

# Risk spillovers from climate policy uncertainty to energy markets: Does climate policy stringency matter? <sup>☆</sup>

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## ABSTRACT

This paper describes the complex risk contagion between climate policy uncertainty (CPU) and the global energy market utilizing an improved high-dimensional time-varying parameter vector autoregressive (HD-TVP-VAR) model. A dual machine learning (DML) approach is applied to test whether strict climate policies can mitigate the risk from CPU to energy market. The results indicate that the CPU is highly associated with the risk of energy markets. The risk spillover of CPU exhibits evident time-varying characteristics, and its impact on the energy markets of various countries varies. Furthermore, we find that climate policy stringency (CPS) plays a significant role in alleviating the risk from CPU to the energy market. These results provide valuable insights into the effective identification of CPU's risk contagion paths in global energy market.

## 1. Introduction

Extreme weather events remain a global challenge (Lane, 2024; Fosten and Nandi, 2025), prompting governments to make clear climate policy commitments. However, the complexity of the global economic situation and the frequency of geopolitical conflicts in recent years, such as the global COVID-19 outbreak and the Russia-Ukraine conflict in 2020, have forced governments to take multiple factors into account when formulating climate policy, including political, economic and social aspects. Due to economic agents having difficulty predicting when or how governments will change their policies, The formulation and implementation path of climate policies may change at any time (Liu et al., 2024). Nevertheless, the uncertainty and discontinuity associated with such policy changes not only lowered investor expectations for the traditional energy sector but also posed challenges to the development of clean energy and new energy technologies, further exacerbating the fragility of the energy supply chains and market uncertainty (Qiao et al., 2024). Against the background of economic globalization and energy market integration, the negative influence of such policy uncertainty is not confined to the domestic energy market, rather, it is rapidly transmitted to other countries through direct and indirect channels, ultimately spreading to the global energy market and triggering risk

resonance throughout the entire energy system (Pescaroli and Alexander, 2016). Specifically, when CPU rises in country  $i$ , it induces volatility in domestic energy production costs (Qiao et al., 2024). This cost disturbance may affect global benchmark prices via physical trade in energy commodities (e.g., crude oil, natural gas, coal, and renewables), thereby directly impacting country  $j$  or other nations engaged in international trade (Tao et al., 2025). Simultaneously, multinational energy firms facing heightened policy risk may trigger cross-border capital reallocation, with the risk directly transmitted to other countries through cross-border investment (Kim et al., 2024; Qin et al., 2024). Furthermore, investors may adjust expectations by selling energy-related assets and rotating into safe-haven instruments, with the risk potentially propagating to country  $j$  or other nations via financial market integration (Cui and Maghyreh, 2025). Therefore, climate policy uncertainty in country  $i$  may affect the energy market in country  $j$ . Addressing the influence of external policy uncertainty on energy markets remains a crucial shared challenge for nations worldwide.

Preventing and mitigating risk shocks in the energy market through energy transition to enhance energy independence has long been recognized as an effective strategy (Wen et al., 2024). Accordingly, countries have increasingly tightened their climate policy frameworks to accelerate this transition. Higher CPS typically entails rigorous carbon

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regulations, mandatory shifts in the energy mix, and intensified compliance standards (Bergquist and Warshaw, 2023). Intuitively, such adjustments should enhance energy independence by reducing reliance on fossil fuels (Bergquist and Warshaw, 2023). However, CPS exerts two opposing effects on the risk spillover from external CPU. On one hand, strict regulations may induce transition frictions that heighten market vulnerability (Mille et al., 2025; Rickman et al., 2024). Abrupt tightening imposes immediate compliance costs and elevates the risk of stranded assets, potentially straining the financial health of energy firms (Egli et al., 2022). These internal frictions and capital reallocations can make the domestic energy market more fragile, thereby increasing its exposure to shocks arising from external CPU (Egli et al., 2022). Furthermore, if firms relocate to jurisdictions with looser regulations to evade costs, the resulting disruption in supply chains could further amplify the market's sensitivity to external policy uncertainty (Pescaroli and Alexander, 2016). On the other hand, high stringency fosters structural resilience against external shocks (Bergquist and Warshaw, 2023). By forcing a shift toward localized renewable energy, strict policies reduce reliance on global fossil fuel markets, thereby limiting the transmission channels of external CPU to a certain extent (Bergquist and Warshaw, 2023). Moreover, unlike vague policies, a stringent regulatory environment signals a firm government commitment. This commitment acts as an anchor for investor expectations, buffering the domestic market against the panic or contagion effects typically triggered by spikes in external CPU (Payne et al., 2025). This gives rise to a question: Does higher CPS mitigate or amplify the risk spillover from external CPU to national energy markets?

Given that systemic risk propagates under a complex network structure, examining the risk contagion of policy uncertainty on energy markets from a complex network perspective has become a general consensus in academic research (Chen et al., 2024; Fianu et al., 2022; Dai et al., 2022). In complex networks, shocks arising from uncertainty risks spread within the system and eventually evolve into overall systemic risks (Elder and Payne, 2024; Gunay et al., 2025). Especially in the case of extreme events, the risk linkage within the system leads to local risks spreading quickly to other individuals within the system, which leads to systemic risk amplification throughout the energy market (Gunay et al., 2025). Systemic risk contagion stems not only from the dynamic changes in the associations between individuals but also from the numerous individuals involved and the intricate variability of their interactions. Previous studies have validated the time-varying characteristics of systemic risk contagion through the spillover index method, and some scholars have broken the constraints of variable dimension to explore the high-dimensional complexity of risk network structure (Payne and Sun, 2023; Demirer et al., 2018). However, accurately representing a complex network structure that encompasses both “time-varying” and “high-dimensional” characteristics remains a significant challenge for current research on systemic risk contagion, with effective estimation methods requiring further exploration. Moreover, enhancing the independence and stability of its energy system is an effective means of countering the impacts of external climate policy uncertainties, and the independence of the energy market is strongly correlated to the stringency of climate policies (Bretschger, 2024). While strict policies are effective tools for promoting energy transition and enhancing the independence of the energy market, it remains to be studied whether they can serve as decelerators of systemic risk contagion during their implementation. Current research has not yet focused on this aspect, but understanding how CPS affects the risk contagion from external policy uncertainty to energy markets may help to explore feasible pathways to prevent external shocks from the perspective of policy strictness. Thus, a complex network that incorporates both “time-varying” and “high-dimensional” features is essential for establishing a more comprehensive macroprudential framework for managing energy-related risks. Precisely grasping the stringency of climate policies is an important manifestation of understanding the dynamic evolution of risk networks in depth.

This paper explores the risk spillovers of CPU on national energy markets from a complex network perspective and examines the effectiveness of CPS in mitigating risk contagion. The marginal contributions are as follows: First, we identify the risk resonance phenomenon in the international energy market system under CPU conditions and the dynamic characteristics of CPU-induced risk spillovers across national energy markets. Unlike previous studies, which primarily focused on risk spillovers for specific energy attribute markets, we are not limited to the study of market risk contagion of a single energy attribute. Taking into account the gradual promotion of energy market diversification, this article, from a global perspective, discusses the risk contagion of CPU across the entire energy system. Second, recognizing the complex interaction between national energy markets, we employ a high-dimensional time-varying parameter vector autoregressive (HD-TVP-VAR) model to describe the dynamic risk spillover network among national energy markets in the case of CPU. Compared with conventional studies relying on rolling window methods, this paper not only circumvents the window selection problem but also minimizes the loss of sample information, achieving the time-varying spillover evolution of a high-dimensional risk network. From a “high-dimensional” perspective, the differences in risk spillovers from CPU to different countries' energy markets can be compared more deeply in cross-section, helping policymakers accurately identify their country's systemic importance and enhance the effectiveness of “targeted risk prevention”. The “time-varying” dimension enables a more responsive analysis of the shocks to external policy uncertainty over time, assisting policymakers in testing and refining market management strategies, thereby effectively preventing the “risk of risk management”. The complex network correlation structure captured by the combination of the two is a scientific tool needed to improve the mitigation of systemic risk prevention in energy markets. Thirdly, because of the advantages of machine learning algorithms in high-dimensional and non-parametric prediction, this paper applies the dual machine learning model to test the role of CPS in the risk spillover of CPU on the energy market. This approach effectively addresses the “curse of dimensionality” and model specification bias challenges encountered in conventional econometric models, reinforcing the reliability of the research conclusions. To our knowledge, this research displays the inaugural attempt to evaluate the impact of its own policy stringency on mitigating external risk spillovers, providing policymakers with an empirical basis for grasping accurately the optimal stringency of their climate policies.

The study proceeds as follows: Literature review and econometric methodology are described in Section 2 and Section 3, respectively. The data sources and description are elaborated in Section 4. Section 5 discusses the empirical results, and Section 6 concludes with policy recommendations.

## 2. Literature review and theoretical analysis

### 2.1. Literature review

Given the impact of climate policy changes on energy markets, the risk linkages between CPU and energy markets have garnered substantial attention from scholars (He et al., 2024; Yan, 2024). Some scholars have confirmed that uncertainty in policy changes may upset the balance in energy markets, resulting in price volatility and adjustments in energy supply chains, ultimately triggering energy market risks (Lin et al., 2024; Zhang and Chen, 2024). For instance, the uncertainty-induced changes in energy infrastructure may require significant investment and be accompanied by long-term uncertainty (Qiao et al., 2024). However, the unpredictability of policy directions means energy firms are likely to delay investment decisions to avoid potential losses, while financial institutions may also adopt more conservative risk assessments and tighten credit constraints, further raising firms' financing costs (Payne et al., 2025; Cui and Maghyereh, 2025). This not only raises investment risks for firms but also exacerbates supply-side rigidity and

price volatility, reducing the energy system's ability to respond to market changes, amplifies overall market volatility (Qiao et al., 2024). Such supply-side cost fluctuations and supply chain adjustments, in turn, prompt energy consumers and downstream industries to seek alternative energy sources due to substitution effects, further amplifying systemic risks across the energy market (Mille et al., 2025).

