale conflict. Although European countries and other markets quickly implemented various response measures, including increasing liquefied natural gas (LNG) imports, expanding other supply sources, and strengthening natural gas reserves (Kotov, 2022; Halser and Paraschiv, 2022), these measures were unable to fully meet the electricity demand gaps in these European countries, nor could they maintain natural gas's original role in the electricity market. The long-term impact of other fossil fuels on external shock risks to the wholesale electricity market showed no significant changes. This may be for reasons similar to those of other renewable energy sources, where other fossil fuels also merely serve as supplements for power shortages and do not account for a high proportion of total power generation. Therefore, due to their low share, their impact remains relatively small (Zakeri et al., 2022).

Next, we compared Tables 16 and 18. The impact of renewable energy sources, such as bioenergy, wind, hydro, and solar, on the wholesale electricity market has undergone significant changes. These changes are not limited to their roles in low-risk or stable market environments but have expanded to play a critical role in times of rising risk. Before the conflict, renewable energy was primarily used to reduce market volatility and provide a stable power supply. However, after the conflict, as supply chains were disrupted and energy demand surged, the focus of these energy sources shifted toward maintaining energy supply and market stability under unstable conditions (Humpenöder et al., 2018). In a full-scale conflict environment, as the uncertainty of traditional energy supplies increased, governments and the energy sector accelerated investments and deployment of renewable energy technologies. This was not only because renewable energy provided an alternative to counter supply disruptions, but also because it could quickly increase power generation capacity without adding environmental burdens. For instance, wind and solar projects can be completed within months, whereas coal-fired power plants take years to construct (Pouran, 2018; Nechaieva, 2021).

Additionally, the market's acceptance of these technologies is also rising, with many power companies and independent market operators increasingly relying on renewable energy to manage price fluctuations and supply uncertainties. This reliance is not limited to a single source but involves a mixed-energy strategy, combining bioenergy, wind, hydro, and solar to optimize the energy mix and enhance overall system resilience. On the policy front, many countries have implemented incentives such as tax breaks, direct subsidies, and renewable energy quota systems, further promoting the application and development of renewable energy in the electricity market. With this policy support, renewable energy is increasingly viewed as an essential tool for maintaining energy security and economic stability in high-risk scenarios. However, due to the inherent volatility of renewable energy, it may not consistently provide a stable power supply in low external-risk situations. While renewable energy can significantly reduce reliance on unstable energy sources and enhance the overall resilience of the system during geopolitical conflicts or other high-risk periods, its output uncertainty in everyday low-risk environments may increase the complexity of power system operations. This could lead to positive effects in risk-reducing quantiles.

Overall, the enhanced role and importance of renewable energy during geopolitical conflicts not only altered their function in the electricity market but also reinforced their position as an indispensable part of future energy transition and market adaptation strategies. These energy sources are now viewed as frontline defenses in risk management and addressing global energy supply challenges. The short-term impact of other renewables on external shock risks to the wholesale electricity market showed little change before and after the conflict. The short-term impact of other renewables on external shock risks to the wholesale electricity market only showed significant negative effects at some stable risk quantiles, likely because these types of energy (such as geothermal and tidal energy) account for a relatively small share of the overall energy structure, and their technological applications and market scale have not yet reached the level needed to significantly affect market fluctuations (Chowdhury et al., 2020). Furthermore, the supply characteristics of these energies are relatively stable and less likely to be directly affected by geopolitical conflicts. Therefore, their impact on market risk remained relatively stable in the short term, with no significant changes observed (Dhar et al., 2020).

The short-term impact of coal on external shock risks to the wholesale electricity market shifted from entirely positive effects before the conflict to negative effects at some stable and rising risk quantiles. This change may be due to the conflict causing tightness in energy supply chains, particularly with natural gas supply constraints, prompting the market to rely on coal as an emergency energy source to ensure power supply during extreme risk increases (Wang et al., 2020). However, due to environmental policies and long-term energy transition pressures, coal is no longer seen as the preferred choice in more stable market environments, only showing risk-reducing capabilities in certain emergency situations (Ma et al., 2021).

