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Unveiling High-Dimensional Time-Varying Extreme Risk Spillovers: AI-Driven Warning Signals in the Global Energy Market

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Abstract

This paper investigates extreme risk spillovers in global energy markets using the enhanced high-dimensional time-varying parameter vector autoregressive spillover (HD-TVP-VAR-SP) model. We employ the Long Short Term Memory (LSTM) model to develop an energy risk warning system, identifying key factors in risk contagion. Our findings reveal robust connectivity in global energy market risks, characterized by high-dimensional complex networks with marked temporal variations. The Americas region emerges as the leading contributor to systemic risk shocks, primarily through positive spillovers in its energy markets. The LSTM model demonstrates superior extreme risk prediction compared to other machine learning models like Gradient Boosting Machines, Random Forest, and Decision Trees. The oil market is identified as a critical driver of risk contagion in the energy sector. These insights provide valuable guidance for effectively identifying and managing global energy market risks and enhancing risk warning systems.

Keywords: Global energy markets; Risk spillovers; High-dimensional TVP-VAR spillover model; Risk warning system; Machine learning model

1. Introduction

Energy, as a fundamental pillar for human society's survival and development, plays a crucial role in output growth and industrial production (D'Ecclesia et al., 2024). The swift growth of modern industry has resulted in escalating energy needs, rendering the dependability of energy provision a vital element in both national economic advancement and the stability of energy markets (Zhu et al., 2023). Ensuring a balance between supply and demand in the energy market is a primary objective for nations. However, the complexity and unpredictability of the global energy supply, along with the uneven distribution of major energy sources and extended supply chains, expose national energy markets to multilevel risks. These risks arise from geopolitics, natural disasters, policy shifts, and technological advancements (Xie and Tang, 2022) and can rapidly propagate through the market, preventing stability and inducing dynamic fluctuations (Hung and Vo, 2021). Furthermore, the convergence of energy and financial markets has escalated energy-related financial flows, heightening the risk in energy markets during extreme uncertainties. This leads to volatility in energy prices, supply-demand imbalances, and economic unpredictability (Zhu et al., 2023). Amidst increasing economic globalization, the interconnections in global energy supply and demand are intensifying, leading to a highly integrated energy market. This integration elevates the significance of energy security for nations, as risks in energy markets are no longer isolated but have cross-border and cross-regional implications (Gong et al., 2023). Particularly in times of extreme uncertainty, the linkages between energy markets can abruptly intensify, rapidly affecting other countries in the supply chain and causing widespread risk resonance. Given the time-varying and high-dimensional complexity of these risk linkages, this prompts several critical questions: How can we more accurately identify the characteristics of risk contagion in global energy markets? What approaches can be used to develop an effective energy risk early warning system for risk mitigation? And importantly, how can we discern the factors influencing energy risk transmission to better manage and control these risks?

In recent years, academic consensus has emerged on examining systemic risk transmission in energy markets through the lens of correlation. Such risk correlations can transform individual risk events into systemic risks across the energy market (Ji et al., 2023). However, a consistent quantitative approach to effectively measure and assess risk correlation in energy markets is lacking. This is due to the generation and spread of systemic risks occurring within a complex network structure. Recognizing the intricate nature of systemic risk, scholars have started employing the spillover index method to depict the variable correlation structure of energy risks (Al-Yahyaee et al., 2019). Nonetheless, analyzing systemic risk generation and contagion under this complex network structure faces two major challenges: The 'time-varying' and 'high-dimensional' nature of risk networks, primarily rooted in complex inter-institutional linkages (Le et al., 2022). This complexity is evident in both the dynamic nature of correlations and the multitude of institutions involved, along with their evolving interactions. Although empirical evidence has established the time-varying na-

ture of systemic risks, and some studies have addressed the high-dimensional complexity among variables (Uddin et al., 2023), a globally effective estimation method that encompasses both time-varying and high-dimensional aspects of complex networks is yet to be developed. Moreover, an essential strategy for mitigating energy market risks is the implementation of early warning systems. Timely warnings allow market participants to respond more effectively and minimize losses. However, current research on this aspect is limited, hindering the development of a comprehensive risk management system. Given the critical importance of energy security, nations require more sophisticated risk management in energy markets. Enhancing risk warning levels is thus a key direction for energy market regulation. Consequently, a complex network correlation structure that integrates ‘time-varying’ and ‘high-dimensional’ characteristics is vital for establishing a macro-prudential management framework for energy risk. Developing and applying an accurate and effective risk early warning mechanism is crucial for a deep understanding and management of the dynamic evolution of the risk network.

This paper investigates systemic risk contagion and early warning in the global energy market, utilizing complex network and artificial intelligence approaches. Specifically, this study aims to develop a comprehensive framework that captures both the time-varying and high-dimensional nature of extreme risk spillovers across global energy markets. Additionally, we seek to construct an AI-driven early warning system capable of identifying key factors influencing risk propagation and providing timely signals for risk mitigation. By doing so, we address the critical questions raised earlier regarding the identification of risk contagion features and the development of an effective early warning mechanism. (1) on the fundamental characteristic of global energy market risk linkages, prior studies predominantly centered on aggregate market risk as opposed to extreme risk, while those studies that do explore extreme risks often confine their examination to individual energy subtypes (Uddin et al., 2023; Gong et al., 2023), with no systematic evaluation of the interconnected nature of extreme risks across national energy markets. Meanwhile, the deepening integration of global energy markets and the financialization of energy trade (Ji et al., 2020) imply inherent interconnectedness among major energy markets. To fill this gap, we propose Hypothesis 1.1 to verify whether extreme risks in major energy markets form a tightly linked network. (2) concerning the regional source of systemic risk spillovers, existing literature has not explicitly identified the dominant regional contributor to global energy risk spillover. The Americas, endowed with abundant unconventional energy resources and advanced development technologies, and featuring highly financialized energy markets, is widely recognized as a core hub of global energy supply and trade (Cheng and Hung, 2011). However, its specific role in risk spillover remains unquantified. Thus, we propose Hypothesis 1.2 to clarify the regional leadership in systemic risk transmission. (3) regarding the dynamic nature of risk linkages, existing studies either ignore the time-varying nature of high-dimensional risk networks (Uddin et al., 2023) or rely on rolling window methods that suffer from information loss (Xie et al., 2023). In reality, macroeconomic cycles, geopolitical conflicts and

financial crises (Liao and Pan, 2022; Laborda and Olmo, 2021) continuously reshape the intensity of cross-market risk transmission. To address this limitation, we propose Hypothesis 2.1 to test whether risk connections among global energy markets evolve with key events. (4) focusing on the dynamic net spillover role of the Americas, while Hypothesis 1.2 verifies the static contribution of the Americas, the region's long-term status as a net risk transmitter driven by its sustained energy supply dominance (Wang et al., 2021) and price leadership (Antonakakis et al., 2014) has not been confirmed in dynamic contexts. We therefore propose Hypothesis 2.2 to examine the stability of its risk transmission role over time. (5) for the core driver of risk contagion, traditional linear early warning models fail to capture nonlinear relationships between risk drivers and spillover effects, and existing studies lack a consensus on the dominant factor in energy risk transmission (Zhang et al., 2025). Given that crude oil serves as the cornerstone of global energy consumption and acts as a pivotal bridge connecting natural gas, coal, and renewable energy markets (Güntner and Öhlinger, 2022), we propose Hypothesis 3 to identify the key oil-related drivers that affect cross-market risk spillovers, laying the foundation for effective risk warning systems. To verify the aforementioned research hypotheses, this study conducts empirical analysis using two core methods. One approach is to introduce an enhanced High-Dimensional Time-Varying Parameter Vector Autoregressive Spillover (HD-TVP-VAR-SP) model to test Hypothesis 1.1, Hypothesis 1.2, Hypothesis 2.1, and Hypothesis 2.2. Another approach is to adopt the Long Short-Term Memory (LSTM) neural network model to focus on testing Hypothesis 3. The complementary application of these two types of models not only ensures the accurate characterization of risk spillover characteristics but also enables the effective identification of risk drivers.

The key contributions of this study are as follows. Firstly, while existing research primarily centres on general risk in the energy market (Singh et al., 2019; Uddin et al., 2023; Cheng and Hung, 2011; D'Ecclesia and Clementi, 2021), there is a notable gap in the examination of extreme risk spillovers. Some existing studies do address extreme risk spillovers in energy markets, but these are often confined to analyses of markets with specific types of energy (Gatfaoui, 2013; Gong et al., 2023). Our paper aims to fill this gap by offering a more comprehensive and systematic exploration of extreme risk spillovers across different energy markets. To achieve this, we have employed a variety of volatility models, selecting the optimal one to simulate the time-varying volatility of risks. We then calculated the extreme risks in the energy markets of 22 major countries. Our global analysis reveals the resonance phenomenon of extreme risks within the energy market system, alongside its dynamic characteristics. Additionally, we scrutinize the influence of extreme events on the proliferation of risks in the energy market. Secondly, we introduce the HD-TVP-VAR-SP model to establish a risk connection network among energy markets. This model, an advancement of the TVP-VAR overflow model popularly deployed in recent studies (e.g., Lang et al., 2024; Wei et al., 2023; Xie et al., 2023; Gong et al., 2021), accommodates both high dimensionality and the time-varying nature of variables. It effectively addresses the dimensionality issue present in

the original TVP-VAR overflow model, especially when dealing with a high number of variables, and dynamically characterizes the global structure of high-dimensional energy market networks. Although Uddin et al. [2023] have utilised high-dimensional networks for constructing risk spillover path in energy companies to tackle the dimensionality challenge, their reliance on the VAR model falls short in capturing the time-varying evolution of risk spillovers. Other researchers, such as Wu and Jiang [2023] and Finta and Aboura [2020], have attempted to overcome this limitation using the rolling window method. However, this approach is heavily dependent on the choice of the window and might result in the loss of some sample information (Xie et al., 2023). Consequently, our proposed HD-TVP-VAR-SP model effectively encapsulates both ‘high-dimensional’ and ‘time-varying’ aspects, rendering it practically valuable. Its ‘high-dimensional’ feature allows for a deeper comparison of complexities across different energy markets, while its ‘time-varying’ trait facilitates a more sensitive analysis of the impact of external shocks over time. Thirdly, this paper develops a cross-market risk early warning model to facilitate risk alerts for the global energy market. While extensive literature exists on risk contagion characteristics in energy markets, there is a scarcity of research on predicting and issuing early warnings for risk signals across different markets (Fabra and Reguant, 2024). Recent advancements in artificial intelligence have led some scholars to propose various machine learning models for financial risk prediction. However, these models often fall short in capturing complex system dynamics and in effectively discerning nonlinear relationships between variables. To address this gap, our study employs the LSTM approach to construct a nonlinear, cross-market risk early warning model. We also utilize the LSTM machine learning model to evaluate the key factors influencing risk propagation. Although numerous studies have explored the determinants of risk spillovers, most have relied on parametric linear early warning models (Frankel and Rose, 1996). These linear models frequently suffer from mis-specified settings and overlook potential nonlinear interactions among variables, which is at odds with the commonly observed nonlinear nature of risk drivers (Rad et al., 2023; Wu and Yan, 2019; D’Amato et al., 2021). In contrast, the LSTM deep learning framework excels in learning nonlinear dynamic changes and in modeling complex issues by processing large-scale time series data, thereby enhancing the accuracy of risk warnings.

Our analysis yields several key findings that advance the understanding of extreme risk transmission in global energy markets. First, the enhanced HD-TVP-VAR-SP model confirms that extreme risk spillovers form a highly interconnected and time-varying network across the 22 major energy markets examined. The total connectedness index reaches 78.36%, underscoring the high degree of systemic interdependency. Second, the Americas, particularly the United States, Canada, and Brazil, are identified as the dominant contributors to systemic risk shocks, with notably high net spillover effects, a phenomenon attributable to their pivotal roles in both conventional and unconventional energy production and financialization. Third, risk linkages exhibit significant time-varying properties, intensifying markedly during major crises such as the 2008 financial col-

lapse, the 2014–2016 oil price plunge, and the COVID-19 pandemic. Regionally, energy markets in China and Australia serve as persistent net transmitters of risk within the Asia-Pacific, while several European markets (e.g., the UK, France, Italy, Spain, and Norway) also consistently export risks, aided by their financial market depth and renewable transition strategies. Fourth, in the construction of the risk early warning system, the LSTM model we adopted shows obvious advantages over traditional machine learning models, which effectively solves the problem that linear models and other machine learning models are difficult to capture nonlinear relationships and long-term dependencies in risk transmission. Finally, through the analysis of variable importance, we found that the oil market is the core driver of risk contagion in the global energy sector: the West Texas Intermediate (WTI) index and the Oil Volatility Index (OVX) rank first and second in terms of importance, respectively. This is because oil accounts for 42% of the world's final energy consumption, and its price fluctuations directly affect the supply-demand balance and cost structure of the entire energy market, while its close connection with natural gas, coal, and renewable energy markets further amplifies its risk spillover effect. This finding clearly points out the key factors that need to be focused on in energy risk management. These findings not only clarify the characteristics and drivers of risk contagion in global energy markets but also provide a practical basis for optimizing risk early warning mechanisms and formulating targeted risk management policies.

The structure of this study is as follows: Section 2 provides a literature review and outlines the theoretical assumptions. Section 3 summarises the research methodology. Data sources and their descriptions are detailed in Section 4. Empirical results and discussions are presented in Section 5. Section 6 concludes the study with conclusions and policy recommendations.