Irrational investor behaviour in the context of CPU is also a significant driver of heightened risk spillovers (Liu et al., 2024). Traditional economic theory posits that market participants are rational actors who can correctly process all available information and respond appropriately to maximize utility (Cui and Maghyereh, 2025). However, more recent studies reveal that energy markets are not entirely efficient, and in practice, market participants often deviate from rational decision-making (Liu et al., 2024). Specifically, amid climate policy uncertainty, confusing market signals may lead investors to engage in behaviors such as over-investing in a certain type of energy or making short-term divestments—irrational choices that further exacerbate market volatility and risk (Jin et al., 2024). In particular, when the direction and intensity of policy adjustments are unpredictable, investors' risk aversion often increases (Egli et al., 2022). This aversion leads to asset reallocation, with investors reducing their exposure to high-risk energy markets (Tang et al., 2024). In the context of global financial integration, CPU can exacerbate cross-border energy market volatility through international capital flows and asset price linkages (Kim et al., 2024; Cui and Maghyereh, 2025). For example, when a major economy's climate policy changes cause energy market price fluctuations, such shocks can quickly spread to other economies through cross-border capital allocation, resulting in the global diffusion of systemic risks (He et al., 2024). Therefore, it is essential to examine the energy market spillover effects in conjunction with CPU to construct a comprehensive and refined energy market risk management system. The intensity and direction of the risk energy market risk spillover in response to external shocks remain key issues that urgently need to be addressed.

However, the existing research still has several aspects that can be further expanded. In terms of research content, the current literature often focuses only on the spillover effects within individual national energy markets (Guo et al., 2024) or their research scope is often restricted to specific energy markets, such as the clean energy market (Qiao et al., 2024) and the oil market (He et al., 2024). With the rising prominence of renewable energy and the diversification of energy structures, interactions within the energy system have become increasingly dynamic (Qiao et al., 2024). Single-attribute energy data can no longer represent the entire complex energy market. Considering that economic globalization has strengthened interconnections among countries, national energy markets have developed complex interconnected networks through various channels such as asset holdings, cross-shareholding, and capital lending (Jin et al., 2024). Neither isolated single-region analysis nor the examination of specific energy markets accurately reflects the risk contagion of CPU to energy markets. Therefore, analyzing the complex network connectivity of CPU's spillover effects on global energy markets is particularly important.

In terms of research methods, traditional TVP-VAR network spillover mode faces the “curse of dimensionality” when estimating time-varying parameters in high-dimensional global networks, resulting from a large number of variables (Demirer et al., 2018). To cope with the challenges posed by high-dimensional data, Demirer et al. (2018) applied LASSO regression on the basis of the network method of Diebold and Yilmaz (2014), enabling dimensionality reduction for complex global networks. This method has become a common means of dimensionality reduction adopted by scholars at present. However, when high correlations exist between variables, LASSO may lead to sparse coefficient matrices and unstable estimates due to under-identification or excessive neglect of non-critical coefficients (Zou and Hastie, 2005). Therefore, an effective global estimation method that simultaneously captures the “time-varying” and “high-dimensional” characteristics of complex networks remains a gap in current research. To bridge this gap, this paper introduces

the Elastic Net estimation, constructing a complex network based on a high-dimensional time-varying parameter vector autoregressive model (HD-TVP-VAR). This approach eliminates the need for window size selection in traditional spillover methods, avoids information loss during data processing, and effectively mitigates the “curse of dimensionality”. This achieves the depiction of the time-varying and high-dimensional features of the network of CPU's risk spillover to the energy market, offering a basis for building an effective systemic risk assessment and early warning mechanism.

Additionally, earlier work has overlooked CPS's role in the risk spillover from external CPU to national energy markets. Some studies have examined the environmental impacts of stringent climate policies, including effects on carbon emissions (Georgatzi et al., 2020), renewable energy consumption (Hassan et al., 2024), and energy technology innovation (Herman and Xiang, 2019). Nonetheless, these studies primarily address the direct influence of policy strictness on environmental and energy fields rather than its role in the risk contagion. Although some scholars have employed ordinary panel regression models to analyze the link between environmental policy stringency and banking risks (Lee et al., 2024), the potential moderating on the risk spillover from CPU to energy markets remain scarce. Moreover, most existing models use conventional multivariate linear regression, which may introduce estimation bias due to nonlinear relationships among variables and endogeneity arising from omitted variables. While adding control variables could mitigate omitted variable bias, it can also lead to reduced degrees of freedom, multicollinearity, and the “curse of dimensionality”, compromising the stability of estimates (Wei and Xia, 2024). To this end, a dual machine learning model has been proposed (Chernozhukov et al., 2017). This approach allows for controlling a larger number of covariates without imposing functional form constraints, thus reducing potential biases from omitted variables and functional form misspecification (Wei and Xia, 2024). In light of these advantages, this study employs a double machine learning approach to examine the role of CPS in the risk contagion process from external CPU to energy markets.

## 2.2. Theoretical analysis

According to energy economics, energy possesses both commodity and financial attributes. Therefore, risks may shock the energy system through both energy and non-energy channels (Gu et al., 2024; Bai et al., 2022). To better understand the risk spillover effects of CPU on the energy market, Fig. 1 illustrates the risk spillover mechanism. As shown in the figure, for energy firms, the real options theory suggests that corporate investment decisions are often irreversible (Zhang and Chen, 2024). Under heightened CPU, energy firms may prefer to delay investment decisions and maintain liquidity to accommodate potential policy changes (Payne et al., 2025; Cui and Maghyereh, 2025). From the perspective of financial frictions, financial institutions also tend to adopt more conservative risk assessments of energy firms, leading to tighter credit constraints that further limit firms' access to financing (Liu et al., 2024). Insufficient funding not only exerts short-term pressures on production but also reduces supply-side flexibility, exacerbating supply-demand imbalances in energy markets (Gu et al., 2024). Furthermore, financing difficulties may increase the likelihood of fossil fuel assets becoming stranded assets, intensifying systemic risks (Rickman et al., 2024). For energy consumers and downstream industries, uncertainties related to climate policies, such as carbon taxes and emission restrictions, may result in sustained fluctuations in fossil fuel costs, affecting the relative price structure of energy (Mille et al., 2025). Consumers and downstream industries are prone to adjust their energy choices due to substitution effects, further amplifying demand-side uncertainty in energy markets (Gu et al., 2024). Such demand-side uncertainty, through the dynamic evolution of energy consumption patterns, disturbs resource allocation in markets, thereby triggering the risk of the energy market. For investors, CPU is a critical factor affecting

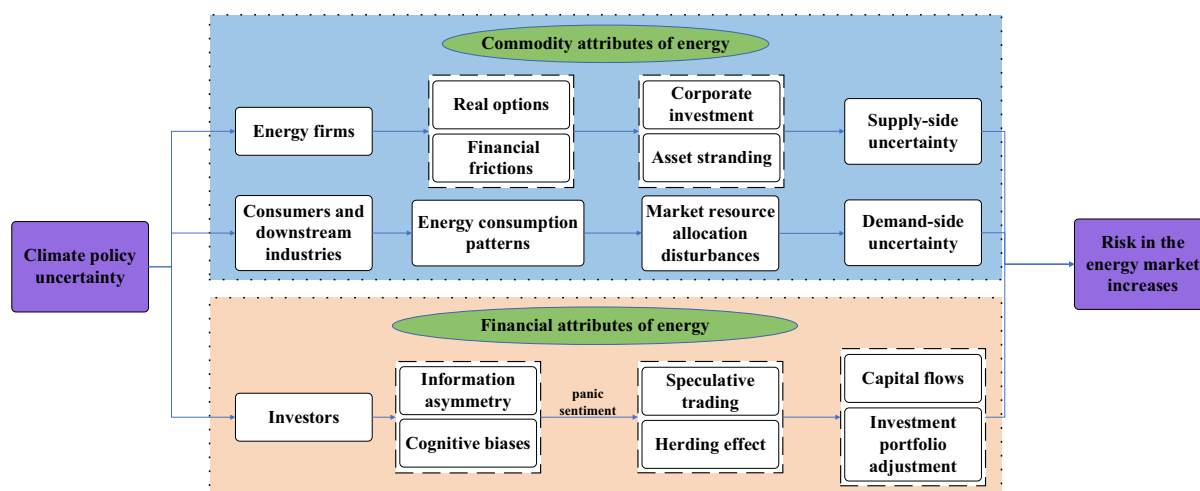


Fig. 1. Risk spillover mechanism of CPU on the energy market.

individual investment decisions (Tang et al., 2024). Behavioral finance theory suggests that investors' decisions are influenced by information asymmetry and cognitive biases, making them more prone to panic and negative expectations in high-uncertainty environments (Cui and Maghyereh, 2025). This may further induce investors to engage in speculative trading and herd behaviour, quickly adjusting their portfolios to pursue short-term, high-yield speculative assets (Liu et al., 2024). Such portfolio shifts can drive capital flow changes that heighten energy market volatility (He et al., 2024). In highly interconnected markets, this volatility may trigger risk contagion across international energy markets (He et al., 2024). Based on this, we propose the following hypothesis:

**Hypothesis 1.** There is a significant risk linkage between CPU and national energy markets.

Theoretically, when CPU rises in major economies or globally influential countries—for instance, repeated adjustments to carbon pricing rules, abrupt cancellation of subsidies, or fluctuating enforcement of international climate agreements—it rapidly alters energy firms' expected investment returns, production costs, and long-term capital expenditure plans, thereby triggering sharp fluctuations in energy prices, output, and inventories (Liu et al., 2024; Qiao et al., 2024). These fluctuations are rapidly transmitted to other countries through direct and indirect channels, including physical commodity trade, cross-border investment, and financial market integration, leading to a marked strengthening of risk linkages across global energy markets in the short term and generating a pronounced “risk resonance” phenomenon (Tao et al., 2025; Kim et al., 2024). During periods of relatively low CPU, firms and investors can better plan the transition to clean energy and the phase-out of traditional energy sources, resulting in more stable market expectations and correspondingly weaker cross-border risk spillovers (Wen et al., 2024). Furthermore, the outbreak of extreme events such as geopolitical conflicts, extreme climate events, and financial crises may further increase investors' sensitivity to and aversion toward unknown risks (Cui and Maghyereh, 2025). During such periods, investors' concerns about climate policy uncertainty will further reinforce their bounded rationality, causing panic sentiment to spread rapidly and become contagious across global energy markets, which may lead to abrupt surges in systemic risk (Cui and Maghyereh, 2025). Based on this, we propose the following hypothesis:

**Hypothesis 2.** The risk linkage between CPU and national energy markets exhibits significant time-varying characteristics.