After the conflict, the short-term impact of natural gas and other fossil fuels on external shock risks to the wholesale electricity market showed significant positive effects across nearly all risk quantiles. Geopolitical conflicts typically lead to substantial positive impacts of natural gas and other fossil fuels in the wholesale electricity market, mainly due to supply chain disruptions and price volatility. Conflicts often affect countries dependent on resources from geopolitically sensitive regions, such as oil from the Middle East or restricted natural gas from Russia, leading to supply shortages and driving up energy prices (Pereira et al., 2022; Do et al., 2024). Moreover, due to insecure import routes, countries may seek expensive alternatives or increase stockpiles, further driving up prices. Market expectations of uncertainty and speculative behavior can also push up prices in anticipation of supply disruptions. Despite the global increase in renewable energy use, many economies still rely on fossil fuels in the short term, and during conflicts, if renewable energy supplies are insufficient, the demand and prices for fossil fuels may rise. Governments may protect domestic energy industries through tariffs, export restrictions, and other measures, which could also lead to increases in wholesale electricity prices. These factors collectively result in significant positive effects of natural gas and other fossil fuels during geopolitical conflicts across all risk quantiles in the electricity market, reflecting the importance of these energy sources in the global energy market and their sensitivity to political and economic stability.

4.2.5. Discussion

Across Tables 9–11, the QARDL results reveal clear state-dependent dynamics in the relationship between energy composition and systemic electricity market risk. Renewable energy mitigates risk at low to medium quantiles but amplifies it at higher quantiles, while fossil fuels exhibit the opposite pattern in the long term and significantly increase risk in the short run. After the full-scale Russia–Ukraine conflict, these nonlinearities became stronger, consistent with tightening gas constraints and the erosion of market flexibility. This distributional heterogeneity extends prior literature by highlighting how the impact of energy structure depends on the prevailing risk regime rather than being uniform across states.

These results complement and refine earlier findings. Cevik and Ninomiya (2022) showed that geopolitical risk raises volatility in energy markets and that renewables' stabilizing role can reverse under stress; our quantile-based evidence identifies precisely where this reversal occurs—mainly at the upper quantiles—and shows that it intensifies after 2022. Likewise, Yang et al. (2021) emphasized the short-term buffering capacity of decentralized renewables during global uncertainty shocks. We confirm this mechanism at the 90–95 percent quantiles, where renewable energy temporarily reduces market risk even in extreme volatility regimes. This aligns with the intermittency and flexibility theories of Green and Vasilakos (2010) and Hirth (2013), which argue that weather-dependent resources can either stabilize or destabilize markets depending on the adequacy of reserve margins and balancing mechanisms. Together with Honkapuro et al. (2023) and Enescu and Szeles (2023), our results reinforce the idea that Europe's integrated power system alone cannot absorb large external shocks without additional flexibility.

The newly constructed War-Induced Energy Instability (WEI) Index offers a distinctive contribution to the “conflict–energy–risk” literature. Unlike the broad Global Geopolitical Risk (GPR) measure, the WEI is specifically designed to capture energy-specific instability induced by armed conflict, integrating information on fuel price shocks, supply disruptions, and wholesale electricity volatility. When embedded in the QARDL framework, the WEI enables a quantile-sensitive identification of how geopolitical events propagate through the energy mix. It shows that renewables act as a hedge in normal conditions but as a volatility source when systemic risk is high, while fossil exposure becomes increasingly destabilizing under geopolitical stress.

From a policy perspective, these findings imply that energy diversification and flexibility are complementary rather than substitutable. Expanding renewables without adequate storage, interconnection, and balancing capacity may shift risks to higher quantiles rather than remove them. Conversely, pairing renewable expansion with resilience instruments – such as flexible generation, storage, and demand response – can transform renewables’ short-term buffering role into a sustained reduction of systemic risk. This echoes the argument of Cherp and Jewell (2014) and Sovacool (2016) that the energy transition, when properly designed, can act as a structural mechanism for long-term geopolitical risk mitigation.