2. Literature review and theoretical assumptions

2.1. Literature review

Extreme weather and geopolitical tensions are likely to sustain energy price volatility as a prominent characteristic of energy markets in the upcoming decades (Reboredo, 2015; Efimova and Serletis, 2014). This volatility in regional energy market prices directly impacts the profitability of the global energy sector, consequently affecting the market prices of national energy stocks (Ratti and Vespignani, 2015). The interconnectedness of stock prices and the risk contagion features within energy markets have garnered significant scholarly interest. Prior research on information spillover in these markets has predominantly centered on return spillovers, as they are instrumental in reflecting the coordinated price movements across variables. Compared to return spillovers, volatility spillovers are more susceptible to extreme events, indicative of risk contagion in financial markets (Diebold and Yilmaz, 2009). This contagion is not confined to individual energy markets but can traverse various energy markets, enabling risk events to rapidly impact others through contagion effects. Therefore, precisely identifying volatility risks in energy markets is critical for establishing cross-market risk connections and pinpointing risk transmission channels.

As the supply of energy becomes more abundant and secure, the global energy market is experiencing continual expansion, with trade among nations evolving towards stability, orientation, and integration (Klepper and Peterson, 2006). In scenarios of heightened network connectivity, the growth in energy market capacity enhances economic expansion and fosters energy structure diversification. However, extreme events can critically influence energy market risks, affecting associated networks both within and beyond the energy sector. Previous research has thoroughly examined energy price volatility risks through these networks, encompassing both energy and other commodity markets (Sun et al., 2023), as well as energy and stock markets (Batten et al., 2021). Nevertheless, the study of risk contagion specifically within energy markets remains relatively underexplored (Troster et al., 2018; Ahmad, 2017). While some researchers, including Singh et al. [2019] and Uddin et al. [2023], have investigated risk spillovers in energy markets, their focus has predominantly been on overall market risk. Numerous studies indicate that shocks from extreme risks are substantially more impactful than those from typical risk spillovers, with extreme risk offering a more accurate measure of risk exposure during crises (Foglia et al., 2022; Yousaf et al., 2023). Therefore, analyzing the complex network correlations of extreme risks among energy markets is also of paramount importance.

From a methodological perspective, the VAR spillover method introduced by Diebold and Yilmaz [2012] and Diebold and Yilmaz [2014] is a widely adopted approach for network connectivity analysis, adept at delineating the extent and direction of spillover effects (Tiwari et al., 2022). For instance, Arouri et al. [2011] utilized this method in analyzing oil market spillovers, while Gong et al. [2023] examined tail-risk contagion in traditional and clean energy markets. These studies typically employ a rolling window method for dynamic spillover analysis. However, this approach may lead to the loss of connectivity information in certain window segments, and the outcomes can be significantly influenced by the choice of window settings. To address these limitations, the TVP-VAR network overflow model has been widely adopted (Wei et al., 2023; Xie et al., 2023). Yet, the estimation results of current TVP-VAR models are hindered by a substantial dimensionality challenge, posing a significant barrier to the validity of findings (McAleer and Da Veiga, 2008). This paper adopts the Elastic Net approach for dimensionality reduction in complex networks, enabling the endogenous identification of critical coefficients for retention (Zou and Hastie, 2005). Consequently, our proposed method effectively captures the time-varying and high-dimensional attributes of risk spillover network. In contrast to conventional techniques, it overcomes the issues of information loss and dimensional complexity inherent in previous TVP-VAR models. This approach more accurately delineates network risk variations across different times and dimensions, enhances risk event identification and prediction, and provides substantial support for risk management and decision-making processes.

Risk warning is a crucial strategy for mitigating and resolving risks in the energy financial market. Current research primarily focuses on systemic risk early warnings in specific energy

subsystems, such as oil and gas, as indicated by (Fabra and Reguant, 2024; An et al., 2023), with limited literature addressing broader energy markets. The extensive use of machine learning in financial forecasting has revealed that Support Vector Machine (SVM) models exhibit high accuracy in predictions (Samitas et al., 2020), while other studies emphasize the effectiveness of Artificial Neural Network (ANN) models (Longo et al., 2022; Naveed et al., 2023). However, traditional machine learning techniques struggle to capture dynamic dependencies among time series data points and accurately characterize time series data correlations, limiting their predictive accuracy. To address autocorrelation in time series data, some researchers have integrated self-feedback and recurrent network structures into Recurrent Neural Networks (RNNs) (Longo et al., 2022). Nonetheless, RNNs are challenged by issues like vanishing or exploding gradients due to their backpropagation algorithm, complicating long-term dependency management. Consequently, the Long Short Term Memory Model (LSTM) has been frequently applied to handle these issues (Klimas and Grabowski, 2023). This model efficiently manages long-term dependencies without the complexity of hyper-parameter tuning and automatically retains historical information over extended periods, overcoming gradient issues associated with traditional cyclic neural networks. This paper aims to apply the LSTM method to assess the early-warning impact of risk factors on risk correlation in the international energy market and identify key variables significantly influencing energy market risk. These insights are intended to assist countries in preventing cross-risk spread among energy markets.

From both theoretical and empirical perspectives, this study advances existing research on energy market risk spillovers and early warning in three key ways. Theoretically, this study addresses two underdeveloped areas in current literature. It extends the analysis of risk spillovers beyond general market risk to extreme risk. It also integrates the 'time-varying' and 'high-dimensional' characteristics of risk networks. Existing studies, such as Uddin et al. [2023], have examined these two attributes in isolation but rarely combined. This integration helps capture the asymmetric and dynamic nature of risk linkages. Extreme events like geopolitical conflicts or financial crises often trigger sudden shifts in risk transmission intensity, which static or low-dimensional models fail to reflect. Furthermore, this study breaks through the linear limitation of traditional early warning models, such as those proposed by Frankel and Rose [1996]. By adopting the LSTM deep learning framework, it can identify nonlinear relationships between risk drivers and spillover effects. This is critical because risk transmission in energy markets is inherently nonlinear, shaped by factors like investor herding behavior and supply chain rigidity that linear models cannot fully characterize (Zhang et al., 2025).

Empirically, the study's contributions stem from tight alignment between research questions and methodological choices, ensuring rigorous validation of theoretical assumptions. To identify the time-invariant characteristics of global energy market risk contagion, the static analysis function of the HD-TVP-VAR-SP model is employed. By calculating the total extreme risk connectivity index

and regional “To” values, the overall risk correlation and regional spillover intensity are quantified. This directly verifies whether global markets are tightly linked and whether the Americas are key spillover sources. For exploring the time-varying evolution of risk linkages, the dynamic analysis module of the HD-TVP-VAR-SP model is utilized. By tracking the time-varying trajectory of the total connectedness index and calculating the dynamic net spillover values of each region, the time-varying nature of risk linkages and the consistent net spillover status of American markets are confirmed. To discern the core driver of cross-market risk transmission, two complementary methods are used. First, the variable importance analysis of the LSTM model identifies the WTI index and OVX as the top two influential factors. Second, this result is combined with theoretical analysis of oil’s 42% share in global final energy consumption and its interconnectedness with other energy sectors. This approach verifies that oil is the core driver of risk transmission.

In terms of methodological innovation, the HD-TVP-VAR-SP model incorporates Elastic Net dimensionality reduction. This solves the “dimensional disaster” problem of traditional TVP-VAR models when dealing with energy market data from 22 countries. It allows for more accurate estimation of high-dimensional risk networks compared to the VAR-based approach (Uddin et al. [2023]). Meanwhile, the LSTM model’s advantage in handling long-term dependencies ensures the reliability of risk early warning results. This provides a more effective tool for practical risk management than conventional machine learning methods.

2.2. Theoretical assumptions

The energy industry is notably interconnected through trade flows among energy companies, and there is an increasing trend in energy market integration (Ciola et al., 2023). Corporate risk in the energy sector of one country can generate externalities affecting other companies in the global supply chain. For instance, upstream supplier closures may precipitate production crises in downstream companies, while downstream closures could result in overcapacity at upstream companies (Singh et al., 2019). Consequently, risks in a country’s energy market can have a significant and lasting impact on the global energy market. Energy, as a commodity, attracts considerable investor interest in financial markets. With the advancing financialization of energy, risk contagion in international energy markets becomes more evident (Ji et al., 2020). Behavioral finance theory indicates that market risk and uncertainty can lead investors to lose rational judgment, resulting in panic-driven decisions and mimicking the behavior of other investors (Qiu et al., 2021). During crises in the international energy industry, irrational investment behaviors, driven by herding and loss aversion, exacerbate risks in energy markets, thereby increasing the complexity of risk linkages (Chen and Chen, 2024). In the context of growing energy integration, the interconnectedness of risks intensifies with the expanding number of countries in the energy network, leading to more extensive and complex spillover effects of energy risk among nations. Based on this understanding, we propose Hypothesis 1.1:

Hypothesis 1.1: Global energy markets are characterized by a high degree of risk correlation.

The theoretical underpinning of this hypothesis rests on market integration theory and systemic risk transmission mechanisms. Deepening trade integration and investment linkages across global energy markets facilitate the cross-market spillover of risks through supply chain and financial channels (Ciola et al., 2023). Meanwhile, the financialization of energy markets amplifies such cross-market risk contagion, fostering a tightly interconnected global energy risk network (Ji et al., 2023). Drawing on these insights, this study infers significant risk correlation among major global energy markets. This hypothesis will be verified through the static connectedness analysis of the HD-TVP-VAR-SP model, with the intensity of risk correlation judged based on the quantitative results of the Total Connectedness Index (TCI).

The stability and reliability of major energy-exporting nations have a profound impact on global energy prices and market confidence, with the Americas playing a pivotal role because of its abundant energy resources, encompassing oil, natural gas, and coal (Chen and Chen, 2024). The U.S., as a major player in global energy production, has notably altered the supply and demand dynamics in the global energy markets through its shale revolution (Gong et al., 2023; Naeem et al., 2023). Canada, ranking as the world's fourth-largest crude oil and third-largest natural gas producer, significantly contributes to energy exports, addressing global energy demands and fostering economic growth (Kang et al., 2015). Similarly, countries like Brazil and Argentina, with substantial energy reserves, have a notable impact on global energy financial markets. Consequently, the Americas are increasingly integral to the global energy supply landscape (Gong et al., 2023). The open energy markets of the Americas have attracted investments from numerous international energy companies (Cheng and Hung, 2011), enhancing the financialization of energy and prompting the construction of large-scale energy and production facilities in the region. This shift positions the Americas as a key node in global energy trade, underlining the growing importance of its energy financial markets in the global energy supply and pricing. Based on these observations, we propose Hypothesis 1.2:

Hypothesis 1.2: The Americas significantly contribute to risk spillover in global energy markets.

The proposal of this hypothesis draws on the theory of energy resource endowment and studies on regional financialization spillover effects. The shale revolution and unconventional energy development in the Americas have established the region as a core hub of global energy supply, with fluctuations in its energy production and trade exerting significant global impacts (Gong et al., 2023; Naeem et al., 2023). Additionally, the open financial markets in the Americas have attracted substantial international energy investment, enhancing the transmission capacity of their risk spillovers (Cheng and Hung, 2011). Building on these insights, this study infers that the Americas make a dominant contribution to risk spillovers in global energy markets. This hypothesis is tested using the regional static spillover analysis of the HD-TVP-VAR-SP model, by calculating the 'To' values and net spillover values (Net) of the Americas.

The interconnections between energy markets in various countries are subject to alteration by a range of complex factors, including macroeconomic trends, geopolitical events, and financial market dynamics. From a macroeconomic perspective, the fluctuations in the global economy exert a direct influence on these risk linkages. During periods of economic growth, increased energy demand bolsters the connections between markets, whereas in economic recessions, a decline in energy demand leads to a relative weakening of these linkages (Bilgen, 2014). Such economic cycles render the risk linkages in national energy markets characteristically time-variant. The unpredictability of geopolitical events can result in disruptions, reduced supplies, or instability in energy provision, thereby intensifying volatility in the energy market. These events facilitate the swift transmission of market risks globally, causing a sudden intensification in the risk linkages of national energy markets due to geopolitical developments (Liao and Pan, 2022). Additionally, the volatility of these linkages is affected by the uncertainties in financial markets, such as changes in monetary policy and financial crises, which can lead to significant fluctuations in energy prices and, consequently, heightened risk sensitivity among global energy market investors (Laborda and Olmo, 2021; D'Ecclesia et al., 2024). These changes inevitably alter the extent and nature of risk linkages between national energy markets, resulting in abrupt and marked changes in their risk spillovers. In light of these considerations, we present Hypothesis 2.1:

Hypothesis 2.1: Risk linkages among global energy markets demonstrate significant temporal variability.

This hypothesis is closely related to the theory of macroeconomic cycles and the theory of geopolitical risk transmission. On the one hand, geopolitical conflicts and other unexpected events can disrupt the inherent equilibrium of energy markets, triggering sudden shifts in the intensity of risk linkages (Liao and Pan, 2022). On the other hand, fluctuations in financial markets and adjustments to monetary policies influence cross-market risk linkages through energy pricing mechanisms, and the time-varying nature of these factors shapes the dynamic evolution of risk connections (Laborda and Olmo, 2021). Drawing on these perspectives, this study expects that risk linkages in global energy markets exhibit significant time-varying characteristics. This hypothesis is verified through the dynamic connectedness analysis of the HD-TVP-VAR-SP model, by tracking the time-series fluctuation characteristics of the Total Connectedness Index.