In recent years, many countries have adopted increasingly stringent climate policies to enhance the stability of their energy markets,

utilizing measures such as reducing dependence on imported fossil fuels and investing in clean energy infrastructure (Payne et al., 2025). However, the tightening of these policies may generate two opposing effects. On the one hand, stronger regulations may initially exert destabilizing effects by imposing rising compliance costs on traditional energy firms and increasing the likelihood that carbon-intensive assets become stranded (Cui and Maghyereh, 2025), as highlighted by the classic green paradox (Okullo et al., 2021). According to real options theory, greater regulatory uncertainty weakens firms' incentives to invest, while higher adjustment costs amplify the sensitivity of asset prices to external uncertainty shocks (Payne et al., 2025; Cui and Maghyereh, 2025). In fossil-fuel-dependent energy systems, policy tightening may trigger capital reallocation or even “greenflation” thereby increasing the domestic economy's exposure to external policy uncertainty (Mille et al., 2025). Moreover, the pollution haven hypothesis suggests that firms facing heavier regulatory burdens may relocate production to countries with laxer environmental standards, disrupting existing supply chains and heightening network fragility, which further accelerates the transmission of external uncertainty into the domestic market (André et al., 2025; Deng et al., 2023). On the other hand, a credible and stringent climate policy can generate stabilizing effects by inducing long-term investment in renewable-energy infrastructure, thereby reducing reliance on fossil fuels and lowering exposure to external CPU (Cui and Maghyereh, 2025). According to irreversible investment theory, greater policy clarity reduces the option value of waiting and conveys clear long-term signals to investors, stabilizing expectations and mitigating the contagion effects that typically accompany spikes in external CPU (Cui and Maghyereh, 2025).

Stringent climate policies may initially impose high adjustment costs on national energy systems, leading to transitional frictions in the process of restructuring energy production and consumption (Cui and Maghyereh, 2025). However, as the policy framework becomes clearer, technological progress accumulates, and the energy system gradually optimizes, these frictions weaken over time (André et al., 2025). In this sense, the risks induced by stringent climate policies can be characterized as temporary adjustment costs, whereas the institutional stability and long-term expectations created by credible policies steadily accumulate and enhance the structural resilience. Once this accumulated resilience offsets the short-term frictions, the stabilizing effect becomes dominant. Consistent with the porter hypothesis, policy clarity and innovation incentives can generate “compensation effects” (André et al., 2025), whereby stringent climate policies do not amplify external uncertainty shocks but instead provide a more durable buffer during structural transition. Based on this, we propose the following hypothesis:

**Hypothesis 3.** CPS can mitigate the risk spillover effect of CPU on energy markets.

### 3. Data sources and descriptions

The subject of this paper is the complex risk contagion between climate policy uncertainty (CPU) and the global energy market. To include as many countries as possible when data is available, this paper uses the MSCI energy index from May 3, 2005, to November 2, 2023 for 21 countries. The index captures the performance of key companies across all sectors of the energy industry, including oil, coal, gas and renewable energy. Data is sourced from the Bloomberg database. The selected countries cover the Asia-Pacific region, Europe, Africa, North America, and Latin America, including China, the United States, India, Austria, Italy, Canada, Brazil, Finland, Hungary, Indonesia, Argentina, Japan, Australia, Thailand, Norway, France, South Korea, Poland, Spain, Turkey, and South Africa. The US, as the largest global economy and energy consumer, significantly influences global energy markets through macroeconomic trends and fluctuations. Therefore, US climate policy uncertainty (CPU) is used as a proxy for global CPU, with monthly data obtained from the Economic Policy Uncertainty website. Following [Ansaram and Mazza \(2024\)](#), we calculate the daily logarithmic returns of the MSCI energy index for each country, that is,  $r_{j,t} = \ln(p_{j,t}) - \ln(p_{j,t-1})$ . Referring to [Zhang et al. \(2023b\)](#), the realized variance (RV) for each month is obtained by  $RV_{j,t} = \sum_{j=1}^m r_{j,t}^2$ .

**Table 1** provides the summary statistics for the CPU and MSCI energy index for each country. The mean CPU value is the highest among the variables, at 0.0066, and exhibits the most volatility, with Argentina and Brazil also displaying high volatility. Skewness and kurtosis statistics reveal skewed distributions and extreme values across most series. For instance, the skewness and kurtosis for Argentina are  $-1.4322$  and  $20.1592$  respectively, indicating left-skewness and high levels of extreme values. These statistics suggest non-normal distributions, confirmed by the Jarque-Bera test. The ADF test indicates that the log-differenced series of each variable is stationary.

According to [Bettarelli et al. \(2024\)](#), the OECD Environmental Policy Stringency (EPS) index is a commonly employed measure of CPS. Therefore, we use environmental policy stringency as a proxy for CPS in this study. This index, mainly associated with climate and air pollution policies, spans from 0 (least stringent) to 6 (most stringent). Since the

data only update ends in 2020 and only includes OECD countries, our balanced panel dataset covers 19 countries from 2005 to 2020, based on data availability. Based on [Li et al. \(2022\)](#) and [Sohag et al. \(2024\)](#), we include trade openness level, forest area, population density, industrialization level, carbon emission level, research and development (R&D) expenditure, government consumption expenditure, renewable energy development level, and economic growth level as the control variables. Following [Hassan et al. \(2024\)](#), trade openness is represented as the share of trade in GDP. Higher trade openness allows countries to spread the impacts of external CPU on domestic energy markets through diversified trade. Forest area, expressed as a percentage of forest area to land area, indicates a country's capacity to address climate change. R&D expenditure is expressed as the share of GDP allocated to R&D, reflecting national innovation capacity. Higher R&D expenditure can foster the development of new energy technologies, reducing dependency on traditional energy sources and alleviating risk spillovers from CPU. Government consumption expenditure is expressed by the share of general government final consumption as a percentage of GDP, which shows the role of the state in public policy and economic regulation. Similar to [Sohag et al. \(2024\)](#), industrialization level is expressed as industrial value added as a proportion of GDP, the level of renewable energy development is indicated by the proportion of renewable energy in total final energy consumption, population density is measured as the number of people per square meter of land, the level of carbon emission level is expressed as carbon dioxide emissions per country (metric tons), and the level of economic growth is measured using GDP (constant 2015 dollars) for each country. Missing data is interpolated, and natural logarithmic transformations were applied to the control variables to achieve unify the dimension.

### 4. Method

#### 4.1. HD-TVP-VAR model

This study introduces an improved HD-TVP-VAR model, which relies on the global network defined by generalized variance decomposition of the VAR model. By leveraging the Kalman filtering process and the Elastic Net approach, this model captures both the “high-dimensional” and “time-varying” characteristics of dynamic complex networks. Compared to traditional VAR spillover model ([Diebold and Yilmaz, 2014](#)), this approach ensures consistent estimation results with minimal

**Table 1**  
Descriptive statistics.

	Mean	St.Dev	Skew	Kurtosis	Jarque-Bera	ADF
CPU	0.0066	0.3891	-0.2699	1.1759	16.4300***	-9.2467***
Argentina	-0.0003	0.0302	-1.4322	20.1592	83,482.3631***	-16.0525***
Australia	0.0000	0.0166	-0.9018	12.2445	30,846.0886***	-17.7155***
Austria	0.0000	0.0218	-0.5345	9.7636	19,427.5369***	-16.3491***
Brazil	0.0001	0.0300	-0.7554	10.3244	21,925.4404***	-16.0381***
Canada	-0.0001	0.0166	-1.2001	20.0977	82,491.5993***	-17.7872***
China	0.0001	0.0196	-0.0552	7.5684	11,538.8087***	-16.9078***
Finland	0.0003	0.0222	0.0659	6.4512	8385.7592***	-16.9839***
France	0.0001	0.0169	-0.2451	11.7765	27,976.6112***	-18.5795***
Hungary	0.0001	0.0196	0.1536	6.6741	8990.4244***	-18.4333***
India	0.0004	0.0167	-0.2487	10.6933	23,076.8126***	-15.4207***
Indonesia	0.0000	0.0256	0.3703	5.5373	6286.3939***	-15.4522***
Italy	-0.0001	0.0173	-0.6252	17.3690	61,061.8794***	-18.1700***
Japan	-0.0001	0.0174	-0.3534	4.3433	3900.7842***	-16.8311***
Korea	0.0001	0.0213	0.4608	8.0140	13,105.3341***	-18.2130***
Norway	0.0001	0.0191	-0.4305	6.8328	9552.3256***	-17.4886***
Poland	0.0000	0.0191	-0.1024	20.1642	81,879.4567***	-17.0570***
South Africa	0.0003	0.0222	-0.0646	3.5337	2519.2251***	-18.1984***
Spain	0.0000	0.0196	-0.1189	8.1917	13,525.7940***	-17.1437***
Thailand	0.0000	0.0170	-1.3456	28.1195	160,667.9357***	-17.2732***
Turkey	0.0008	0.0227	-0.2396	4.3976	3941.9000***	-16.8030***
America	0.0002	0.0185	-0.6922	14.9385	45,322.3722***	-16.8023***

Note: \*\*\* indicates that the results are significant at the 1% level.

information loss. It effectively addresses the “curse of dimensionality” commonly encountered in systemic risk studies (Xie et al., 2023), and more accurately reconstructs and simulates the real-world network connections of energy market risks under CPU across countries. HD-TVP-VAR model can be expressed as:

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

where,  $Y_t$  denote an  $n$  dimensional column vector;  $\Phi_{i,t}$  is the time-varying lag coefficient matrix of  $n \times n$ ;  $p$  and  $\varepsilon_t$  are the lag order and random error term, respectively. Let  $Z_{t-1}(p) = (Y'_{t-1}, Y'_{t-2}, \dots, Y'_{t-p})'$  and  $\Phi_t = (\Phi_{t1}, \Phi_{t2}, \dots, \Phi_{tp})$ , Eq. (1) can be simplified as:

$$Y_t = \Phi_t Z_{t-1}(p) + \varepsilon_t \quad (2)$$

This paper assumes that the model coefficients follow a random walk process:

$$\Phi_t = \Phi_{t-1} + u_t \quad (3)$$

where  $\varepsilon_t \sim N(0, \Sigma_t)$ ,  $u_t \sim N(0, Q_t)$ , with  $\varepsilon_t$  and  $u_t$  being mutually independent for anyt.

For time-varying parameter estimation, existing literature typically utilizes the Markov Chain Monte Carlo (MCMC) method (Primiceri, 2005) and Kalman filtering (Koop and Korobilis, 2013), given a prior distribution assumption of initial parameters. However, the effectiveness of this estimation method heavily relies on the setting of prior probability. When the data is extended to high dimensions, models may become unidentifiable due to the extensive number of parameters to be computed.