5. Conclusion and policy implications

This study introduced the War-Induced Energy Intensity (WEI) Index, a novel indicator based on large language models that captures energy-market sentiment related to the Russia-Ukraine conflict with greater precision. Our analysis shows that the war represented a watershed event in the evolution of Europe's electricity markets, fundamentally reshaping market dynamics across 24 countries. The structural break test further validates this conclusion, identifying a significant market shift in early 2022 that underscores the profound impact of the conflict.

The core findings of this study carry important policy implications. As discussed above, the full-scale Russia-Ukraine conflict has substantially altered the risk structure of the global electricity market, particularly in terms of the changing roles of renewable and fossil energy and their corresponding policy responses. With the growing international emphasis on climate change, fossil fuels face increasing pressure from environmental regulations and decarbonization mandates. This calls for policymakers and market participants to strike a more effective balance between ensuring energy-supply security and achieving climate goals. Our empirical evidence indicates that renewable energy functions not only as an environmental tool but also as a strategic hedge against geopolitical shocks: its generation process is largely decoupled from fossil-fuel supply chains, thereby reducing system exposure to external disruptions. By contrast, fossil fuels – especially natural gas – act as risk amplifiers, as supply constraints and price volatility exacerbate market instability and energy insecurity.

Consequently, renewable-energy policy should shift from capacity-expansion orientation toward a system-resilience orientation. Beyond increasing installed capacity, the focus should be on strengthening the stabilizing contribution of renewables during crises through investment in grid interconnection, storage, and flexibility. Governments can provide tax incentives, subsidies, and financial instruments to encourage both public and private investment in wind, solar, and other renewable projects (Heshmati et al., 2015). In addition, establishing clear, long-term, and credible renewable-energy targets can bolster investor confidence and support sustainable industry growth (Jordaan et al., 2017).

For fossil energy, policy priorities should evolve from expansion to managed exposure and orderly transition. While fossil fuels remain essential for short-term system adequacy, excessive dependence heightens vulnerability to market and supply shocks. Policymakers should focus on improving energy efficiency, advancing cleaner combustion technologies, and promoting the commercial deployment of carbon-capture and storage (CCS) systems (Kotagodahetti et al., 2021). At the same time, governments should pursue energy-diversification strategies that reduce reliance on single import channels and strengthen regional reserves and emergency coordination mechanisms (Monasterolo and Raberto, 2019). At the European level, enhanced cross-border cooperation, harmonized regulation, and joint infrastructure investment are essential to mitigating geopolitical risks and ensuring collective energy security.

Finally, regulatory authorities should adopt a risk-sensitive governance framework by incorporating indicators such as the WEI into market-monitoring and early-warning systems. Integrating these metrics into policy evaluation would enable more responsive interventions—such as strategic storage releases, flexibility procurement, or temporary price stabilization—when systemic stress emerges. Improving market transparency and international coordination can protect consumers, prevent manipulation, and ensure that energy-transition and environmental objectives progress in tandem. Through these integrated measures—treating renewables as stability assets, managing fossil fuels as risk liabilities, and linking policy actions to quantified risk signals—European energy governance can more effectively mitigate conflict-driven market volatility and guide the global electricity system toward a more sustainable, resilient, and policy-responsive future (Heshmati et al., 2015; Jordaan et al., 2017; Kotagodahetti et al., 2021; Monasterolo and Raberto, 2019).

Despite its contributions, this study is still subject to limitations. First, the WEI index relies on news and social media data obtained from Factiva and Twitter, which may carry selection and regional coverage biases. Second, empirical models depend on specific assumptions, such as lag structure and quantile segmentation in the QARDL framework, which may influence parameter stability. Third, potential overlapping shocks – such as the COVID-19 pandemic – may also confound the estimated effects. Future research could expand the scope by integrating multi-source sentiment data, exploring alternative model specifications, and examining how renewable–fossil energy dynamics evolve under simultaneous economic, climatic, and geopolitical stressors.

CRediT authorship contribution statement

Guanghao Wang: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hung Xuan Do:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Chenghao Liu:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis. **Erwann Sbai:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Emilson Silva:** Writing – review & editing, Writing – original draft, Supervision, Project administration.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2026.115083.

Data availability

Data will be made available on request.

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