The Americas, endowed with abundant natural resources like oil, natural gas, and renewable energy, play a pivotal role in global energy production and consumption. Key countries in this region, including the United States, Canada, Mexico, Brazil, Venezuela, and Argentina, are major contributors to the global energy market due to their substantial energy resources, thus significantly influencing the global energy supply (Wang et al., 2021; Naeem et al., 2023). Additionally, the Americas, particularly the United States and Canada, rank among the world's largest energy consumers, heavily impacting the global energy market's supply-demand dynamics and pricing (An-

tonakakis et al., 2014). Consequently, the Americas are integral to the global energy landscape, with their energy production and consumption patterns exerting a profound effect on international energy markets. However, the region's susceptibility to frequent geopolitical, economic, and natural disruptions means that any such event can precipitate energy supply instability (Zhu et al., 2023), leading to heightened risk spillovers. Therefore, considering the significant influence of the Americas on global energy markets and their susceptibility to disruptions, we propose Hypothesis 2.2:

Hypothesis 2.2: Energy markets in the Americas occupy a position of risk diffusion within the context of dynamic net risk spillovers.

The theoretical basis of this hypothesis comes from the theory of regional energy dominance and the theory of dynamic risk spillovers. Studies by Wang et al. [2021] showed that the abundant energy reserves and leading development technologies in the Americas make it occupy a core position in the global energy supply chain, and the spillover effects of its market fluctuations are persistent. As major global energy consumption and production regions, changes in supply and demand in the American markets have a guiding effect on global energy prices, thereby making them net diffusers of dynamic risk spillovers (Antonakakis et al., 2014). Combining these insights, this study proposes the hypothesis that energy markets in the Americas occupy a diffusion position in dynamic net risk spillovers. This hypothesis is tested based on the dynamic net spillover calculation of the HD-TVP-VAR-SP model, by observing the temporal stability of net spillover values of countries in the Americas.

Despite advancements in renewable and alternative energy sources, most countries continue to rely on traditional fossil fuels due to the prohibitive costs of newer energies, as evidenced by Khan et al. [2021]. The oil market, recognised as the most mature and expansive sector in the energy landscape (Omotosho, 2022), is distinguished by its high degree of financialization and the prevalence of financial derivatives like oil futures, options, and derivative trading (Sun et al., 2023). The advanced development of the oil financial market has enhanced its liquidity and activity. This market attracts a diverse array of participants, including investors, fund managers, and traders, leading to substantial transaction volumes and increased market complexity and influence. Consequently, as the world's primary energy resource, oil's price volatility, supply-demand dynamics, and geopolitical factors exert a significant influence on other energy and financial markets (Güntner and Öhlinger, 2022). Disruptions in supply, price fluctuations, or other notable events in the oil market quickly propagate to related energy and financial markets, triggering changes in prices, investor sentiments, and behavioral responses (Aroui et al., 2011). Therefore, the oil market may be regarded as a primary risk spillover factor in energy financial markets. Based on this analysis, we put forward Hypothesis 3:

Hypothesis 3: Risk contagion among global energy markets is predominantly influenced by factors related to oil.

This hypothesis is rooted in the core theory of energy pricing and studies on cross-energy market linkage mechanisms. As a cornerstone of global energy consumption, oil price fluctuations influence the pricing of other energy sources through substitution effects and cost transmission (Sim and Zhou, 2015). Additionally, the oil market exhibits the highest degree of financialization, with derivative transactions and investor behaviors amplifying cross-market risk contagion (Güntner and Öhlinger, 2022). Drawing on these findings, this study infers that oil-related factors are the primary drivers of risk contagion in global energy markets. This hypothesis is verified through the variable importance analysis of the LSTM model, combined with the results of nonlinear causality tests, with a focus on examining the influence weight of oil-related indicators.

3. Methodology

3.1. ARMA-GARCH type model

This section calculates the VaR (Value at Risk) for each energy market based on the ARMA-GARCH-type model. The general form of the ARMA(m, n)-GARCH(p, q) model is as follows in Eq. (1), Eq. (2) and Eq. (3):

$$r_t = \varphi_0 + \sum_{j=1}^m \varphi_j r_{t-j} + \varepsilon_t + \sum_{k=1}^n \theta_k \varepsilon_{t-k}, \quad (1)$$

$$\varepsilon_t = \sigma_t z_t, z_t \sim i.i.d, \quad (2)$$

$$\sigma_t^2 = h_{p,q}(\sigma_{t-1}^2, \varepsilon_{t-1}), \quad (3)$$

where r_t is the gain of energy stock at time t , m and n are the orders of the autoregressive term and the moving average term in the ARMA model, p and q are the orders of GARCH term, respectively. σ_t^2 is the conditional variance of the GARCH model. The ARMA-GARCH-type models we selected include sGARCH, eGARCH, csGARCH, iGARCH and gjrGARCH. The probability distributions of the random error that can be selected by these models include the standard normal distribution (NORM), the partial normal distribution (SNORM), the generalized error distribution (GED), the partial generalized normal distribution (SGED), the student t distribution (STD), the partial student distribution (SSTD), the normal inverse Gaussian distribution (NIG) and the Johnson reparameterization SU distribution (JSU).

The sGARCH(p, q) model (Standard GARCH) can be expressed as Eq. (4) :

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2, \quad (4)$$

where p and q are the order of the GARCH term, respectively.

In order to capture the non-linear characteristics of financial asset sequences, the eGARCH (Exponential GARCH) model introduces an exponential function to model volatility in Eq. (5).

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^p \alpha_i f(z_{t-i}) + \sum_{j=1}^q \beta_j \log(\sigma_{t-j}^2), \quad (5)$$

where $f(z_t) = \theta z_t + \gamma(|z_t| - E|z_t|)$ and $z_t = \varepsilon_t / \sqrt{\sigma_t}$.

To depict the long-term fluctuations of asset prices over time, Engle and White [1999] proposed the csGARCH (Component sGARCH) model, which is expressed as follows in Eq. (6) and Eq. (7):

$$\sigma_t^2 = q_t + \sum_{i=1}^p \alpha_i (\varepsilon_{t-i}^2 - q_{t-i}) + \sum_{j=1}^q \beta_j (\sigma_{t-j}^2 - q_{t-j}), \quad (6)$$

$$q_t = \omega + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2), \quad (7)$$

where q_t denotes the long-term volatility that will converge over time, and $(\varepsilon_{t-1}^2 - q_{t-1})$ represents the short-term volatility.

The iGARCH (Integrated GARCH) model can be applied to time series data with trend, seasonal or periodic characteristics, and can more accurately model the non-constant volatility in the data. The volatility model is set out below in Eq. (8):

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2, \quad (8)$$

where $\omega > 0$ and $\alpha_i + \beta_j = 1$.

To explain the potential asymmetry in ARCH, the gjrGARCH (Glosten-Jagannathan-Runkle GARCH) model is given by in Eq. (9):

$$\sigma_t^2 = \omega + \sum_{i=1}^p (\alpha_i + \gamma_i I_{t-i}) \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2, \quad (9)$$

where $I_{t-i} = \begin{cases} 0, & \text{if } r_{t-i} \geq \mu, \\ 1, & \text{if } r_{t-i} < \mu. \end{cases}$

Finally, we will calculate the VaR of each energy stock based on the model chosen in Eq. (10):

$$VaR_{\tau,t} = -\mu - \sigma_t \cdot D^{-1}(\tau), \quad (10)$$

where $VaR_{\tau,t}$ represents the value at risk of the quantile τ at time t , μ is the expected yield, and $D^{-1}(\tau)$ denotes the τ quantile function of the random error of the selected model.

3.2. High-dimensional TVP-VAR-SP model

This study introduces an enhanced High-Dimensional Time-Varying Parameter Vector Autoregression Spillover (HD-TVP-VAR-SP) model presented by Chen et al. [2021]. Contrasting with the

conventional Vector Autoregression (VAR) spillover model (Diebold and Yilmaz, 2014), our model captures a more comprehensive range of time-varying spillover information. Additionally, it incorporates Elastic Net technology to effectively address the high-dimensional complexity inherent in the TVP-VAR spillover model, particularly when managing high-dimensional time series data (Xie et al., 2023). Our HD-TVP-VAR-SP model builds directly on the TVP-VAR framework, drawing on its core strength of modeling time-varying relationships while addressing two critical gaps in existing TVP-VAR applications: high-dimensional complexity and explicit spillover quantification. While the TVP-VAR model resolves the time-invariance issue of the standard VAR, it still struggles with ‘dimensionality disasters’ when analyzing a large number of variables. As the variables increase, the number of parameters grows geometrically, while the number of observations only increases linearly, leading to inefficient estimates and reduced predictive power. This limitation has restricted previous TVP-VAR applications to small-scale systems (e.g., fewer than 10 variables), failing to capture the full complexity of global energy market interdependencies. Additionally, while the TVP-VAR model can capture dynamic relationships, it does not explicitly quantify spillover effects in a network context. To address these gaps, we introduce the HD-TVP-VAR-SP model, which integrates three key innovations into the TVP-VAR framework: high-dimensional adaptability via Elastic Net regularization, explicit spillover measurement via generalized variance decomposition, and dynamic network characterization. The specific formulation and implementation steps of the HD-TVP-VAR-SP model are as follows:

First, the baseline specification of the HD-TVP-VAR-SP model retains the time-varying coefficient structure of the TVP-VAR model, defined as:

$$Y_t = \sum_{l=1}^p \Phi_{tl} Y_{t-l} + \varepsilon_t, \quad (11)$$

where Y_t is a N dimensional column vector, which represents the extreme risk of the energy market in N countries during the t period, Φ_{tl} is the time-varying lag coefficient matrix of $N \times N$, p represents the lag order of the model and ε_t signifies the random error. Defining $Z_{t-1}(p) = (Y'_{t-1}, \dots, Y'_{t-p})'$ and $\Phi_t = (\Phi_{t1}, \dots, \Phi_{tp})$, Eq. (11) can be reformulated as Eq. (12):

$$Y_t = \Phi_t Z_{t-1}(p) + \varepsilon_t, \quad (12)$$

where Φ_t is usually assumed to satisfy the random walk process in Eq. (13):

$$\Phi_t = \Phi_{t-1} + \mu_t, \quad (13)$$

where $\varepsilon_t \sim N(0, \Sigma_t)$ and $\mu_t \sim N(0, Q_t)$, which ε_t and μ_t for any t are independent of each other.

The HD-TVP-VAR-SP model mentioned above may encounter problems such as unstable estimation and overfitting due to transition parameterization in high-dimensional situations, known as

‘dimensional disasters’. Taking the HD-TVP-VAR-SP model in Eq. (11) as an example, its total coefficients to be estimated have $N \times N \times T \times p$. When N becomes larger, the number of coefficients to be estimated increases geometrically, the number of observations that can be estimated increases only linearly. Clearly, this will lead directly to an increase in the difficulty of estimation.

To address the challenges posed by high-dimensional data, regularization methods are employed to mitigate or entirely negate the impact of certain coefficients, thereby retaining only the pivotal ones. This paper utilises Elastic Net estimation as a means to diminish dimensionality, consequently revealing the initial sparse structure of the coefficients in Eq. (14):

$$\hat{\Phi} = \operatorname{argmin}_{\Phi} \left\{ \sum_{t=1}^T [Y_t - \Phi Z_{t-1}(p)]^2 + \lambda \left[\alpha \|\Phi\|_1 + (1 - \alpha) \|\Phi\|_2^2 \right] \right\}, \quad (14)$$

where $\|\cdot\|_1$ denotes ℓ_1 norm and $\|\cdot\|_2$ represents ℓ_2 norm, λ is the weight of the coefficient penalty, and α shows the weight of ℓ_1 norm penalty term, valuing 0.5.

The interrelation of risks across energy markets in various countries is quantified through the application of the generalized variance decomposition method proposed by Diebold and Yilmaz [2014]:

$$d_{ij,t}^H = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1} (e_i' \Lambda_{ht} \Sigma_t e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Lambda_{ht} \Sigma_t \Lambda_{ht}' e_i)}, \quad (15)$$

where $d_{ij,t}^H$ is the cumulative influence of the variable i in the period t by the impact of the variable j , and represents the spillover effect of the fluctuation of the energy market j to the market i . e_i denotes a vector with element i being 1 and the rest being 0; $\sigma_{jj,t}$ is the j -th diagonal element of the variance covariance matrix of the residuals in the HD-TVP-VAR-SP model; H means the prediction window; Λ_{ht} is the coefficient of the infinite order time-varying vector moving average model corresponding to Eq. (12). We standardized the generalized variance decomposition to obtain Eq. (16):

$$\hat{d}_{ij,t}^H = d_{ij,t}^H \left(\sum_{j=1}^N d_{ij,t}^H \right)^{-1} \quad (16)$$

According to the standardized variance decomposition in Eq. (16), we can construct the Total Connectedness Index (TCI) of energy market risk at the period t in Eq. (17):

$$TCI_t = \frac{1}{N} \sum_{i=1}^N \left(\sum_{j=1, j \neq i}^N \hat{d}_{ij,t}^H \right). \quad (17)$$

Further, defining the risk acceptance (From) in Eq. (18), risk overflow (To) in Eq. (19), and

net risk spillover (Net) in Eq. (20) of the i -th energy market in period t :

$$\text{From}_{i,t} = \sum_{j=1, j \neq i}^N \hat{d}_{ij,t}^H, \quad (18)$$

$$\text{To}_{i,t} = \sum_{i=1, j \neq i}^N \hat{d}_{ij,t}^H, \quad (19)$$

$$\text{Net}_{i,t} = \text{To}_{i,t} - \text{From}_{i,t}. \quad (20)$$

3.3. LSTM model

Advancements in artificial intelligence have spurred the development of diverse machine learning models, each equipped with intelligent algorithms that mimic human cognitive processes and drive breakthroughs in fields like image recognition and natural language processing. Within financial and energy market research, the Long Short-Term Memory (LSTM) network stands out for its proficiency in processing time series data, particularly its ability to address long-term dependency issues that plague traditional models. Unlike conventional machine learning methods, which often struggle with gradient vanishing or explosion when handling sequential data, the LSTM autonomously retains critical historical information over extended periods. This capability is not merely a technical advantage but a critical alignment with the unique dynamics of energy markets, where risk transmission is shaped by both recent shocks and persistent, long-term trends.