To address this, we adopt the Elastic Net algorithm to compress parameters to be estimated, tackling the “curse of dimensionality” often encountered in time-varying parameter models. Specifically, Elastic Net estimation achieves coefficient dimension reduction by incorporating penalty terms into the ordinary least squares optimization objective function (Cepni et al., 2022), and it obtains the initial sparse structure of the coefficients by solving the optimization problem as detailed in Eq. (4):

$$\hat{\Phi} = \underset{\Phi}{\operatorname{argmin}} \left\{ \sum_{t=1}^T [Y_t - \Phi Z_{t-1}(p)]^2 + \delta [\alpha \|\Phi\|_1 + (1 - \alpha) \|\Phi\|_2^2] \right\} \quad (4)$$

where  $\|\cdot\|_1$  refers to the vector  $\ell_1$  norm,  $\|\cdot\|_2$  refers to the vector  $\ell_2$  norm,  $\delta$  is the overall penalty strength selected by 10-fold cross-validation that minimizes mean absolute error (MAE).<sup>①</sup> The mixing parameter  $\alpha$  is set to 0.5 throughout, which corresponds to the genuine Elastic net (Koop and Korobilis, 2013) that simultaneously performs variable selection (Lasso) and coefficient shrinkage while encouraging grouped selection (Ridge). Eq. (4) is solved using the coordinate descent algorithm implemented in the R package glmnet.

Following Diebold and Yilmaz (2014), the generalized variance decomposition method quantifies risk connectivity between CPU and national energy markets:

$$\hat{d}_{ij,t}^H = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1} (e'_i \Lambda_{ht} \Sigma_t e_j)}{\sum_{h=0}^{H-1} (e'_i \Lambda_{ht} \Sigma_t \Lambda'_{ht} e_i)} \quad (5)$$

where  $\hat{d}_{ij,t}^H$  represents the cumulative percentage influence of variable  $j$  on variable  $i$  from period  $t$  to  $t - H + 1$ ;  $e_i$  or  $e_j$  is a selection vector with the  $i$  or  $j$  element set to 1, and others set to 0;  $\sigma_{jj,t}$  is the  $j$  diagonal element of the variance-covariance matrix of the HD-TVP-VAR model residuals;  $h$  ( $h = 1, \dots, H$ ) is the forecast window; and  $\Lambda_{ht}$  is the coefficient of an infinite-order time-varying parameter vector moving average model (TVP-VMA ( $\infty$ )), and its recursive relationship can be expressed as  $\Lambda_{it} = \sum_{j=1}^p \Phi_{jt} \Lambda_{(i-j)t}$ . The generalized variance decomposition matrix is then

normalized to yield:

$$\hat{d}_{ij,t}^H = \hat{d}_{ij,t}^H \left( \sum_{j=1}^N \hat{d}_{ij,t}^H \right)^{-1} \quad (6)$$

$\hat{d}_{ij,t}^H$  measures the cumulative risk spillover effect from variable  $i$  to variable  $j$  at time  $t$ . Based on this, we can construct the Total Connectedness Index (TCI) for the complex network of global energy markets under CPU over period  $t$ :

$$TCI_t = \sum_{i=1}^N \left( \sum_{j=1, j \neq i}^N \hat{d}_{ij,t}^H \right) / N \quad (7)$$

Furthermore, we define the risk reception (From), risk spillover (To), and net risk spillover (Net) of the  $i$  variable at time  $t$ :

$$From_{i,t} = \sum_{j \neq i} \hat{d}_{ij,t}^H / N, To_{i,t} = \sum_{j \neq i} \hat{d}_{ji,t}^H / N \text{ and } Net_{i,t} = To_{i,t} - From_{i,t} \quad (8)$$

#### 4.2. Dual machine learning

To effectively identify whether CPS can mitigate the risk spillovers from CPU to various national energy markets, this work utilizes a Double Machine Learning (DML) model to assess effectiveness of CPS. Unlike traditional causal inference models, this approach allows for control over a high-dimensional set of potential covariates while relaxing the assumption of linear relationships. Thus, it can estimate treatment effect coefficients accurately without requiring predefined relationships among covariates, between covariates and core explanatory variables, and between these variables and the dependent variable.

First, we construct the following partially linear model:

$$To_{it} = \theta_0 CPS_{it} + h(X_{it}) + U_{it} \quad (9)$$

$$E(U_{it} | CPS_{it}, X_{it}) = 0 \quad (10)$$

where,  $i$  denotes the country;  $t$  indicates the year;  $To_{it}$  represents the dependent variable, which is the risk spillover of CPU to energy market of various countries;  $CPS_{it}$  stands for climate policy stringency, a continuous variable, and the coefficient  $\theta_0$  reflects the impact of CPS on risk spillover.  $X_{it}$  is a high-dimensional set of control variables that affects the dependent variable through the function  $h(X)$ . The specific form of  $\hat{h}(X_{it})$  will be estimated via machine learning algorithms, and the error term  $U_{it}$  satisfies the zero-mean assumption.

Traditional parametric regressions often specify  $h(X_{it})$  as fully linear or containing interaction or squared terms, then estimate through OLS, which risks model misspecification and biased estimates. Using nonparametric methods, such as kernel regression, to estimate  $h(X_{it})$  avoids functional form bias but may suffer from the “curse of dimensionality” owing to the high dimensionality of the covariates  $X_{it}$ , rendering the estimation ineffective. For this reason, we employ the random forest method from machine learning to estimate  $h(X_{it})$ , yielding the following treatment effect estimator:

$$\hat{\theta}_0 = \left( \frac{1}{n} \sum_{i \in I, t \in T} CPS_{it}^2 \right)^{-1} \frac{1}{n} \sum_{i \in I, t \in T} CPS_{it} (To_{it} - \hat{h}(X_{it})) \quad (11)$$

where,  $I$  is the total sample at the country level,  $T$  denotes the total sample at the time level, and  $n$  represents the sample size.

To make that the coefficient estimator is unbiased in small samples, the following auxiliary regression is constructed:

$$CPS_{it} = m(X_{it}) + V_{it}, E(V_{it} | X_{it}) = 0 \quad (12)$$

where,  $m(X_{it})$  is a regression function of the treatment variable on high-dimensional covariates, obtained via machine learning algorithms. The error term  $V_{it}$  satisfies the zero-mean assumption. Based on Eq. (11),

**Table 2**  
Static spillover results of CPU and energy markets.

	CPU	Argentina	Australia	Austria	Brazil	Canada	China	Finland	France	Hungary	India	Indonesia	Italy	Japan	Korea	Norway	Poland	SouthAfrica	Spain	Thailand	Turkey	America
CPU	47.19	0.06	0.42	0.57	0.73	0.31	0.02	0.42	0.44	0.29	0.03	15.20	0.39	0.20	0.69	0.08	15.95	15.85	0.22	0.20	0.45	0.31
Argentina	0.11	12.99	6.69	7.46	6.99	7.52	0.53	3.56	7.51	4.87	4.49	0.15	7.19	3.54	3.65	0.76	0.05	0.07	6.14	6.60	1.44	7.69
Australia	1.06	5.17	9.67	6.61	7.01	8.65	0.63	3.81	8.24	4.35	5.35	0.53	6.36	4.31	3.95	1.60	0.39	0.41	5.94	6.46	2.97	6.50
Austria	0.48	5.31	6.09	9.02	6.80	7.42	0.74	4.02	7.48	6.27	5.73	0.35	7.64	4.94	4.10	1.09	0.16	0.18	5.52	6.67	1.85	8.15
Brazil	0.39	5.51	7.20	7.53	10.07	7.88	0.53	3.60	8.16	4.95	5.01	0.34	7.70	4.59	4.23	1.02	0.12	0.13	5.61	6.56	1.21	7.65
Canada	0.62	5.40	8.05	7.48	7.18	9.09	0.56	3.72	8.17	5.38	5.47	0.37	6.89	4.50	3.66	1.51	0.22	0.24	5.37	6.69	2.11	7.32
China	22.49	1.95	2.87	3.61	3.73	3.01	2.41	2.33	3.19	2.76	1.58	11.12	3.20	2.00	2.78	1.99	10.30	10.07	2.44	2.59	0.42	3.17
Finland	7.77	3.55	4.90	5.64	4.65	5.14	0.75	12.59	5.19	4.64	3.75	3.62	5.49	3.32	4.76	0.74	3.59	3.59	4.75	4.44	1.57	5.55
France	0.58	5.18	7.41	7.25	7.12	7.85	0.58	3.59	8.72	5.61	4.96	0.31	7.70	5.09	4.29	1.14	0.20	0.22	6.60	6.58	1.50	7.52
Hungary	24.67	1.61	2.26	3.26	2.78	2.67	0.60	1.98	2.93	3.88	1.88	11.87	2.91	2.28	2.32	0.48	11.72	11.62	2.23	2.37	0.66	3.03
India	18.39	2.42	3.59	4.30	3.78	3.96	0.52	2.13	3.92	3.34	5.93	8.40	3.55	2.97	2.32	1.11	8.67	8.71	2.55	3.75	1.71	3.93
Indonesia	37.49	0.23	0.70	0.91	1.09	0.60	0.15	0.67	0.73	0.54	0.12	17.55	0.68	0.38	0.92	0.21	17.67	17.53	0.46	0.44	0.32	0.59
Italy	0.26	5.18	5.98	7.76	7.01	6.94	0.88	3.96	8.03	5.96	4.62	0.21	9.08	5.18	4.78	0.97	0.09	0.12	6.49	6.57	1.63	8.30
Japan	0.34	3.47	5.36	6.79	5.72	6.13	1.46	3.36	7.26	7.17	5.90	0.27	7.03	12.80	4.18	1.39	0.14	0.19	5.85	5.63	2.29	7.29
Korea	1.40	3.91	5.54	6.18	5.79	5.44	1.86	5.00	6.67	5.81	3.97	0.58	7.14	4.53	13.65	0.86	0.43	0.45	6.28	6.19	1.08	7.18
Norway	19.09	2.92	3.18	3.64	3.64	3.59	2.29	1.85	3.67	2.88	2.85	8.64	3.66	2.20	2.39	2.88	9.61	9.77	2.82	3.36	1.38	3.76
Poland	39.49	0.05	0.35	0.48	0.61	0.26	0.03	0.35	0.36	0.23	0.04	17.95	0.32	0.17	0.57	0.09	18.88	18.77	0.18	0.16	0.41	0.25
SouthAfrica	38.91	0.04	0.33	0.44	0.57	0.23	0.03	0.33	0.33	0.21	0.04	18.24	0.29	0.15	0.52	0.08	19.19	19.12	0.17	0.15	0.42	0.23
Spain	0.46	5.32	6.82	6.75	6.20	6.50	1.02	4.14	8.34	5.54	3.83	0.25	7.92	5.12	5.13	0.80	0.15	0.17	11.13	6.25	0.78	7.37
Thailand	0.38	5.28	6.80	7.53	6.68	7.49	0.78	3.54	7.66	5.58	5.57	0.21	7.36	4.60	4.64	0.88	0.13	0.17	5.74	10.20	0.90	7.88
Turkey	1.29	3.20	4.10	5.06	3.64	5.15	2.07	3.09	4.35	4.31	7.62	0.53	3.69	5.10	2.40	4.90	0.58	0.65	1.84	2.67	29.39	4.39
America	0.28	5.36	5.92	8.03	6.78	7.15	0.94	3.90	7.62	6.36	5.14	0.21	8.05	5.22	4.68	0.96	0.09	0.13	5.89	6.83	1.65	8.83
To	9.82	3.23	4.30	4.88	4.48	4.72	0.77	2.70	5.01	3.96	3.54	4.52	4.78	3.20	3.05	1.03	4.52	4.50	3.78	4.14	1.22	4.91
From	2.40	3.96	4.11	4.14	4.09	4.13	4.44	3.97	4.15	4.37	4.28	3.75	4.13	3.96	3.92	4.41	3.69	3.68	4.04	4.08	3.21	4.14
Net	7.42	-0.72	0.19	0.74	0.39	0.59	-3.66	-1.27	0.86	-0.41	-0.73	0.77	0.65	-0.77	-0.88	-3.38	0.83	0.83	-0.26	0.06	-1.99	0.77
TCI = 87.04																						