The LSTM model is employed in this study to identify key drivers of risk spillovers in the global energy market. The architecture of the LSTM model is particularly suitable for disentangling the complex dynamics of information transmission in energy markets, which are marked by volatility clustering, persistent shocks, and asymmetric information adjustment. Energy markets exhibit unique information transmission patterns, such as the gradual dissipation of shocks from geopolitical events or supply disruptions, which require a modeling approach capable of capturing long-term dependencies and nonlinear relationships. Traditional econometric models often fall short in adequately representing these characteristics due to their reliance on strict assumptions of linearity and short-term memory. In contrast, the LSTM model can learn intricate patterns from historical data, making it a powerful tool for identifying the factors that underpin risk spillovers. The key to memorizing long-term historical information in the LSTM model is how to control the update of unit state c_t and the transmission of hidden state h_t .

The core idea is to introduce gating mechanism to control the flow of information, including Forget Gate, Input Gate and Output Gate. The forget gate operates akin to the market's tendency to weigh recent information more heavily than older data, reflecting the economic intuition that the relevance of historical market events diminishes over time. This is vital in energy markets, where the impact of past supply shocks or policy changes may gradually fade as new information

emerges. The input gate mirrors the market's selective incorporation of new information, such as unexpected changes in oil production or escalating geopolitical tensions, which can significantly alter risk dynamics. Finally, the output gate resembles the decision-making process of market participants as they respond to evolving conditions, determining which stored information is pertinent for understanding current market behavior and potential future movements. Through the learned weights, these gating mechanisms determine whether to allow information to flow through LSTM units. The forgetting gate f_t determines how much of the unit state c_{t-1} at time $t-1$ is retained until time t , and its expression is Eq. (21):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f), \quad (21)$$

where σ is sigmoid activation function, and the value field is $(0, 1)$; the weight matrix of the Forget Gate is W_f ; h_{t-1} represents the output (hidden state) at time $t-1$; x_t is the input value of the network at time t ; b_f is the Forget Gate bias term. The expression for Input Gate i_t is Eq. (22):

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \quad (22)$$

where the Input Gate i_t determines how much input x_t of the network is saved to unit state c_t at time t ; W_i refers to the weight matrix of the Input Gate and b_i is the bias term of the Input Gate. We calculate the unit state $\tilde{c}_t$ used to describe the current input i_t in Eq. (23):

$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c), \quad (23)$$

where $\tanh$ is the tangent activation function. The unit state c_t at time t can be calculated as Eq. (24):

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t, \quad (24)$$

where $\circ$ means multiply by element.

The LSTM model combines the current memory and long-term memory to form a new unit state. Because of the control of the Forget Gate, it can save the previous information. By regulating the Input Gate, it can also avoid the current insignificant content into the memory. The Output Gate o_t dominates the influence of the current cell state on the output (hidden state) at the next moment, which can be calculated as Eq. (25):

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (25)$$

The final output of LSTM is determined by the Output Gate and the cell state. The Output Gate uses the function to convert the current cell state to the final output (hidden state) in Eq.

(26):

$$h_t = o_t \circ \tanh(c_t) \quad (26)$$

The cell structure of the above LSTM can be shown by Figure 1:

[PLEASE INSERT Figure 1 HERE]

In the context of this study, the LSTM model is utilized to identify the key drivers of risk spillovers rather than purely for prediction. The model leverages a set of features carefully chosen for their relevance to energy market risks. These include: (1) energy price and oil market-specific indicators form the core of the feature set, as they directly underpin volatility in energy markets: the West Texas Intermediate (WTI) index (capturing benchmark oil price movements, a primary source of cross-market risk spillover), the Oil Volatility Index (OVX) (reflecting oil market uncertainty that triggers heightened risk transmission); (2) broader market sentiment and financial condition indicators are included to account for macro-financial linkages to energy markets: the Stock Market Panic Index (VIX) (indicating broader financial market sentiment whose panic often spills over to energy sectors), the Goldman Sachs Energy Index (GSEN) (gauging global financial conditions that shape energy investment and risk-taking); (3) macroeconomic and currency indicators address systemic factors influencing energy market dynamics: the US Dollar Index (DXY) (influencing dollar-denominated energy prices and cross-border risk transmission), Interest rate levels (Rate, specifically US Treasury bill rates, affecting energy firms' capital costs and investor decisions); (4) renewable energy sector indicators are integrated to reflect the growing role of renewables in the global energy system: the Solar energy index and Wind energy index (capturing performance and risk trends in key renewable subsectors with growing links to traditional energy markets), and the Clean energy index (providing a broader measure of renewable energy dynamics to complement subsector indices). The rationale for selecting these predictors is further tied to our study's focus: together, they cover energy-specific, financial, macroeconomic and renewable energy dimensions, which are critical to understanding and predicting comprehensive energy market risk spillovers. By applying the LSTM model to these features, this study aims to uncover the critical factors that contribute to risk transmission in the energy sector, offering insights that can inform more effective risk management strategies and regulatory policies.

The HD-TVP-VAR-SP and LSTM models employed in this study offer complementary strengths that together provide a more complete analysis of risk spillovers and early warning in global energy markets. The HD-TVP-VAR-SP model, with its robust capacity to handle high-dimensional time-varying parameter vector autoregressive spillovers, excels in capturing the intricate and dynamic interdependencies among various energy markets. This model adeptly addresses the challenges posed by the high-dimensional nature and temporal variations of risk networks, providing a comprehensive framework for analyzing the complex structure of risk spillovers. Its primary advantage

lies in its ability to effectively model and estimate the evolving connections between multiple markets over time, which is essential for understanding the nuanced dynamics of global energy market risks. However, the HD-TVP-VAR-SP model also has limitations. Its complexity and computational demands can be substantial, especially when dealing with large datasets encompassing numerous variables. Moreover, while it captures the linear relationships and temporal dynamics of risk spillovers well, it may fall short in identifying and modeling non-linear dependencies and complex interactions that are equally critical in risk transmission.

In contrast, the LSTM model, a type of recurrent neural network, offers distinct advantages in handling non-linear time series data and long-term dependencies. Its unique architecture, featuring gating mechanisms, enables it to learn and retain information over extended periods, making it particularly suited for capturing the persistent effects and complex patterns in energy market risk data. The LSTM model's strength lies in its ability to model non-linear dynamics and intricate relationships, which are often overlooked by traditional linear models. Nevertheless, the LSTM model is not without its drawbacks. It requires substantial amounts of data for training to achieve optimal performance, and its "black box" nature can make the interpretation of results challenging. Additionally, while it excels in capturing non-linear patterns, it may not perform as well in scenarios where linear relationships dominate or when the focus is on understanding the specific structural forms of risk spillovers.

In essence, the HD-TVP-VAR-SP and LSTM models complement each other by combining the former's prowess in modeling high-dimensional, time-varying linear relationships with the latter's ability to capture non-linear dynamics and long-term dependencies. By leveraging the strengths of both models, we can gain a more holistic and nuanced understanding of energy market risk spillovers, enhancing the accuracy and robustness of risk early warning systems. This integrated approach facilitates a more comprehensive analysis, enabling policymakers and market participants to make better-informed decisions in managing and mitigating energy market risks.

4. Data source and description

We compiled the MSCI energy stock index data for 22 countries from the Bloomberg database. These countries represent a diverse geographical spectrum, encompassing regions such as the Asia Pacific, Africa, Europe, North America, and Latin America. The selection includes China, India, Japan, South Korea, Australia, Malaysia, Thailand, South Africa, the United Kingdom, France, Spain, Italy, Turkey, Poland, Norway, the United States, Russia, Brazil, Canada, Argentina, Austria, and Hungary. To maximize the inclusion of energy-focused countries where data were accessible, this study utilized all available daily data spanning from 5 January 2005 to 8 March 2022. [Table 1](#) presents the optimal ARMA-GARCH-type model for assessing energy market risk in each country, including the standardized residual distribution and the lag order determined by the BIC

information criterion. The results reveal distinct energy index models and residual distributions for each country, highlighting the varying characteristics of energy risk across different nations.

[PLEASE INSERT Table 1 HERE]

Table 2 presents the descriptive statistics for the extreme risk series in the energy markets of various countries. Notably, Brazil exhibited the highest absolute value of mean extreme risk (0.0528), closely followed by Argentina (0.0470). Poland has the lowest standard deviation (0.0078) and hence its extreme risk fluctuates the least. The kurtosis and skewness results indicate a consistent leftward tilt with a long left tail and high kurtosis across all series, suggesting that they do not follow a normal distribution, as confirmed by the Jarque-Bera test. The Augmented Dickey-Fuller (ADF) test rejects the null hypothesis of unit roots at the 5% significance level, thereby affirming the stability of these series. Figure 2 illustrates a dynamic representation of the extreme risk series for energy markets in different countries. The diagram highlights the evident aggregation effect in the fluctuations of each series, particularly during several crisis periods, underscoring the profound impact of crisis events on the risk dynamics within each country's energy market.

[PLEASE INSERT Table 2 AND Figure 2 HERE]

5. Results and discussion

5.1. Risk spillovers between energy markets

5.1.1. Static risk spillover analysis

Table 3 provides an analysis of static connectivity to extreme risk in energy markets. The total connectivity of extreme risk is calculated at 78.36%, demonstrating strong risk linkages between national energy markets, thus corroborating Hypothesis 1.1. In the global supply chain network, energy enterprises from various countries enhance cross-border investment and risk connections through cooperative modes with specialized labor divisions. These links manifest not only in supply chain interdependence and resource-market sharing but also extend to technological, market, and political domains, culminating in increasingly complex and interconnected risk linkages among energy companies. Additionally, the financialisation of energy markets has further deepened these risk connections. When the energy sector significantly contributes to a country's economic growth, it can exert a considerable impact on the global energy sector.

The 'To' value in Table 3 indicates that Russia, despite being a major oil exporter, does not substantially influence systemic risk spillover. This finding aligns with Singh et al. [2019], who observed a moderate post-crisis impact of Russia on the overall energy market. Consequently, the 'energy status' of large oil exporters does not necessarily dictate the level of risk connectivity in the energy system. In contrast, some European countries, including the UK, France, Spain, Italy,

and Norway, exhibit high risk spillovers to the system, despite not being major oil or gas producers. This discrepancy is attributed to their extensive supply-chain and infrastructure connections with other energy markets, particularly through key infrastructures like supply lines, pipelines, and transportation channels. As major energy market consumers, these countries significantly influence the energy market. Their developed financial markets also create conducive environments for attracting international investors and energy companies. Domestic energy firms in these countries are able to secure financing from international capital markets for participation in energy projects abroad, including through acquisitions and investments. This dynamic elucidates the heightened risk spillovers from the international energy market in European countries such as Britain, France, Italy, and Spain.

A striking observation from the 'Net' results is the divergent roles of the United States and Malaysia: the U.S. stands as the dominant net transmitter of extreme risk, while Malaysia emerges as the highest net receiver. This pattern is not random but stems from three interrelated aspects of Malaysia's energy system: its inherent market structure, integration into global energy networks, and constraints on risk mitigation. First, despite being a natural gas exporter, Malaysia remains highly dependent on imported crude and refined petroleum products, making it vulnerable to external supply shocks and price volatility. This import dependence translates rising global energy costs directly into domestic price pressures, forcing absorption rather than transmission of risk. Second, Malaysia's energy system lacks diversification. With limited renewable integration and concentrated reliance on fossil fuels, the market has few buffers against external disruptions. Moreover, its infrastructure is deeply embedded in regional supply chains dominated by net risk transmitters, limiting its capacity to decouple from foreign volatility. Third, institutional and financial constraints hinder effective risk management. Unlike the U.S., where deep derivatives markets enable hedging, Malaysia's energy sector largely governed by state linked entities has limited access to financial instruments for offsetting price risks. Consequently, unhedged exposure at both corporate and consumer levels exacerbates the domestic absorption of global risk. These factors collectively reinforce Malaysia's role as a net receiver within the risk spillover network.

To examine interregional risk spillovers, we categorized energy markets into three regions: Asia Pacific and Africa, Europe, and the Americas. We assessed their connectivity using the regional average of energy market connectedness, as outlined by [Singh et al. \[2019\]](#). Our analysis revealed that the Americas have the highest 'To' value within the system, signifying the most significant risk shock originating from this region. This finding can be attributed to recent advancements in oil and gas exploration and extraction technologies, which have unlocked the potential of unconventional energy sources in the Americas, thereby elevating the region's prominence in the global energy supply landscape. Consequently, this has shifted the global energy center towards the Americas, where the regional influence and risk spillover capacity of energy markets have notably increased.

Our study highlights that the risk spillovers from the energy markets of American countries

are also remarkably high, indicating a general trend of substantial risk spillovers from this region's energy risks. This trend is partly due to the US' role in spearheading the shale revolution, which has not only increased its energy self-sufficiency but also transformed neighboring countries like Canada and Brazil into stable oil suppliers, thereby strengthening the interconnectivity of energy markets in the Americas. The US's oil and gas production, which surpassed Russia and Saudi Arabia in 2017 and 2020 respectively, now plays a pivotal role similar to Saudi Arabia's in influencing international energy prices, thus enhancing the risk spillover capacity of the US energy system. This accounts for the dominant position of the US energy market in terms of extreme risk spillover. Furthermore, Canada's oil sands, Brazil's deep-sea oil and gas reserves, and Argentina's energy and mineral resources contribute significantly, but the instability in global economic and political landscapes has adversely impacted the energy supply in these regions, leading to a pronounced spillover effect of energy risk. This observation also explains the high risk spillover stance of many oil-producing countries in the Americas, thus corroborating our Hypothesis 1.2.

[PLEASE INSERT [Table 3](#) HERE]

5.1.2. *Dynamic risk spillove analysis*

While the static connectivity metric provides an average overview of extreme risk connectedness in energy markets, it falls short in depicting the dynamic evolution of risk connectivity across these markets over time. To address this gap, we have computed time-varying risk spillovers between national energy markets to better capture the dynamics of these risk linkages.

[Figure 3](#) displays the dynamic trends in total risk spillover within energy systems. Analysis of the figure reveals that the dynamic total connectedness index of risk fluctuates between 61% and 93% during the sample period, indicating time-variant risk linkages between energy markets. This fluctuation aligns closely with the occurrence of key risk events, each of which corresponds to a surge in total connectedness. The first significant phase spanned from 2007 to the end of 2008, marked by a substantial influx of international investment funds into energy markets. This period was characterized by a disregard for fundamental supply-demand relationships and price discipline, leading to inflated energy prices ([Singh et al., 2019](#)). However, the ensuing financial crisis precipitated a sharp decline in energy prices and heightened sensitivity of energy markets to external financial conditions, thereby amplifying energy price volatility and increasing risk dependency in energy markets.

The second phase, occurring from late 2014 to early 2016, coincided with a strong US dollar, anticipated expansion in shale oil capacity, and a projected downturn in global demand. This convergence of factors triggered a notable decrease in international oil prices, raising investor concerns about the energy market and amplifying uncertainty risks, subsequently enhancing risk linkages in energy markets. The third upswing, beginning in 2018 and culminating with the peak of the coronavirus pandemic in 2020, was influenced by the Sino-US trade conflict. As major global economies,

trade tensions between China and the United States not only disrupted their energy cooperation but also affected the global energy market, escalating risk contagion between energy systems. The intermittent nature of these trade frictions, alternating between escalation and detente, resulted in no significant shift in energy system risk linkages until the onset of the pandemic, which significantly increased energy market connectivity. The dynamic evolution of risk spillovers between energy markets thus substantiates our Hypothesis 2.1.

[PLEASE INSERT Figure 3 HERE]

Figure 4 illustrates the dynamic net spillover of extreme risk across various countries, highlighting regional heterogeneity in global energy market risk sources. In the Asia-Pacific and Africa regions, predominantly Australia and China have consistently acted as net conveyors of systemic risk spillovers. Australia, as a major energy producer and exporter with self-sufficient energy supply, mitigates the impact of short-term risk factors on its energy security (Batten et al., 2019). Additionally, its significant energy supply and export capacities render Australian energy price volatility a contagion factor to other nations, positioning it as a systemic risk transmitter. China, being the world's largest energy consumer with considerable overseas energy dependency, can influence neighboring countries' energy markets through regional cooperation, particularly when fluctuations in energy supply occur (He et al., 2021). The close collaboration between Australia and China in both traditional and renewable energy sectors means that risk events in either country's energy sector can be mutually transmitted, making them key regional risk sources (Lehkonen and Heimonen, 2014).

In Europe, only France, the United Kingdom, Spain, Italy, and Norway exhibit average positive net-risk spillovers. This tendency can be attributed to the dominance of real-asset investors, hedge funds, and energy traders in the international financial markets within these countries (Singh et al., 2019). The significant global market share and trading activity of their financial markets, along with their investment behaviors and risk-taking capabilities, considerably influence global financial markets (Xie et al., 2023). Furthermore, these countries' focus on developing renewable energy sources, such as nuclear and photovoltaic energy, has reduced their reliance on traditional energy sources and eased energy constraints across various industries (Detemple et al., 2024; Jäger-Waldau et al., 2011). This shift has partly mitigated the contagion effect within their energy systems, leading to a positive risk spillover effect.

Contrastingly, the energy markets of all countries in the Americas have consistently exhibited a positive net risk spillover. This trend is largely a result of the region's vast reserves of energy resources, including oil, gas, and coal (Wang et al., 2021). The exploitation and exportation of these resources have yielded substantial economic benefits and stability in energy supply for the region. Additionally, the Americas, being at the forefront of the oil and gas revolution, have achieved significant advancements in energy-technology innovation, particularly in the production of

unconventional and renewable energy sources (Gong et al., 2021). The widespread use of renewable energy in the Americas further solidifies its position in the energy market. Moreover, the region's proactive energy development strategy, focusing on enhancing energy efficiency, reducing carbon emissions, and promoting sustainable energy development, allows it to meet its own energy needs and play a vital role in the spillover of global energy risks (McKibbin et al., 2014). These findings substantiate Hypothesis 2.2, which posits that countries in the Americas act as net spreaders of time-varying risk spillovers.

[PLEASE INSERT Figure 4 HERE]

5.2. Identifying TCI drivers using machine learning techniques

Examining the risk interconnections among global energy markets uncovers substantial cross-market risk transmission. Understanding the drivers behind these linkages is crucial for policymakers to craft effective macroprudential policies that curb the spread of financial risks across markets. To identify these drivers, we employ multiple machine learning techniques including Long Short-Term Memory (LSTM), Gradient Boosting Machines (GBM), Random Forest (RF), and Decision Trees (DT). Among the machine learning techniques employed, the LSTM model demonstrated superior performance in identifying the key drivers of risk spillovers due to its ability to capture long-term temporal dependencies in the data. We will adopt these methods to help uncover complex, non-linear relationships between market variables and risk spillovers measured by the Total Connectedness Index (TCI).

Drawing on previous research by Ghabri et al. [2022], Saeed et al. [2021], and Haugom et al. [2014], we identified key potential drivers of risk contagion within the energy market. The oil market, as the most mature and largest sector within the energy landscape, likely plays a pivotal role in risk transmission, with its fluctuations being highly influential. In this context, the Oil Volatility Index (OVX) and West Texas Intermediate (WTI) are pertinent indicators closely associated with the oil market. Additionally, we incorporated relevant energy indicators such as GSEN, Solar, Wind, and Clean into our analysis.

The Stock Market Panic Index (VIX) is also included as it serves as a barometer for market risk and sentiment; a higher VIX value signifies stronger expectations of future volatility (Whaley, 2009). Moreover, the US dollar index and US Treasury bills with a one-month maturity are integrated into the analysis. The US dollar's relative stability against other currencies renders energy prices in USD more predictable (Gong et al., 2021). Furthermore, US Treasuries with a one-month maturity, often used as a proxy for the risk-free rate, are crucial for assessing market risk and risk premiums (Yang and Zhou, 2017), thereby justifying their inclusion. Definitions and sources of these indicators are given in Table A1.

To validate whether these variables can serve as reliable indicators for risk spillovers in energy markets, we initially utilize the nonparametric Granger causality test to examine the non-linear

correlations between the selected variables and the TCI. Given that financial variables often display intricate non-linear relationships (Geng et al., 2017), this approach helps establish their relevance as potential drivers. Utilising the nonparametric Granger causality test developed by Diks and Panchenko [2006], we examined the causal relationships between various variables and the TCI. Table 4 presents the outcomes of these causality tests, assessing the relationship of the TCI with its determinants at lags of 1-3 orders. The results, as detailed in the table, demonstrate significant non-linear correlations between the driving variables and the TCI at these lags. This finding underscores the complex non-linear interaction between the considered drivers and risk spillover in the energy market.

[PLEASE INSERT Table 4 HERE]

To further validate the presence of nonlinear dynamics in the relationship between the early warning indicators and risk spillovers, we employ the Brock–Dechert–Scheinkman (BDS) test for independence. The BDS test is a powerful nonparametric method for detecting general temporal dependence and nonlinear structure in time series data, particularly after removing linear autocorrelation. Its null hypothesis is that the residuals of the series are independently and identically distributed, a rejection of which implies the presence of omitted nonlinear structure. We applied the BDS test to the residuals obtained from a linear regressive model with the selected driving variables to the TCI variable. The test was implemented across embedding dimensions (m) of 2 to 4 to ensure robustness of the non-linearity detection and the BDS test results are reported in Table 5. The results strongly reject the null hypothesis across multiple embedding dimensions and distance thresholds, providing robust statistical evidence of nonlinear dependencies in the energy market risk spillovers. This finding corroborates the earlier Granger causality outcomes and underscores the necessity of employing nonlinear modeling frameworks to adequately capture the complex and non-random nature of risk propagation mechanisms in global energy markets.

[PLEASE INSERT Table 5 HERE]

The LSTM model, a type of recurrent neural network, excels in handling long-term dependencies compared to traditional cyclic neural networks (Klimas and Grabowski, 2023). Consequently, the LSTM model has been employed to discern the long-term dependencies of the TCI and its contributing factors. Figure 5 depicts the learning outcomes of the LSTM model for both the training and test sets, where the training set constructs the model, and the test set evaluates the model's generalization capabilities. The ratio of the training set to the test set is 1:4. The high congruence between the predicted and actual values in both sets indicates that the LSTM model demonstrates effective learning outcomes. The learning error and R^2 values of the LSTM model, as shown in Table 6, further affirm its superiority. With its minimal learning error and high goodness of fit, the LSTM model exhibits robust generalization capacity. These outcomes suggest that the

LSTM-based risk spillover prediction system can capture the long-term dependencies of the risk spillover index and early warning factors, thereby demonstrating strong predictive capabilities.

[PLEASE INSERT Figure 5 AND Table 6 HERE]

To demonstrate the efficacy of our training model, we employed a comparative analysis with the GBM, RF and DT models. Figure 6 presents the training outcomes of each model. An examination of the figure reveals that the test results for RF and DT models are suboptimal, while GBM's performance closely rivals that of the LSTM model. For a more comprehensive evaluation, we calculated the learning error and goodness of fit for each model, both on the training and test sets, as depicted in Table 6. The RF and DT models exhibit higher learning errors and lower goodness of fit in both sets, indicating subpar training outcomes and limited generalization capabilities. Conversely, while the GBM model shows improved learning outcomes, its learning error and goodness of fit still fall short of the LSTM model's performance. This suggests that the LSTM model surpasses the random forest, decision tree, and gradient boosting machines in terms of predictive power for risk spillover.

[PLEASE INSERT Figure 6 HERE]

Utilising the LSTM model, we were able to calculate the importance of each variable, as depicted in Figure 7. The analysis indicates that the West Texas Intermediate (WTI) index is the most influential in predicting risk spillovers in the energy market, closely followed by the Oil Volatility Index (OVX). This finding underscores the pivotal role of the oil market in dictating the magnitude of risk spillover in the energy system, thereby corroborating Hypothesis 3. This outcome can be elucidated as follows. Firstly, oil constitutes 42% of the world's final energy consumption, making it a key component in the energy market (Sim and Zhou, 2015). Oil price fluctuations significantly affect the supply-demand dynamics, cost structures, and investment decisions within the energy market, thereby directly influencing risk spillovers from energy systems. Secondly, the interconnectedness of the energy system's various segments, including natural gas, coal, and renewable energies, with the oil system is profound (Wei et al., 2023; Güntner and Öhlinger, 2022). Fluctuations in oil prices have cascading effects on the pricing and supply-demand equilibrium of other energy resources. Consequently, the oil market's dynamics are intimately tied to the risk contagion within the energy system, exerting a substantial impact on the overall risk spillover in the energy market. This study enhances our understanding of risks in the energy market, aiding in the development of appropriate risk management strategies and decision-making.

[PLEASE INSERT Figure 7 HERE]

5.3. Robustness test

In order to verify the robustness of the results, we change the forecast period H ; lag period p , α and λ values in elastic net estimation to test the robustness of the results, as shown in Figure 8. As can be seen from Figure 8(a), the overall trend of the total risk connectivity is almost the same as the initial situation after setting the forecast period H to 20 and 40 days respectively, confirming the robustness of our results. We also found that the total connectivity increased with the increase of the forecast period, which may be because with the increase of the forecast step, the linkage between variables will gradually accumulate, resulting in the increase of the risk contribution rate (Tiwari et al., 2022). Figure 8(b) shows risk spillovers for different lag orders. It can be found that the trend of the total risk connectivity of the energy market at the 2nd and 3rd order lags is very similar to the trend of the original 1st order lags, which verifies the robustness of the empirical results. Further, we set the α values to 0.01 and 0.99, respectively. From Figure 8(c), we can see that after changing the α value, the overall trend of the energy market general connectivity has not changed significantly, proving that the result of risk spillover is robust. Finally, Figure 8(d) gives the risk spillover results of the minimum and maximum λ values and the optimal λ values. From the figure, we can see that the general trend of the connection under the minimum λ and maximum λ values is basically consistent with the optimal λ value, which shows that the results in the previous paper are robust. Combined with Figure 8(c) and (d), the risk relation of energy market decreases with the increase of α and λ . This is because with the increase of α and λ , the coefficient between the variables decreases, thus reducing the risk between variables (Zou and Hastie, 2005). In short, the dynamic risk relationship between the energy market trends have not changed after changing the forecast period, lag period, α value and λ value, which proves the robustness of the results.