we obtain the residual term  $\hat{V}_{it} = CPS_{it} - \hat{m}(X_{it})$ .

Yield an unbiased coefficient estimator through regression:

$$\hat{\theta}_0 = \left( \frac{1}{n} \sum_{i \in I, t \in T} \hat{V}_{it} CPS_{it} \right)^{-1} \frac{1}{n} \sum_{i \in I, t \in T} \hat{V}_{it} (TO_{it+1} - \hat{h}(X_{it})) \quad (13)$$

## 5. Empirical results

### 5.1. Static spillover

We investigate the risk spillovers between the international energy market and the CPU, and Table 2 reports the static spillover results. From the table, the CPU is the strongest risk spillover, but also the largest net risk spillover. As energy markets become more globalized, changes in one country's key policies can rapidly affect energy prices and supply chains in other countries (Zhu et al., 2024). This means that any change in the CPU is likely to trigger fluctuations in global energy prices and adjustments in energy supply chains (He et al., 2024). In global supply chain networks, many countries are interconnected by sharing energy infrastructure, such as pipelines, power grids, and trade routes (Jin et al., 2024). At the same time, energy enterprises among countries have formed a fine division of labour cooperation model, and energy markets among countries are interdependent (Singh et al., 2019). When impacted by CPU, disruptions or uncertainty in one region can quickly spread to other countries and even entire networks, amplifying risks. In the context of the financialization of energy markets, the behaviour of national energy companies, such as capital consolidation and cross-border investment, means that CPU may affect the sentiment and behaviour of global investors, with capital flows increasing and risk contagion accelerating (Qiao et al., 2024; Zhang et al., 2023a). Our static spillover analysis indicates that France's contribution to systemic risk in energy is only after the CPU and that its net risk spillover is second. Similarly, Jin et al. (2024) found that the French energy market ranks first in terms of systemic importance among various countries. France's role in the global energy system may be partly associated with the active participation of major energy companies, such as Total, Engie, and EDF, in international energy investments (Li et al., 2021). According to existing literature, such extensive cross-border business interaction could facilitate greater connectivity between the French energy market and those of other countries, with potential implications for risk transmission (Li et al., 2021). French energy investors not only excel in holding foreign energy stocks but also attract numerous international investors to their energy stock market (Li et al., 2017). The high degree of financialization in the energy sector, along with frequent capital flows and information exchanges, may offer a possible explanation for France's influential role observed in our analysis.

### 5.2. Network spillover

To offer a more intuitive view of the risk spillover effects of CPU with global energy markets, Fig. 2 illustrates the net risk spillover effects of CPU on national energy markets. The arrows represent the direction of risk transmission between nodes, while the line thickness reflects the intensity of the spillover. To simplify and clarify the risk contagion among variables, the network graph displays only the lines with weights in the top 50%. The size of each node reflects its net spillover in the risk network. Green nodes represent net recipients of risk, whereas red nodes are net initiators. It can be seen that the risk connectivity network is connected densely, which proves that there is a complex risk relationship among energy markets across countries under the CPU situation. This finding recalls the outcome of Gong et al. (2023), as they found that risks between international energy markets can easily be cross-communicated by market linkages, i.e., there are strong linkages between risk contagion in international energy markets. Next, we focus on the size and direction of CPU risk spillovers. As shown in Fig. 2, the CPU,

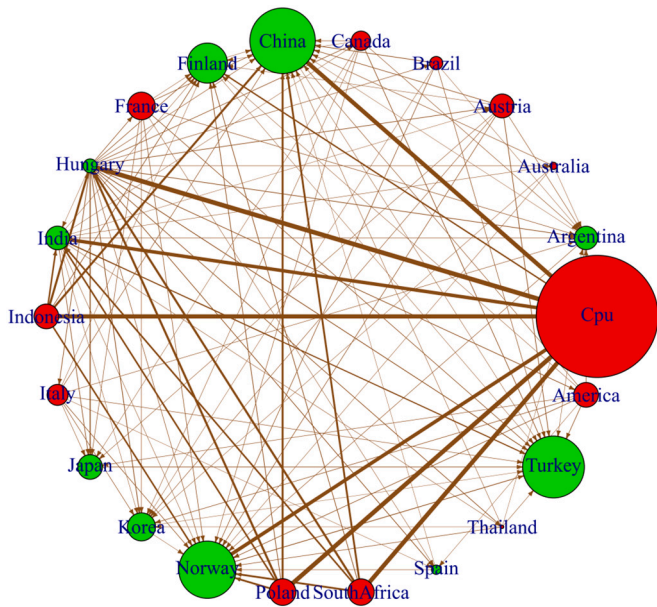


Fig. 2. The risk spillover network between CPU and national energy markets.

as the largest net risk spillover among network nodes, has varying degrees of spillover effects on the energy markets of different countries. This indicates that the CPU exerts a broad influence on the global energy market, which will directly affect the market expectations and policy responses of other nations. When the CPU changes, companies and investors reassess their investments in energy projects, leading to fluctuations in capital markets and sharp changes in energy prices across countries (Qiao et al., 2024).

Our static spillover analysis reveals that Poland, South Africa, Indonesia, Hungary, China, Norway, and India exhibit stronger connections with the CPU, indicating that the CPU exerts a relatively significant risk spillover effect on the energy markets of these countries. This phenomenon appears to align with the energy structures of these nations. Poland and Hungary are highly dependent on fossil fuels, South Africa, Indonesia, and Norway are important exporters, and China and India are the world's largest consumers of fossil fuels (Saba, 2023). Such structural characteristics are often associated with limited flexibility in responding to sudden events (Mille et al., 2025; Pescaroli and Alexander, 2016). High fossil fuel dependence tends to coincide with relatively unstable energy supply chains, and these countries may face elevated adjustment costs and market risks amid global price fluctuations related to climate policy shifts (Wang et al., 2025; Gourdel et al., 2025). Furthermore, a lack of diversified energy sources is generally considered to reduce the capacity to adapt quickly to external shocks (Mille et al., 2025). As CPU increases, capital markets may reassess the risk premium of energy firms in these nations (Qiao et al., 2024). From the perspective of behavioral finance, investors tend to divest from energy assets in countries that are highly dependent on fossil fuels in favour of those with more independent energy structures (Cui and Maghyereh, 2025; Tissaoui and Zaghdoudi, 2025). In such cases, capital outflows and market turmoil could ensue, which in turn may create risks in energy markets (Qiao et al., 2024). The colour and size of nodes indicate that Indonesia, Poland, and South Africa's energy markets have large positive net spillover values in the systemic risk network. This means that, in the case of CPU, these countries' energy markets could become the main channel for risk spillovers. In other words, while they accept that the risk spilling out from the CPU is greater, they may transmit the risk to other countries through a network of systemic risks. This may be linked to their extensive energy trading links. Poland is not

only a key transit country for gas deliveries in Europe, but also a member of the European electricity market (Do et al., 2024). South Africa and Indonesia, as major coal exporters, are important players in the energy trade (Muteba Mwamba and Mwambi, 2021). When CPU increases, Poland, South Africa, and Indonesia can easily spill risk into other countries' energy markets through international energy trade. Additionally, France, Austria and the United States also play a more important role in "risk spillover" in the systemic risk network. This outcome supports the results of Akyildirim et al. (2022). He noted that these countries were almost always net spillovers over the sample period. One possible reason is that they have established strong energy partnerships with others. France and Austria actively participate in cross-border energy infrastructure projects within the EU. As the world's largest oil and gas producer, the US also exerts substantial influence on the international market through its energy trade and cooperation with other countries. Such energy collaborations help these nations enhance their capacity to transmit risk within the global energy system. However, the direct impact of CPU on them is relatively small, which may be closely related to the special status of their financial markets. The mature financial systems of France, Austria and the United States provide sufficient liquidity to their energy markets, allowing them to quickly secure funding through diversified financing channels in times of risk. Moreover, due to the international influence of their financial markets, risks can often be diversified across borders, which enhances their ability to resist risks.

### 5.3. CPU dynamic risk spillover to energy markets

While network connectivity represents the overall level of CPU risk spillover to national energy markets, it is not sufficient to reveal the dynamic changes of CPU risk spillover to national energy markets over the entire time span. To capture the dynamic features of CPU spillover risk to national energy markets, we calculate the time-varying risk spillover of CPU to national energy markets.