[PLEASE INSERT Figure 8 HERE]

6. Conclusion and policy implication

6.1. Key findings and discussion

Against the backdrop of deepening global energy market integration, transnational energy investments and transactions have intensified the complexity of risk linkages within energy systems. Extreme events in individual countries' energy markets can trigger cross-border risk spillovers, making the analysis of extreme risk connectivity critical for risk prevention. This study utilized MSCI energy index data from 22 countries, combined with the HD-TVP-VAR-SP model and LSTM model, to explore extreme risk spillovers and early warning mechanisms in global energy markets, yielding findings that align with and extend existing research.

In terms of static risk connectivity, the global energy market exhibits a high degree of risk interconnection, with the total connectedness of extreme risk reaching 78.36%. This confirms that

national energy markets form a tightly linked high-dimensional complex network, where risks are no longer isolated—a result that supports the theoretical expectation of enhanced risk correlation amid market integration (Ciola et al., 2023). Notably, some European countries (the UK, France, Spain, Italy, Norway) emerge as major sources of extreme risk spillovers, despite not being top oil or gas producers. This is attributed to their extensive supply chain infrastructure (e.g., energy pipelines, transportation channels) and developed financial markets, which attract international energy investments and strengthen risk linkages. In contrast, Russia, though a major oil exporter, exerts relatively limited influence on systemic risk spillover, indicating that “energy resource endowment” alone does not determine a country’s role in risk transmission.

From a regional perspective, the Americas stand out as the primary contributor to systemic risk shocks. The region has the highest ‘To’ value in static analysis, and all American countries consistently display positive net risk spillovers in dynamic analysis. This is driven by the region’s leading energy technology and resource base: the U.S. shale revolution has boosted its energy self-sufficiency and transformed neighboring Canada and Brazil into stable oil suppliers, while Canada’s oil sands, Brazil’s deep-sea oil and gas, and Argentina’s energy reserves further enhance its risk spillover capacity. These findings validate the argument that regional energy market integration and technological innovation amplify risk transmission (Gong et al., 2023; Naeem et al., 2023).

In dynamic terms, the total connectedness index (TCI) of global energy market risk fluctuates between 61% and 93% over the sample period, with surges closely tied to major events: the 2007–2008 financial crisis, 2014–2016 international oil price slump, 2018–2020 Sino-U.S. trade friction, and 2020 COVID-19 pandemic. This confirms the time-varying nature of risk linkages, as macroeconomic cycles, geopolitical tensions, and financial market uncertainties reshape the intensity of cross-market risk transmission (Liao and Pan, 2022; Laborda and Olmo, 2021). Additionally, dynamic net spillover analysis reveals regional heterogeneity: China and Australia act as net risk transmitters in the Asia-Pacific, France, the UK, Spain, Italy, and Norway do so in Europe, while all American countries maintain positive net spillovers, highlighting the uneven distribution of risk sources globally.

In risk early warning, the LSTM model outperforms traditional machine learning models (GBM, RF, DT) in identifying the relationship between extreme risk spillovers and their driving factors. This advantage stems from the LSTM’s ability to capture long-term dependencies and nonlinear relationships in time series data, addressing the limitations of linear models (e.g., Frankel and Rose [1996]) that overlook nonlinear interactions between risk drivers. Variable importance analysis further identifies the oil market as the core driver of risk contagion: the WTI index and OVX rank first and second in influence, respectively. This reflects oil’s 42% share of global final energy consumption and its interconnectedness with natural gas, coal, and renewable energy markets, where oil price fluctuations cascade through the entire energy system (Sim and Zhou, 2015; Güntner and Öhlinger, 2022).

6.2. Theoretical and practical implications

Theoretically, this study advances the understanding of risk spillovers in energy markets by addressing two underdeveloped areas in current literature. First, it extends the analysis of risk spillovers beyond general market risk to extreme risk and integrates the ‘time-varying’ and ‘high-dimensional’ characteristics of risk networks. This integration helps capture the asymmetric and dynamic nature of risk linkages, as extreme events often trigger sudden shifts in risk transmission intensity, which static or low-dimensional models fail to reflect. Second, it breaks through the linear limitation of traditional early warning models by adopting the LSTM deep learning framework, which can identify nonlinear relationships between risk drivers and spillover effects. This is critical because risk transmission in energy markets is inherently nonlinear, shaped by factors such as investor herding behavior and supply chain rigidity that linear models cannot fully characterize.

The findings of this study carry significant practical implications for policymakers, investors, and market participants. For policymakers, the results underscore the need for enhanced cross-border coordination and information sharing to mitigate risk spillovers. Given the prominent role of the Americas in systemic risk shocks, countries in this region should collaborate to strengthen information sharing and coordination mechanisms. Such efforts are crucial for ensuring the accuracy and timeliness of information, which is fundamental for effectively addressing emergencies and market volatility. Additionally, the study highlights the importance of monitoring domestic energy system risks while also scrutinizing the origins and characteristics of energy risks from net information-sending countries. The application and intensity of policy tools should be judiciously managed to mitigate risk contagion among energy systems. For investors, the identification of key risk spillover sources and net contributors provides valuable insights for portfolio construction and risk management. The results suggest that investors should closely monitor regions such as China, Australia, several European countries, and the Americas, incorporating them as focal countries in portfolio strategies. Furthermore, the risk warning results indicate that oil is a principal factor in risk contagion within the energy system. Consequently, countries must tailor their approach to risk management by developing scientifically sound risk impact indicators and early warning methods, with a particular emphasis on monitoring and early warning of oil price volatility.

6.3. Limitations and future research

This study has several limitations that offer avenues for future research. The analysis focuses on 22 major energy markets; expanding the coverage to include emerging economies and other energy subtypes could provide a more comprehensive view of global risk networks. Additionally, while the HD-TVP-VAR-SP model captures dynamic connectedness, it does not explicitly incorporate fundamental economic variables or policy events, which could deepen the interpretability of spillover mechanisms. Future studies could integrate mixed-frequency models or hybrid approaches that combine network analysis with structural models to identify causal channels of risk transmission more

clearly. Furthermore, the application of quantile-based regression frameworks could help uncover how extreme risk spillovers behave across different market states, thereby offering more tailored early warning signals under varying conditions. Finally, although the LSTM model demonstrates high predictive accuracy, its opacity remains a practical constraint; developing interpretable AI frameworks, such as quantile recurrent neural networks or explainable anomaly detection systems, for financial risk forecasting represents a promising direction for further work.

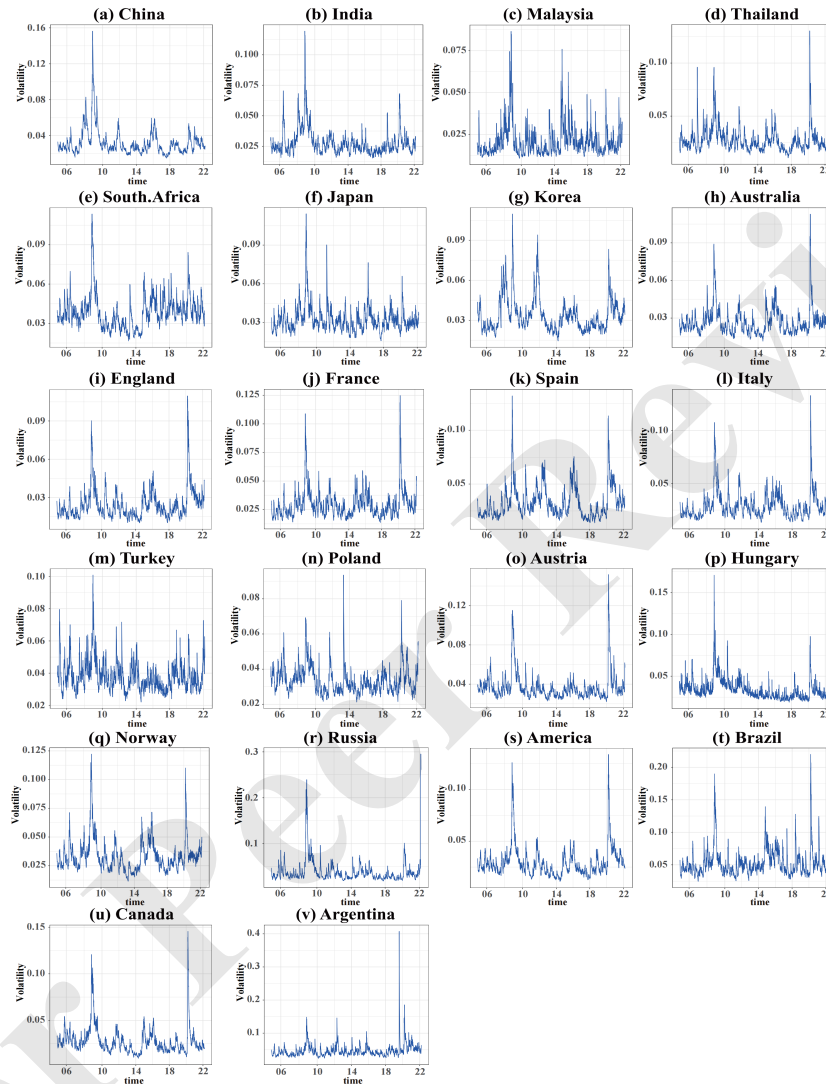


Figure 2: Extreme risk sequence of energy markets by country

Figure 2 dynamically represents the fluctuations in extreme risk within energy markets across a range of countries, highlighting the variability over time. Each graph demonstrates the aggregation effect during various time periods, showing pronounced spikes that correlate with global or local crisis events. The spikes in risk levels are indicative of the significant impact that crises have on energy market risk dynamics, demonstrating how sensitive each country's energy sector is to these disruptive events. The horizontal axis represents the time period over which the risk was measured, with specific years marked to indicate the timeline. The vertical axis measures the magnitude of extreme risk, with higher values indicating greater risk levels. While all countries exhibit volatility in their extreme risk series, the intensity and frequency of spikes vary, reflecting the unique risk profiles and crisis responsiveness of each nation's energy market.



Figure 3: Dynamic total spillover of extreme risk

Figure 3 tracks the dynamic total spillover of extreme risk within energy systems over time, showcasing the time-varying nature of risk connectivity. The Total Connectedness Index (TCI) fluctuates significantly, ranging from 61% to 93% throughout the observed period, indicating variable risk interconnections among energy markets. The dynamic pattern of TCI over time allows for an understanding of how energy market risks are interconnected globally and how they respond to international events.

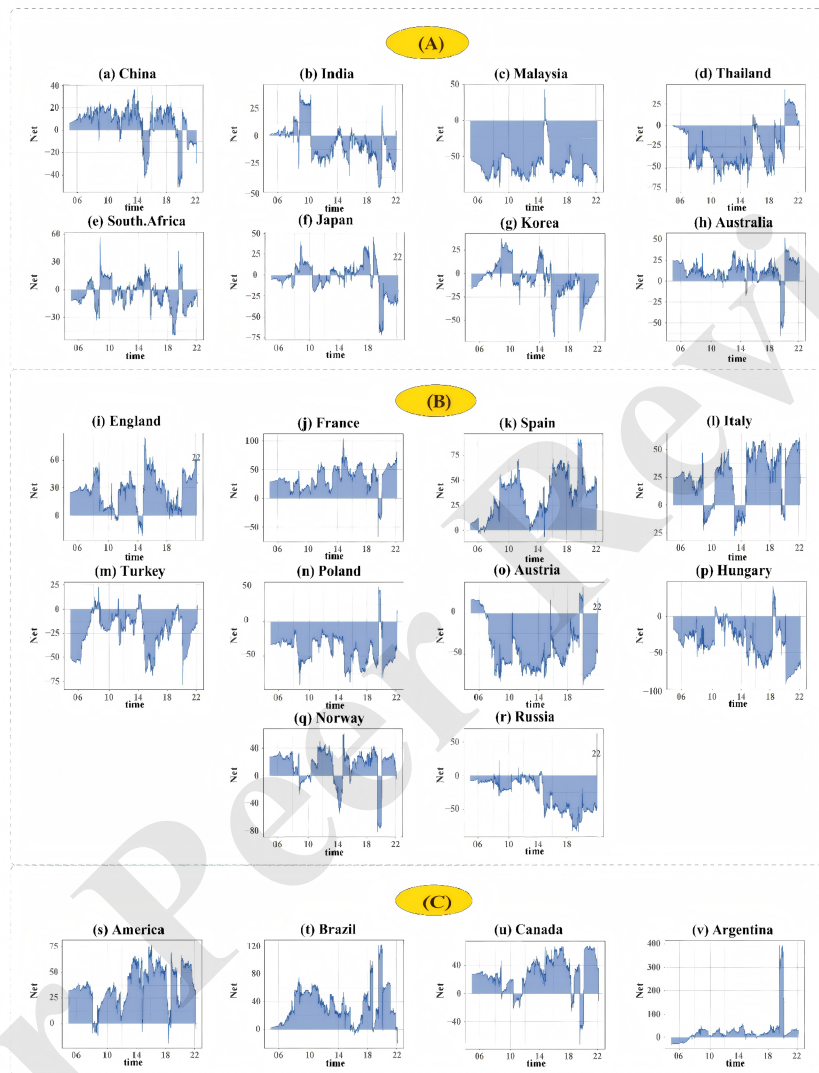


Figure 4: Dynamic net spillover of extreme risk from national energy markets to the energy system
 Figure 4 captures the dynamic net spillover of extreme risk in energy markets, delineating how countries contribute to or absorb risk within their regions. Subfigures (a) to (h) plot the net risk spillovers of countries in Asia Pacific and Africa; subfigures (i) to (r) correspond to Europe; and subfigures (s) to (v) represent the Americas. Each subgraph within a region depicts the net spillover dynamics for a specific country.

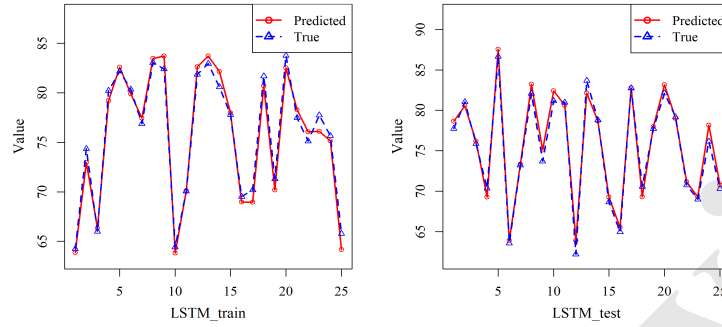


Figure 5: LSTM learning results

Figure 5 illustrates the learning performance of the LSTM model, comparing predicted values against actual ones for the Total Connectedness Index (TCI) across training and testing datasets. The model was trained on a set of data (left plot) and then tested on a separate set of data (right plot) to assess how well it can generalize beyond the data it was trained on. The closeness of the 'Predicted' and 'True' values suggests the LSTM model is capable of accurately capturing the patterns in the data. The alignment of predicted and actual values signifies that the LSTM model effectively captures long-term dependencies in risk spillover, confirming its potential as a reliable forecasting tool. These results demonstrate that the LSTM-based system can effectively be used for predicting the TCI, suggesting its utility in forecasting and managing risk in financial markets.

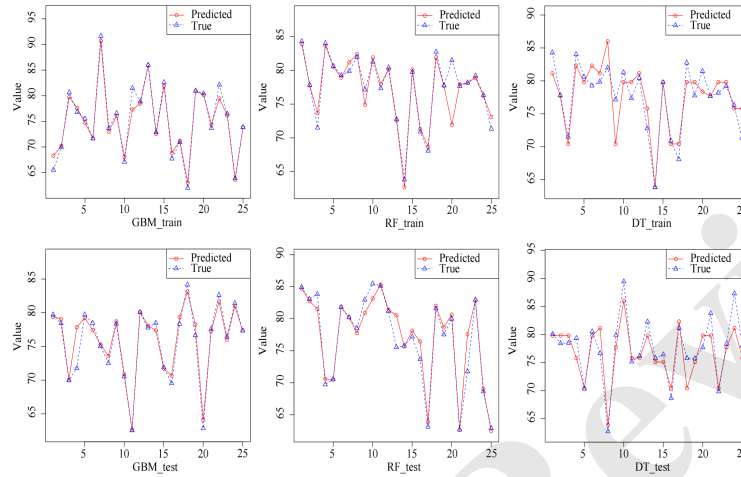


Figure 6: Multi model learning results

Figure 6 displays a comparison of predicted versus actual values for the GBM, RF, and DT models, both during the training phase (upper charts) and the testing phase (lower charts). The alignment of predicted values with actual values indicates model performance, with a closer alignment suggesting a better predictive model. GBM shows a close match between prediction and reality, suggesting strong model performance. RF and DT display a larger discrepancy between predicted and actual values, indicating a less accurate model. The RF and DT models present larger errors and a weaker fit, as evidenced by their greater divergence from the actual values, especially in the test phase. GBM's test results are closer to the LSTM's performance than RF and DT, indicating better generalization beyond the training data. The suboptimal performance of the RF and DT models, compared with the GBM and LSTM models, suggests that LSTM holds the strongest predictive power for modeling risk spillover.

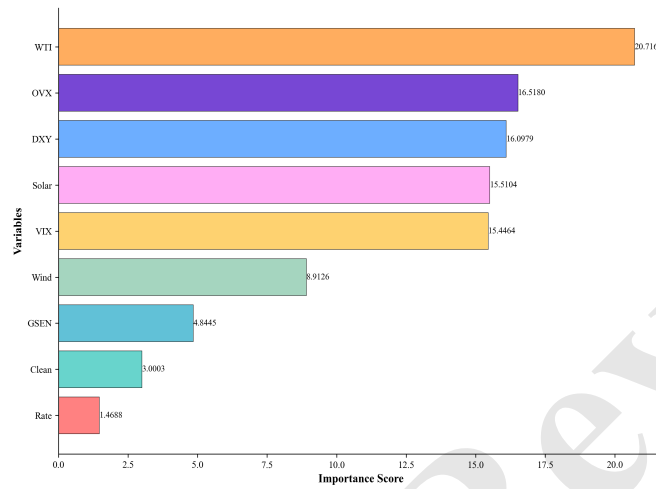


Figure 7: The characteristic importance of each variable

Figure 7 visually represents the importance of each variable in the context of predicting risk spillover, as determined by the LSTM model. West Texas Intermediate (WTI) index is shown to have the highest importance score, highlighting its significant impact on risk spillover in the energy market. The Oil Volatility Index (OVX) follows closely, underlining the volatility in oil prices as a critical factor. The interconnected nature of different energy sectors with the oil market means that oil price movements can have far-reaching consequences on other energy commodities.

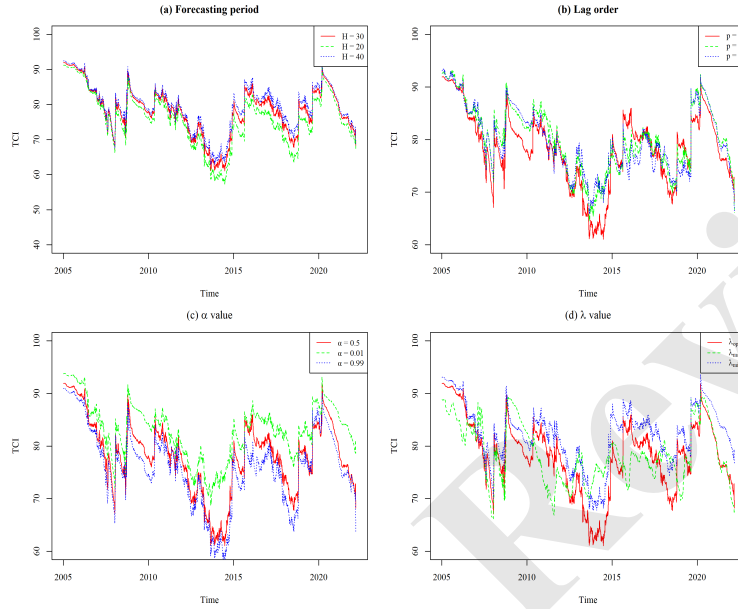


Figure 8: Dynamic total spillover of extreme risk with different model parameters

Figure 8 evaluates the robustness of dynamic total spillover of extreme risk in the energy market under different model parameters. Different forecast horizons ($H=20$, $H=30$, $H=40$ days) are examined in Figure 8(a). The consistency in trend across these periods suggests the stability of the model's performance. Figure 8(b) illustrates that varying the lag order ($p=1$, $p=2$, $p=3$) maintains a similar trend in total risk connectivity, indicating reliable results across different temporal dependencies. In Figure 8(c), the total risk connectivity is tested with extreme and median alpha values ($\alpha=0.01$, $\alpha=0.5$, $\alpha=0.99$). The trend remains consistent despite these changes, affirming the robustness of the spillover effect identified. Figure 8(d) displays results with the minimum, maximum, and optimal lambda (λ) values. The overall trend aligns across these parameters, supporting the empirical findings' solidity.

Table 1: Optimal model selection

Notes: Table 1 presents the optimal financial time series model selected for each country based on statistical tests. The acronym ARMA defines Autoregressive Moving Average and the numbers in parentheses represent the order of the autoregressive (AR) and moving average (MA) components, respectively. GARCH stands for Generalized Autoregressive Conditional Heteroskedasticity, with the numbers in parentheses indicating the order of the model. Error distribution column lists the assumed distribution of the residuals in the GARCH models, std stands for standard normal distribution, nig for normal inverse Gaussian distribution, jsu for Johnson SU distribution, and sst for skewed student-t distribution. iGARCH stands for integrated GARCH model, eGARCH for Exponential GARCH model, sGARCH for Standard GARCH model and gjrGARCH for Glosten-Jagannathan-Runkle GARCH model.

	ARMA model	GARCH model	Error distribution
China	ARMA (1, 1)	iGARCH (1, 1)	std
India	ARMA (1, 1)	eGARCH (1, 1)	std
Japan	ARMA (1, 1)	eGARCH (1, 1)	std
Korea	ARMA (1, 1)	eGARCH (1, 1)	std
Australia	ARMA (1, 1)	eGARCH (1, 1)	std
Malaysia	ARMA (1, 1)	iGARCH (1, 1)	std
Thailand	ARMA (1, 1)	eGARCH (1, 1)	std
South.Africa	ARMA (1, 1)	eGARCH (1, 1)	std
England	ARMA (1, 1)	eGARCH (1, 1)	std
France	ARMA (1, 1)	eGARCH (1, 1)	nig
Spain	ARMA (1, 1)	eGARCH (1, 1)	jsu
Italy	ARMA (1, 1)	eGARCH (1, 1)	jsu
Turkey	ARMA (1, 1)	eGARCH (1, 1)	std
Poland	ARMA (1, 1)	eGARCH (1, 1)	std
Norway	ARMA (1, 1)	eGARCH (1, 1)	jsu
America	ARMA (1, 1)	eGARCH (1, 1)	jsu
Russia	ARMA (2, 2)	sGARCH (2, 2)	jsu
Brazil	ARMA (1, 1)	eGARCH (1, 1)	jsu
Canada	ARMA (1, 1)	eGARCH (1, 1)	jsu
Argentina	ARMA (1, 1)	eGARCH (1, 1)	std
Austria	ARMA (1, 1)	sGARCH (1, 1)	sstd
Hungary	ARMA (1, 1)	gjrGARCH (1, 1)	std

Table 2: Descriptive statistics of extreme risk series

Table 2 presents the descriptive statistics for the extreme risk series in the energy markets of various countries. Mean represents the average extreme risk value for each country's energy market. The highest absolute value of mean is found in Brazil (0.0528), followed by Argentina (0.0470). Std.Dev. (Standard Deviation) measures the amount of variation or dispersion in the extreme risk series. Poland has the lowest standard deviation (0.0078), indicating the least fluctuation in extreme risk. Skewness indicates the degree of asymmetry of the risk series distribution relative to the normal distribution. Kurtosis measures the 'tailedness' of the distribution. Jarque-Bera is a test statistic for checking if the series has the skewness and kurtosis matching a normal distribution. ADF test (Augmented Dickey-Fuller) tests for the presence of unit roots in the series. *** and ** indicate that the test results are significant at 1% and 5% level, respectively. The consistently negative skewness and high kurtosis values across all countries suggest that the extreme risk series exhibit a leftward tilt with long left tails, which is characteristic of financial return series. These results, combined with the significant Jarque-Bera statistics, confirm that the series do not follow a normal distribution.

	Mean	Std.Dev.	Skew	Kurtosis	Jarque-Bera	ADF test
China	-0.0320	0.0147	-3.2564	18.9237	36306.8090***	-4.8534***
India	-0.0279	0.0107	-3.1091	18.4132	33884.5450***	-6.2214***
Japan	-0.0323	0.0099	-2.7366	16.0571	24587.6940***	-6.5845***
Korea	-0.0339	0.0129	-1.8149	7.2649	3847.4840***	-4.8637***
Australia	-0.0269	0.0108	-2.8356	16.1354	25109.8320***	-5.8525***
Malaysia	-0.0208	0.0091	-2.5483	12.3589	13930.6320***	-6.5464***
Thailand	-0.0275	0.0115	-2.8399	16.4938	26292.6930***	-6.7071***
South.Africa	-0.0386	0.0125	-1.6998	8.8175	5569.2470***	-5.3758***
England	-0.0243	0.0117	-2.7093	14.0757	18649.3710***	-5.5001***
France	-0.0292	0.0119	-2.7814	15.6326	23371.3330***	-6.2688***
Spain	-0.0327	0.0149	-1.8777	8.4325	5350.0840***	-5.2403***
Italy	-0.0291	0.0126	-2.7067	14.5871	20063.8670***	-5.9820***
Turkey	-0.0383	0.0095	-1.5712	7.1448	3318.6050***	-6.9746***
Poland	-0.0338	0.0078	-1.8260	8.7335	5668.3800***	-6.2619***
Norway	-0.0334	0.0139	-2.2756	11.0809	10551.0750***	-5.1058***
America	-0.0294	0.0146	-3.0385	16.1645	25788.5130***	-5.1209***
Russia	-0.0379	0.0246	-4.9263	36.4311	149004.4950***	-3.4923**
Brazil	-0.0528	0.0209	-2.7530	14.5877	20189.7260***	-7.0102***
Canada	-0.0274	0.0146	-3.2732	18.5605	34957.8150***	-5.7024***
Argentina	-0.0470	0.0203	-5.8972	72.2876	605957.8220***	-8.3622***
Austria	-0.0368	0.0140	-3.5875	19.8744	41243.6280***	-5.8965***
Hungary	-0.0334	0.0121	-3.1304	21.2808	45801.7880***	-6.2091***

Table 3: Static risk connectedness
Notes: Table 3 shows the static risk connectedness in energy markets across 22 countries. The countries are numbered for reference: 1 for China, 2 for India, 3 for Malaysia, 4 for Thailand, 5 for South Africa, 6 for Japan, 7 for South Korea, 8 for Australia, 9 for the United Kingdom, 10 for France, 11 for Spain, 12 for Italy, 13 for Turkey, 14 for Poland, 15 for Austria, 16 for Hungary, 17 for Norway, 18 for Russia, 19 for the United States, 20 for Brazil, 21 for Canada, and 22 for Argentina. The countries are grouped into regions: A represents Asia Pacific and Africa, B represents Europe, and C represents the Americas. The total connectivity score is 78.36%, indicating strong risk linkages between national energy markets. The 'To' values indicate how much risk a country contributes to the system. The 'From' values reflect the susceptibility of countries to risk spillovers from other countries. The Net values represent the difference between the 'To' and 'From' values. The financialisation of energy markets and the presence of developed financial sectors in countries like the US, Canada, and Brazil amplify risk connections due to increased investments and international capital movement.