Fig. 3 shows the results of the dynamic evolution of CPU risk spillover to national energy markets. The time-varying risk spillover from CPU to national energy markets shows heterogeneity. However, the response times of these energy markets to CPU are nearly synchronous.

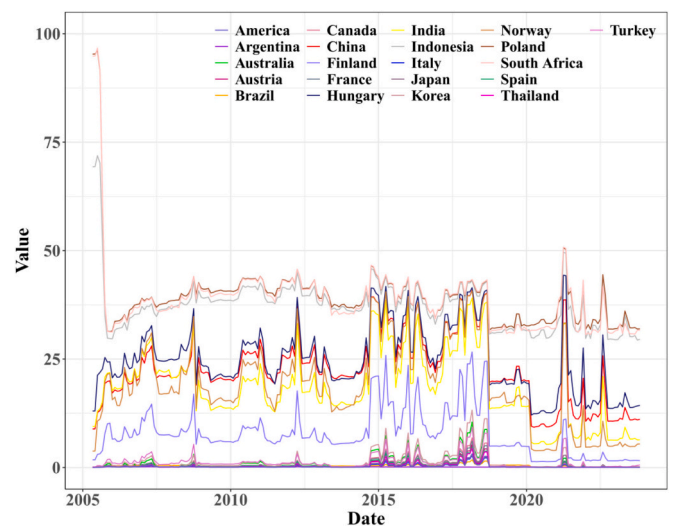


Fig. 3. Dynamic risk spillover of CPU to national energy markets.

This indicates that CPU risk spillovers can rapidly spread within the system to affect energy markets across countries. Each phase of strong risk spillovers from CPU to national energy markets is often accompanied by the occurrence of extreme events.

The first phase was from April 2008 to February 2009. During this period, risk spillovers increased rapidly, reaching a peak in October 2008 in particular. This period coincided with the emergence of the global financial crisis (Apergis and Payne, 2018). The financial crisis led to a sharp drop in energy demand and disruptions in energy production and distribution (Do et al., 2024). Energy markets are less stable and far more risk-sensitive. The formulation of climate policy has become more uncertain due to increasing economic pressures, which has caused the energy market to react more intensely to CPU, leading to a surge in CPU-to-energy risk spillovers.

The second stage was from March 2012 to June 2012, with risk spillovers peaking again in April 2012. During this period, extreme weather events occurred frequently around the world, posing multiple challenges to climate policy. In February 2012, Europe experienced severe cold weather, leading to a surge in heating demand and resulting in energy shortages and skyrocketing prices in the energy market. At the same time, the U.S. East Coast was struck by “Superstorm” Sandy, which severely damaged energy infrastructure and forced the shutdown of refineries and power grids. These extreme climate events not only disrupted global energy supply but also increased uncertainty in the legislative and enforcement aspects of climate policy in various countries, leading to heightened fluctuations in expectations regarding the energy market (Zhang and Chen, 2024). Consequently, the spillover of CPU risk to energy markets became more severe.

The third phase spans from August 2014 to September 2018. Notably, during this period, CPU risk spillovers remained at a high level for an extended time. This may be related to the 2016 Brexit referendum and the escalation of US-China trade tensions (Xiao et al., 2024). These events heightened uncertainty around international cooperation, prompting countries to take a more cautious approach to climate-related policies, delaying or reassessing various emission reduction measures. Additionally, trade tensions increased the costs of energy transition, leading to fluctuations in the energy market and intensifying CPU risk spillovers to the energy sector (Cheng et al., 2023). Interestingly, risk spillovers fell significantly between February 2020 and April 2020, suggesting that climate policy-related risks have a relatively mild impact on the energy market. This may be related to the government's reduced focus on climate policy amid the COVID-19 pandemic. During this period, policy makers prioritized economic recovery (Mišák and Nosko, 2023). Countries implemented a series of economic stimulus measures in response to the pandemic, rather than pursuing long-term climate policy goals. At the same time, there was a delay in both the legislation and enforcement of climate policies in many countries (Mišák and Nosko, 2023). As a result, the shift in government attention might have temporarily weakened the risk spillover effect of CPU on the energy market.

The fourth phase, from March 2021 to October 2022, saw a renewed rise in risk spillovers from CPU to national energy markets (Liu et al., 2021). On one hand, the drawbacks of the post-pandemic era are gradually emerging, with the energy market still facing persistent supply and demand imbalances and a slow recovery. At the same time, the increased frequency of extreme weather events makes the already fragile supply chain more susceptible to disruptions, heightening risks within energy markets (Cheng et al., 2023). On the other hand, geopolitical conflicts further exacerbated these effects. For example, the Russia-Ukraine conflict has prompted a global energy market realignment, with countries accelerating policy adjustments to address supply chain

risks and energy security concerns. These adjustments have led to increased energy price volatility and market uncertainty, increasing investor sensitivity to climate policy-related risks. The combination of these multiple risk factors has significantly amplified the risk transmission effects of CPU on the energy market.

Moreover, at the national level, the energy markets of South Africa, Poland, Indonesia, Hungary, India, Norway, China, and Finland experience relatively high CPU risk spillovers, aligning with static spillover results. Among these, CPU has the strongest impact on the energy markets of South Africa, Poland, and Indonesia, likely due to slow progress in their energy transition policies (Bekun, 2024; Igliński et al., 2022). For instance, South Africa aims to raise its renewable energy share to 30% by 2030, yet by 2022, it had only reached 13%. Similarly, Indonesia's goal of achieving a 23% renewable energy share by 2025 stood at just 12% in 2022. Poland's energy transition has also lagged, with renewable energy growth from 2015 to 2020 at only around 5%, significantly below the EU average. Although Poland has pledged to phase out coal by 2049, as of 2023, coal still accounts for over 70% of its electricity generation. Overall, these countries' slow energy transitions and heavy reliance on fossil fuels reduce their flexibility in responding to CPU risks, increasing their market vulnerability and making them more susceptible to spillover risks.

#### 5.4. The relationship between CPS on CPU risk spillover

The network connectivity results reveal a clear dynamic risk spillover effect of CPU on energy markets across countries. Examining whether the stringency of national climate policy can effectively mitigate this dynamic spillover effect is essential, as it can help policymakers in adjusting macroprudential policy to control the risk contagion posed by foreign CPU. For this purpose, we further investigate the relationship between CPS and CPU's risk spillovers.

This article utilizes a double machine learning (DML) method to examine the association between CPS and the risk spillover effect of CPU on energy markets across countries. Following Wang et al. (2024), the ratio of sample segmentation is 1:4, and the primary and auxiliary regressions are solved using random forest algorithm. The empirical findings are presented in Table 3. In column (1), which includes national fixed effects, time fixed effects, and other country variables. The regression coefficient of CPS on risk spillover is  $-0.081$  ( $p < 0.01$ ), suggesting that CPS can significantly reduce the risk spillover effect of CPU on energy markets in various countries. Countries with stricter climate policy are better equipped to counteract the contagion effects stemming from external CPU. Similarly, column (2) displays the outcomes controlling for time fixed effects, and both linear and quadratic terms of other country variables. The regression coefficient of CPS on risk spillover effect has changed, but the estimated coefficient remains significantly negative, not altering the previous conclusion, thereby

**Table 3**  
Impact of CPS on CPU risk spillovers.

Variables	(1) To	(2) To	(3) To	(4) To
CPS	$-0.081^{***}$ (0.028)	$-0.057^*$ (0.034)	$-0.084^{***}$ (0.029)	$-0.083^{***}$ (0.029)
Linear term	Yes	Yes	Yes	Yes
Quadratic term	No	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes
Country FE	Yes	No	Yes	Yes
Sample size	304	304	304	304

Note:  $*** p < 0.01$ ,  $** p < 0.05$ ,  $* p < 0.1$ . Standard errors are in parentheses.

confirming the results of column (1). Next, column (3), after controlling for country fixed effects, and both linear and quadratic terms of other country variables, is similar to the results of model (1), further supporting the mitigating role of CPS in risk spillover effects. Based on models (1), (2), and (3), after controlling for time fixed effects, country fixed effects, and the linear and quadratic terms of other country variables in model (4), the regression coefficient remains significantly negative at the 1% level, and its value is very close to those in models (1) and (3). This suggests that CPS can effectively mitigate the risk spillover of external CPU on the domestic energy market. This result may be attributed to countries with stringent climate policies fostering diverse energy structures and robust regulatory frameworks. By promoting renewable energy, boosting energy efficiency, and decreasing fossil fuel dependence, these countries enhance the resilience and autonomy of their energy markets. Consequently, stringent policy countries show reduced sensitivity to fluctuations in external policy uncertainty.

5.5. Robustness test

To test the robustness of the dynamic risk spillover of CPU to national energy markets, we adjusted the prediction horizon of the model and re-evaluated this spillover effect.<sup>2</sup> The results of the dynamic risk spillover of CPU to national energy markets when the prediction horizon is set to 20 and 40 are presented in Fig. 4 and Fig. 5, respectively. As is clearly shown in the figures, the results obtained with the prediction horizons of 20 and 40 are very close to the estimates under the benchmark prediction horizon of 30, which verifies the robustness of our findings. Second, we modified the  $\alpha$  value to examine the robustness of our findings. Fig. 6 and Fig. 7 depict the dynamic risk spillover of CPU to national energy markets when  $\alpha = 0.2$  and  $\alpha = 0.8$ , respectively. As illustrated in figures, the overall trend in dynamic risk spillover of CPU closely aligns with the original results when  $\alpha$  is adjusted to 0.2 and 0.8, proving that the result of risk spillover is robust.

To avoid potential biases in model setting arising from the double machine learning (DML) method, this study conducts robustness test by resetting the DML model. First, the sample split ratio in the DML model setting is changed from 1:4 in the baseline regression to 1:2 and 1:6 to verify whether changes in the sample split ratio will affect the baseline

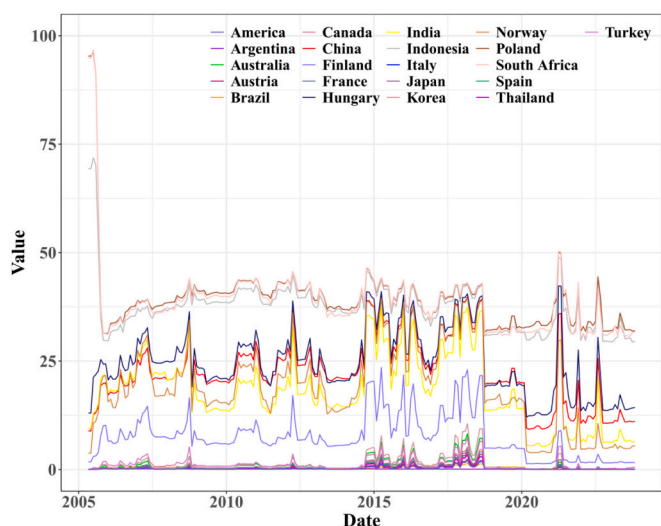


Fig. 4. Dynamic risk spillover of CPU to national energy markets when the prediction horizon is set to 20.