	1	2	3	4	5	6	7	8	A	9	10	11	12	13	14	15	16	17	18	B	19	20	21	22	C
1	30.88	5.54	1.41	2.54	4.78	4.91	6.01	8.10	4.16	2.38	2.49	3.99	2.28	2.92	1.04	1.27	1.98	2.41	3.25	2.40	3.29	3.25	2.65	2.64	2.96
2	4.73	32.90	0.59	3.70	3.00	3.01	3.48	3.38	2.74	2.23	2.16	3.57	1.97	4.63	2.65	2.37	7.21	2.05	2.29	3.11	3.14	3.99	3.36	3.58	3.52
3	3.41	2.68	8.96	4.23	2.85	3.78	2.02	3.33	2.79	6.61	7.40	5.19	7.17	1.47	2.55	2.39	1.40	7.44	4.47	4.63	5.35	7.51	5.78	3.52	5.62
4	3.07	2.72	1.40	14.18	2.18	3.02	1.96	3.04	2.17	6.57	6.95	5.55	6.76	1.17	2.73	3.45	2.74	6.28	2.78	4.50	6.47	5.90	6.94	4.14	5.86
5	3.82	2.80	2.35	2.35	24.67	2.43	2.90	5.71	2.80	4.08	4.79	4.88	4.95	2.41	2.56	2.39	4.65	3.92	2.67	3.75	4.46	3.77	3.85	3.38	3.87
6	6.44	3.88	0.85	2.39	4.16	31.00	4.18	7.11	3.63	3.24	4.01	4.30	3.67	1.97	1.36	1.07	1.31	3.62	1.84	2.66	3.74	3.45	3.48	2.72	3.35
7	6.66	3.27	2.46	1.96	3.84	3.14	40.32	7.02	3.54	2.25	2.05	3.24	2.23	2.07	1.26	2.62	1.03	2.18	1.26	2.02	3.11	2.36	2.63	3.05	2.79
8	7.04	3.81	2.49	2.40	7.19	4.84	5.31	25.29	4.11	3.30	2.70	3.33	2.47	2.40	1.65	1.30	2.19	2.33	1.42	2.51	5.39	3.65	4.01	3.49	4.19
9	4.40	3.39	1.47	3.40	3.50	3.14	3.34	3.24	4.33	4.07	4.33	3.94	4.30	2.40	2.18	2.30	2.80	2.33	2.40	2.50	3.45	3.29	4.01	4.08	4.02
10	2.10	2.20	0.15	2.43	2.63	3.43	1.16	4.11	2.63	13.29	12.99	7.34	7.10	1.28	1.38	2.10	2.29	7.40	2.32	8.25	5.51	7.34	7.51	7.34	7.34
11	2.72	2.64	0.79	2.68	2.62	2.67	2.41	3.68	2.65	8.82	12.99	7.34	9.21	1.28	1.28	2.07	1.38	0.96	6.66	2.28	4.04	6.87	5.99	6.20	6.33
12	2.88	2.52	0.52	1.76	2.41	3.02	2.36	4.07	2.44	7.04	8.60	24.45	7.91	1.28	1.28	2.07	1.38	0.75	4.43	3.45	6.40	4.67	4.73	5.27	5.30
13	2.12	2.03	1.92	2.87	2.19	3.01	1.32	2.97	2.22	8.65	10.57	7.68	13.16	1.07	2.14	1.94	1.08	1.75	0.97	3.76	1.79	2.73	3.88	3.51	3.39
14	3.09	2.28	2.08	1.86	3.77	2.18	2.45	3.74	2.68	4.14	4.67	4.14	4.67	37.32	1.54	1.75	0.97	3.76	1.79	2.73	3.88	3.51	3.39	3.75	3.48
15	2.50	2.81	1.27	3.60	3.15	2.27	1.39	2.46	2.46	5.49	5.99	4.32	5.91	2.45	17.78	5.30	4.01	5.47	3.99	4.29	5.29	5.09	5.51	5.31	4.91
16	2.51	2.46	1.08	2.92	2.64	2.76	1.61	3.10	2.39	7.35	7.81	6.42	7.26	1.40	2.36	9.01	2.22	6.26	2.40	4.35	7.91	7.41	7.38	5.50	7.10
17	3.54	3.03	1.22	4.24	2.13	2.59	1.98	2.54	2.66	4.99	5.66	4.45	5.38	2.03	2.83	4.17	20.25	5.46	3.87	3.88	5.24	5.00	5.36	3.86	4.92
18	3.25	2.44	1.65	3.72	3.76	4.03	1.80	4.11	3.10	8.13	8.36	5.62	7.44	1.24	2.98	1.81	0.96	12.15	3.57	3.92	6.90	6.02	7.47	3.50	5.97
19	3.68	2.32	1.25	3.65	2.63	2.85	1.86	2.68	2.62	5.88	6.55	4.70	6.42	1.63	3.12	2.46	2.46	6.66	19.76	3.99	4.93	5.27	5.20	4.05	4.86
20	2.87	2.47	1.15	2.97	2.89	2.80	1.90	3.35	2.56	6.05	6.72	5.17	6.15	1.38	1.75	2.21	1.42	5.28	2.37	3.64	6.36	5.64	5.69	4.79	5.70
21	2.74	2.43	0.70	2.60	3.31	2.68	1.71	4.14	2.54	7.95	7.46	6.21	6.33	1.48	1.75	2.11	1.80	6.33	2.19	4.16	14.14	6.41	9.08	5.36	5.44
22	3.14	2.85	1.11	2.63	3.21	2.89	1.88	3.78	2.69	5.44	5.41	5.10	4.99	1.62	1.56	1.51	1.07	5.23	2.31	3.19	7.33	24.51	7.23	5.20	4.94
23	3.29	3.10	0.78	2.95	4.07	3.62	1.98	4.35	3.02	5.83	6.22	5.08	5.61	1.72	1.89	3.06	3.80	5.91	2.44	3.92	9.80	6.53	13.33	4.33	5.17
24	3.07	2.83	0.79	2.54	3.49	2.90	1.86	4.07	2.69	5.64	5.61	5.79	5.33	1.88	1.46	1.17	1.12	2.74	1.75	2.42	7.04	6.34	4.97	35.51	4.39
25	3.07	2.83	0.79	2.54	3.49	2.90	1.86	4.07	2.69	5.64	5.61	5.79	5.33	1.88	1.46	1.17	1.12	2.74	1.75	2.42	7.04	6.34	4.97	35.51	4.39
FROM	76.12	67.40	26.45	38.92	71.58	63.72	52.32	67.11	62.50	83.71	82.14	83.25	80.37	60.8	48.0	49.6	1.95	5.10	3.42	6.04	48.2	55.5	37.2	4.0	16.23
TO	67.12	67.40	26.45	38.92	71.58	63.72	52.32	67.11	62.50	83.71	82.14	83.25	80.37	60.8	48.0	49.6	1.95	5.10	3.42	6.04	48.2	55.5	37.2	4.0	16.23
NET	7.12	65.35	64.59	38.50	41.74	3.28	7.36	12.70	41.68	27.18	35.13	24.61	26.12	23.32	40.56	40.41	33.24	15.82	27.57	33.12	37.04	34.12	28.33	25.14	31.15

TCI = 78.36

Table 4: Nonlinear causality test between driving variables and TCI

Table 4 reports the results of a nonparametric Granger causality test, showing the influence of various market indicators on the Total Connectedness Index (TCI) over different lag orders. VIX is Volatility Index, representing market uncertainty. WTI is West Texas Intermediate oil prices, representing energy prices. DXY is US Dollar Index, representing currency strength. OVX is Oil Volatility Index, reflecting volatility in oil prices. Solar is Solar energy index, representing renewable energy sector performance. Wind is Wind energy index, for the renewable energy sector. GSFEN is Goldman Sachs Financial Condition Index, representing financial market conditions. Clean is Clean energy index, also reflecting renewable energy market performance. Rate is Interest rate levels. The lag order 'p' (1-3) represents the number of time steps at which the causality is tested. A lag of 1 means the previous time step, lag 2 the one before last, and so on. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The significant values at different lags support the hypothesis of a non-linear interaction between the market variables and the TCI, indicating the potential of these indicators as early warning signals for changes in the TCI.

	VIX	WTI	DXY	OVX	Solar	Wind	GSFN	Clean	Rate
$p = 1$	4.889***	2.565***	4.044***	4.397***	4.595***	4.869***	4.689***	4.208***	2.547***
$p = 2$	3.941***	2.481***	3.164***	3.544***	3.672***	3.983***	3.647***	3.136***	2.599***
$p = 3$	3.252***	1.865**	2.031**	2.736***	2.572***	2.824***	2.530***	1.838**	1.464*

Table 5: BDS test between driving variables and TCI

Table 5 presents the results of the Brock-Dechert-Scheinkman (BDS) test, designed to detect non-linear dynamics in the relationship between driving indicators and the Total Connectedness Index (TCI). Embedding dimension (m) (ranging from 2 to 4) represents the number of consecutive time series observations used to capture temporal dependencies, a standard range in financial time series non-linearity testing. Neighborhood radius (1.9639, 3.9278, 5.8917, 7.8556) is set based on the standard deviation of TCI residuals, ensuring consistent sensitivity to non-linear patterns across different test specifications. BDS statistic measures the deviation of the residual series from independent and identically distributed behavior that larger values indicate stronger evidence of non-linearity. All reported BDS statistics are significant at the 1% level ($p < 0.01$), confirming that linear models fail to fully capture the complexity of interactions between the selected indicators and TCI.

Neighborhood radius	$m = 2$	$m = 3$	$m = 4$
1.9639	385.415***	710.411***	1437.220***
3.9278	212.611***	270.825***	354.849***
5.8917	154.162***	164.901***	177.386***
7.8556	141.414***	138.981***	136.356***

Table 6: Multiple model learning errors and goodness of fit

Table 6 presents the learning errors and goodness of fit for multiple models. LSTM is Long Short-Term Memory model, known for handling long-term dependencies, shows strong predictive performance with low error rates (MAE and MSE) and high R^2 values on both test and train sets. GBM is Gradient Boosting Machine, while competitive, shows higher errors and slightly lower R^2 than LSTM, indicating good but not superior performance. RF is Random Forest exhibits higher error metrics and significantly lower R^2 compared to LSTM, suggesting less predictive accuracy. DT is Decision Tree has the highest errors and lowest R^2 values, indicating it has the least predictive power among the evaluated models. MAE (Mean Absolute Error) measures the average magnitude of errors in a set of predictions, without considering their direction. MSE (Mean Squared Error) measures the average squared difference between the estimated values and the actual value. R^2 (Coefficient of Determination) indicates the proportion of the variance in the dependent variable that is predictable from the independent variables, with a higher R^2 suggesting a better fit. The models were trained on one subset of the data (training set) and tested on another (test set) to evaluate their generalization capabilities. Comparing the test set performance, the LSTM model shows the best generalization ability, indicating its suitability for predicting TCI and its contributing factors. The outcomes suggest that the LSTM model, with its minimal learning errors and high goodness of fit, is more adept at capturing long-term dependencies relevant to risk spillover prediction in comparison to GBM, RF, and DT models.

	LSTM		GBM		RF		DT	
	Test set	Train set	Test set	Train set	Test set	Train set	Test set	Train set
MAE	0.7465	0.8321	0.8043	0.8338	1.1116	0.9823	1.9460	1.9142
MSE	0.8562	0.8954	2.0532	1.5715	3.4750	4.3794	6.4562	6.2477
R^2	0.9831	0.9827	0.9347	0.9756	0.9339	0.8335	0.8113	0.7605

Data availability

Data will be made available on request.

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Declaration of Conflicts of Interest

No conflicts of interest to declare.

Appendix

Table A1 compiles the summary statistics of all early warning indicators utilized in this study for energy market risk spillover analysis. These indicators span multiple key domains closely related to energy market dynamics, covering both traditional energy market factors and macro-financial, renewable energy-related variables that influence risk transmission. The table provides essential statistical metrics for each indicator, including measures reflecting central tendency and data dispersion, based on the study's designated sample period and data frequency.

Table A1: Summary statistics of the early warning indicators

Indicator	Definition	Data Source	Mean	Std. Dev.
VIX	CBOT Volatility Index	Chicago Board Options Exchange	20.3345	9.6862
WTI	West Texas Intermediate	U.S. Energy Information Administration	71.7270	23.4771
DXY	U.S. Dollar Index	The New York Stock Exchange	87.4635	8.5598
OVX	CBOE Crude Oil Volatility	Chicago Board Options Exchange	38.4363	18.6572
Solar	Solar Energy Index	S&P Dow Jones Indices	299.7750	278.5989
Wind	Global Wind Energy Index	Nasdaq Global Indexes	164.1509	64.2462
GSEN	Goldman Sachs Energy Index	S&P Dow Jones Indices	246.6369	78.0872
Clean	Global Clean Energy Index	S&P Dow Jones Indices	1061.7329	764.2126
Rate	Federal Funds Effective Rate	Federal Reserve System	0.6732	1.0602

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