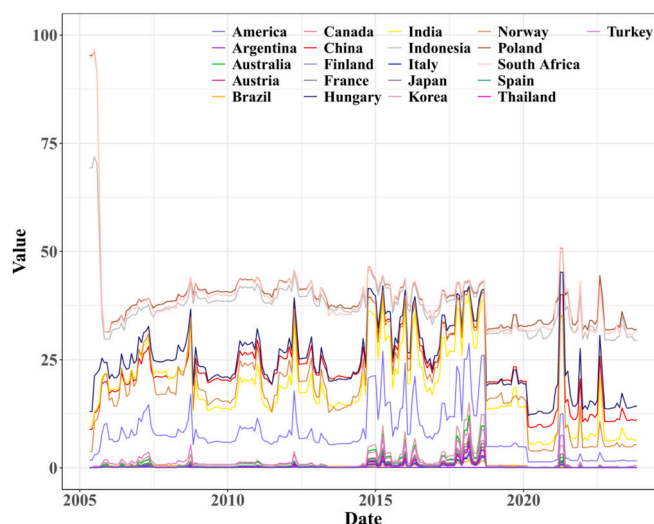


Fig. 5. Dynamic risk spillover of CPU to national energy markets when the prediction horizon is set to 40.

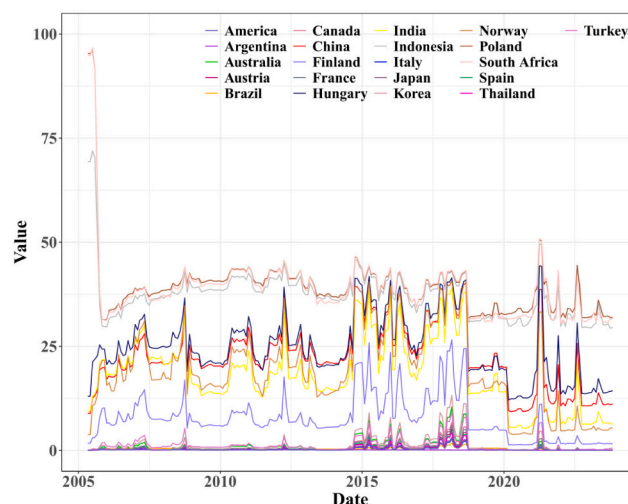


Fig. 6. Dynamic risk spillover of CPU to national energy markets at  $\alpha = 0.2$ .

conclusion. Second, the machine learning algorithm is replaced, changing the previously used random forest for prediction to support vector machine, gradient boosting, and neural network to test the possible impact of algorithm change on the conclusion of this paper. Table 4(1) and (2) present the robustness test of the reset DML model. Notably, neither adjusting the sample split ratio nor changing the machine learning algorithm alters the significant negative association between CPS and CPU's risk spillovers. Furthermore, while U.S. policy shifts historically exert substantial international spillovers due to the country's economic dominance and leadership in global climate negotiations, climate policy shifts and associated uncertainty are increasingly shaped by a diverse set of jurisdictions worldwide. To address this concern, we re-estimate the risk spillovers using the global climate

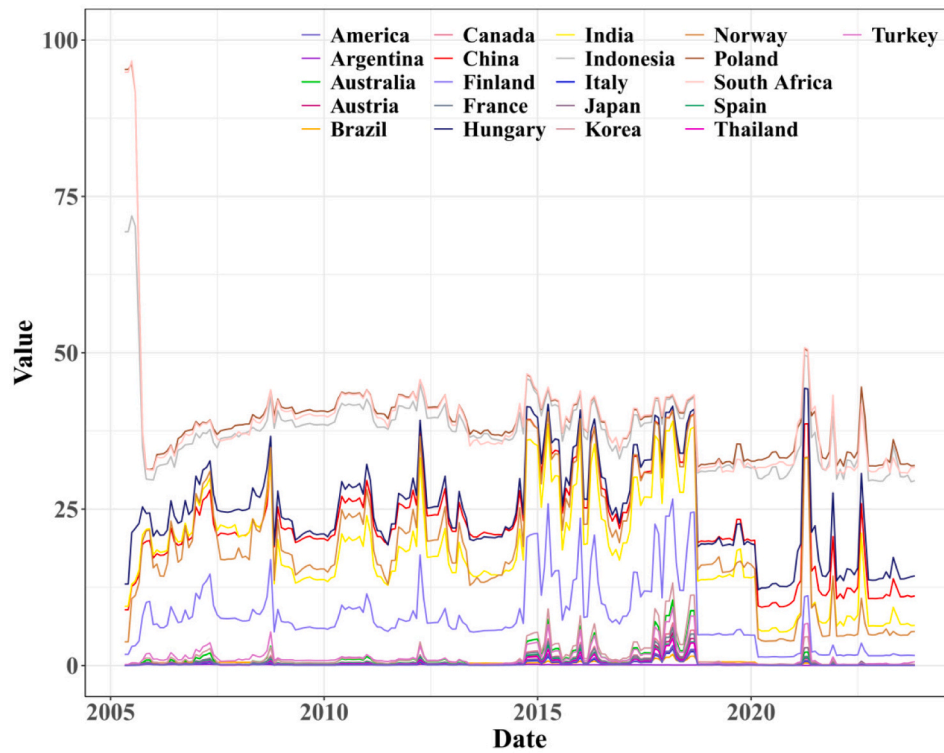


Fig. 7. Dynamic risk spillover of CPU to national energy markets at  $\alpha = 0.8$ .

Table 4

Robustness test.

Variables	(1) Replacing machine learning methods		(2) Altering the sample split ratio			(3) Replacing the dependent variable
	Svm	Nnet	Gradboost	Kfolds = 3	Kfolds = 7	
CPS	-0.079*** (0.017)	-0.738* (0.403)	-0.067*** (0.025)	-0.058** (0.026)	-0.088** (0.035)	-0.716* (0.408)
Linear term	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic term	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	304	304	304	304	304	304

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Standard errors are in parentheses.

policy uncertainty (GCPU) index<sup>1</sup> developed by Ma et al. (2024), and then replaced the dependent variable with the risk spillovers from GCPU to energy markets to conduct the regression via the DML method. As shown in column (3) of Table 4, the core conclusion of this paper remains consistent.

## 6. Conclusion

The increase in CPU has triggered global concerns about the energy market. Due to the interdependence of energy markets across countries, an increase in CPU not only causes turmoil in domestic energy markets but also risks spillover to other countries through energy trade or other channels, thereby triggering a series of chain reactions on a global scale. In light of this, this paper first uses the improved high-dimensional time-varying parameter vector autoregressive spillover (HD-TVP-VAR) model to discuss the risk connectivity between CPU and the global energy

market and examine the dynamic risk spillover of CPU to various countries. To explore the role played by CPS, this article further employs DML to test the role of CPS in the risk contagion of CPU to the energy market.

In terms of static connectivity, the systemic risk contagion within global energy markets under the situation of CPU demonstrates a high connectivity. Network diagram analysis reveals that the risk connections between CPU and national energy markets are quite tight, showing a high-dimensional, complex network structure. CPU exerts varying levels of risk spillover effects across countries' energy markets. Especially for countries such as Poland, South Africa, Indonesia, Hungary, China, Norway, and India, the CPU risk spillover they receive is relatively significant. However, among these, the energy markets of Indonesia, Poland, and South Africa contribute significantly to systemic risk connectivity within the systemic risk network. France, Austria, and the United States also act as significant "risk spillovers" within the systemic risk network, despite a relatively moderate direct impact from CPU to them. In terms of dynamic connectivity, the risk spillovers from CPU to national energy markets exhibit obvious time-varying characteristics and are almost always accompanied by typical climate risk-related events during the upward phase of risk spillovers. At the country

<sup>1</sup> This index is constructed as the scaled frequency of articles discussing climate policy uncertainty in leading newspapers from twelve countries across six continents: Australia, Brazil, Canada, China, France, Germany, India, Japan, South Africa, South Korea, the United Kingdom, and the United States.

level, there are marked differences in the dynamic risk spillover from CPU to energy systems of different countries. Similar to the static connectivity results, the energy markets in South Africa, Poland, Indonesia, Hungary, India, Norway, China, and Finland have received relatively larger dynamic risk spillover from CPU. Notably, the dynamic risk spillovers into South African, Polish, and Indonesian energy markets are particularly prominent. Furthermore, the stringency of climate policies contributes significantly to mitigating the risk spillovers from CPU to energy markets, alleviating the adverse effects of external CPU on the stability of domestic energy markets.

This study reveals that global energy market risk connectivity is notably high under CPU conditions, implying a strong risk contagion among national energy systems amid CPU fluctuations. Countries around the world need to work together, utilizing international cooperation mechanisms, to strengthen cross-border data sharing and information transparency, and to enhance risk management in global energy markets. Establishing a cohesive cross-border regulatory framework for risk contagion control is essential, fostering a unified and robust defence system. Given the varied intensity of CPU spillover effects across countries, policymakers should tailor risk management strategies to the unique contagion characteristics of their energy systems. Especially for Poland, South Africa, Indonesia, Hungary, China and other countries, diversifying the energy mix and reducing the vulnerability of the energy systems are crucial. Specifically, governments can encourage clean-energy initiatives through tax incentives, subsidies, and financial incentives to enhance the energy system's independence. Additionally, international climate cooperation—through global climate accords or bilateral agreements—can provide technological and financial assistance to strengthen energy system resilience. In response to CPU fluctuations, countries need to manage not only their own exposure to CPU spillovers but also be vigilant about potential contagion from other countries, especially risk net-transmitting countries such as Indonesia, Poland, and South Africa. Establishing comprehensive early-warning systems and response mechanisms will be vital in bolstering market resilience and stability. As key net senders of information in systemic risk networks, France, Austria, and the United States, they need to consider risk sources and transmission characteristics while regulating their energy systems, despite their relatively lower direct exposure to CPU. This can help them effectively control the direction and intensity of policy instruments to mitigate the strength of risk contagion between energy systems.

Considering the time-varying characteristic of the dynamic spillover effects of CPU on energy systems, policymakers in various countries need to strengthen the construction of real-time monitoring and early warning systems for the energy market, particularly during periods of frequent extreme climate events. In other words, governments need to establish a dynamic energy market risk monitoring mechanism to promptly capture fluctuations caused by uncertainties in climate policies. With real-time surveillance, countries can quickly identify critical moments when risks escalate and take appropriate measures to avoid large-scale systemic risk transmission. In particular, countries experiencing pronounced spillover effects—such as South Africa, Poland, and Indonesia—need to be highly vigilant about the influence of external

climate policy changes on their energy markets and track their dynamic contagion paths in a timely manner. Investors also need to pay special attention to these countries when formulating investment portfolio strategies and consider them as key countries for constructing investment portfolios. In fact, governments can formulate reasonable risk prevention mechanisms according to the risk transmission characteristics of different periods. During periods of frequent CPU fluctuation spillovers, establishing energy security reserves provides short-term buffers when the energy supply chain faces external shocks, maintaining basic stability in the energy market. Strengthen energy market monitoring, tracking and analyzing the potential impact of international climate policy changes on domestic markets in real-time. During periods of relatively stable CPU fluctuation spillovers, enhance the energy market feedback mechanism to provide strong support for policy adjustments in the long term. Identifying potential weak links in the market to reduce the chances of systemic risk outbreaks is also essential. We found that stricter climate policies help mitigate the risk of contagion brought by CPU. Countries need to be informed of the role of CPS in stabilizing energy systems. In practice, strengthens the implementation of scientifically sound and reasonable climate policies, enhances the resilience of energy systems, and mitigates the influence of external policy uncertainty. Improve the construction of energy financial industry prevention mechanisms to reduce the risk interaction effects of energy systems due to CPU fluctuation.

While our study provides new findings regarding risk spillovers of CPU on energy markets, several promising avenues remain for future research. First, future work may further explore the underlying transmission mechanisms by explicitly incorporating macro-financial channels such as interest rates, exchange rates, commodity prices, and investor sentiment. Second, future research could further examine how differences in financial market development and market conditions (e.g., bull versus bear regimes) shape the dynamics of risk transmission.

#### **CRedit authorship contribution statement**

Qingyuan Zhu: Methodology, Supervision, Software, Resources, Data curation, Visualization, review – original draft; Di Ma: Conceptualization, Methodology, Software, Resources, Data curation, Visualization, Writing - original draft; Muhammad Ali Nasir: Conceptualization, Methodology, Software, Resources, Data curation, Writing - review & editing.

#### **Declaration of competing interest**

The authors declare no conflicts of interests.

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#### **Appendix A. Robustness of dynamic risk spillovers under alternative model specifications**

To further evaluate the robustness of the risk spillover estimates, we re-estimated the HD-TVP-VAR model under alternative prediction horizons and alternative Elastic Net mixing parameters. This appendix presents the differences between these robustness estimates and the baseline specification. Specifically, [Figs. A.1 and A.2](#) plot the time-varying differences in CPU spillovers for each national energy market, while [Tables A.1 and A.2](#) further report the corresponding mean and maximum absolute differences. As shown in the figures and tables, under alternative  $\alpha$  values, both the mean and maximum absolute differences remain extremely small across all countries. Under alternative prediction horizons, although the differences are relatively larger for a few countries during certain periods, their overall magnitudes remain modest and do not alter the core conclusions of the paper. These findings confirm that the estimated dynamic spillover patterns are highly robust to alternative model specifications.

(a) prediction horizon=20

(b) prediction horizon=40

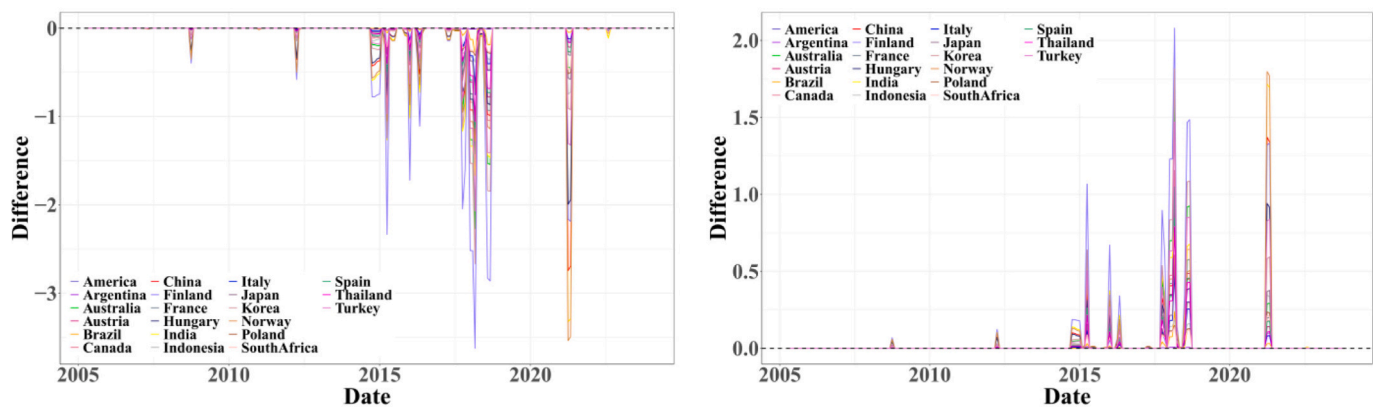


Fig. A.1. Difference under alternative prediction horizons.

(a)  $\alpha = 0.2$

(b)  $\alpha = 0.8$

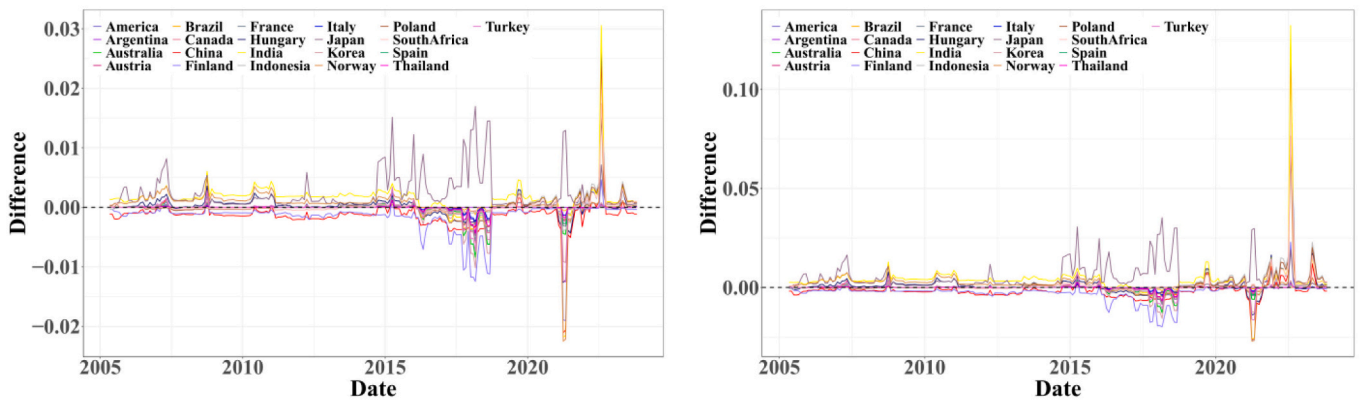


Fig. A.2. Difference under alternative  $\alpha$ .

Table A.1

the numerical statistics of difference under alternative prediction horizons.

Country	Prediction Horizon = 20		Prediction Horizon = 40	
	mean	max	mean	max
Argentina	0.0007	0.0212	0.0003	0.0114
Australia	0.0641	2.2711	0.0337	1.5915
Austria	0.0297	1.2068	0.0167	0.8978
Brazil	0.0060	0.3080	0.0037	0.2387
Canada	0.0414	1.5830	0.0226	1.1554
China	0.0822	2.7470	0.0322	1.3706
Finland	0.1571	3.6250	0.0687	2.0788
France	0.0374	1.4220	0.0206	1.0466
Hungary	0.0700	1.9942	0.0258	0.9410
India	0.1124	3.3283	0.0444	1.7179
Indonesia	0.0269	0.7470	0.0100	0.3460
Italy	0.0152	0.6412	0.0088	0.4899
Japan	0.0226	0.7272	0.0130	0.5536
Korea	0.0806	2.6675	0.0420	1.8149
Norway	0.1028	3.5383	0.0394	1.7969
Poland	0.0210	0.5157	0.0076	0.2361
South Africa	0.0202	0.4684	0.0072	0.2124
Spain	0.0302	1.1325	0.0167	0.8458
Thailand	0.0262	1.0557	0.0147	0.7913
Turkey	0.0666	2.0697	0.0360	1.4693
America	0.0181	0.7541	0.0104	0.5733

**Table A.2**  
the numerical statistics of difference under alternative  $\alpha$ .

Country	$\alpha = 0.2$		$\alpha = 0.8$	
	mean	max	mean	max
Argentina	0.0000	0.0000	0.0000	0.0001
Australia	0.0004	0.0084	0.0007	0.0127
Austria	0.0002	0.0047	0.0003	0.0071
Brazil	0.0001	0.0012	0.0001	0.0017
Canada	0.0003	0.0060	0.0004	0.0080
China	0.0018	0.0262	0.0035	0.1222
Finland	0.0018	0.0191	0.0033	0.0269
France	0.0002	0.0056	0.0004	0.0086
Hungary	0.0011	0.0282	0.0029	0.1262
India	0.0022	0.0305	0.0049	0.1323
Indonesia	0.0008	0.0157	0.0023	0.0684
Italy	0.0001	0.0027	0.0002	0.0042
Japan	0.0023	0.0170	0.0047	0.0353
Korea	0.0005	0.0102	0.0009	0.0156
Norway	0.0014	0.0225	0.0031	0.0739
Poland	0.0007	0.0151	0.0020	0.0657
South Africa	0.0006	0.0174	0.0017	0.0765
Spain	0.0002	0.0045	0.0003	0.0068
Thailand	0.0002	0.0044	0.0003	0.0068
Turkey	0.0005	0.0126	0.0008	0.0164
America	0.0001	0.0031	0.0002	0.0047

## Appendix B. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.eneco.2026.109359>.

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