

Article

How Major Events Reconfigure Technology–Energy Risk Spillovers in China: Implications for Energy Security

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Abstract

The rapid expansion of artificial intelligence is tightening the interdependence between digital infrastructure and energy systems, making the linkages between technology and energy increasingly important for understanding energy security. This study examines how major events reshape risk spillovers between China's technology and energy sectors, with particular attention to the asymmetric effects of policy shocks, external technological shocks, and domestic technological breakthroughs. Focusing on four events, namely the announcement of the carbon peaking and carbon neutrality goals, the launch of the East Data and West Computing project, the release of ChatGPT 3.5, and the release of DeepSeek R1, the study explores whether different shocks alter risk transmission between sectors in distinct ways. Using interval data for 16 representative listed firms from 2021 to 2025, the analysis combines firm-level spillover networks with sector-level robustness tests. The results suggest that policy-driven events are associated with stronger systemic connectedness and changes in the direction of predictive spillovers between the technology and energy sectors, although the Dual Carbon result is sensitive to the selected event window, whereas ChatGPT 3.5 is associated with short-term risk decoupling under the baseline specification, although this result also shows some sensitivity to the event horizon. DeepSeek R1 shows the largest baseline increase in overall spillovers and a relatively stable positive pattern across alternative event windows. The precision of the estimated changes also varies across events. The findings suggest that domestic advances in large language models are not only innovation milestones, but also potential sources of persistent pressure on energy security.

Keywords: energy security; risk spillovers; technology and energy; major events; asymmetric effects



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1. Introduction

The rapid advancement of artificial intelligence has transformed digital innovation into a broader question of social governance [1]. As large language models, intelligent computing platforms, and data centers continue to expand, the technology sector has become increasingly dependent on computing capacity, electricity supply, and energy infrastructure [2,3]. At the same time, the low-carbon transition of energy systems, intelligent dispatch, and efficiency improvement are becoming more reliant on digital technologies and algorithmic capabilities [4]. The relationship between technology and energy can therefore no longer be understood simply as industrial coordination or technological empowerment. It is evolving into a more deeply embedded structure of mutual dependence [5]. In this

context, major policy adjustments, external technological breakthroughs, and domestic innovation shocks could all transmit uncertainty across various sectors. This could also affect industrial stability, financial resilience, and energy security [6]. Understanding how major events alter the risk connections between technology and energy is thus not merely a question of market volatility [2]. It is also a broader social science question concerning digital transformation, green development, and the governance of systemic interdependence [7,8]. In this study, risk refers to market uncertainty reflected in the price movements of firms in the technology and energy sectors. It is measured using daily interval returns constructed from the high and low prices of listed firms, which retain information on within-day price variation. Risk transmission refers to the predictive connectedness through which shocks associated with one firm or sector contribute to the forecast uncertainty of another. It therefore describes changes in the intensity and direction of market connectedness rather than structural causal transmission.

China provides a particularly important setting in which to examine this issue [9]. In recent years, the country has advanced a dual transition centered on the carbon peaking and carbon neutrality agenda and the restructuring of digital infrastructure through the East Data and West Computing project [10]. These developments have tightened the connections among technological development, computing capacity allocation, electricity provision, and energy security [11]. At the same time, the release of ChatGPT 3.5 prompted a global revaluation of generative artificial intelligence [12], while the launch of DeepSeek R1 marked an important breakthrough in domestic large language model capability [13]. Although both events were associated with artificial intelligence, their implications were not identical. The former primarily represented an external technology shock that reshaped market expectations and industrial imagination, whereas the latter was more likely to affect the internal linkages between technology and energy in China through domestic demand for computing capacity, policy response, and industrial coordination [13,14]. China is therefore not only a representative case of parallel digital and green transitions, but also an appropriate context in which to compare the distinct effects of policy shocks, external technology shocks, and domestic technological breakthroughs [15].

Building on this background, this study examines how different types of major events reshape risk spillovers between the technology and energy sectors and whether these changes exhibit asymmetric and persistent patterns. The study further considers the implications of these changes for energy security. This study makes three main contributions. First, it connects energy security to cross-sectoral risk transmission in the age of artificial intelligence, thereby extending the conventional understanding of energy security beyond resource supply, price stability, and low-carbon transition. The study argues that energy security increasingly depends on whether the expansion of digital infrastructure remains compatible with the carrying capacity of the energy system. Second, it develops a comparative perspective on major events by examining the heterogeneous effects of policy events, external technology shocks, and domestic technological breakthroughs within a single framework. Therefore, it highlights the asymmetric mechanisms through which different events reshape technology energy-risk networks. Third, it brings the question of domestic artificial intelligence breakthroughs into the analysis of systemic risk and energy security. This provides a new perspective on how digital transformation and green transition interact under conditions of deepening sectoral interdependence.

The rest of the study is organized as follows. Section 2 reviews the literature and develops the research hypotheses. Section 3 presents the research design, data, and methodology. Section 4 reports the empirical results. Section 5 concludes and discusses policy implications and limitations.

2. Literature Review and Research Hypotheses

2.1. Literature Review

Existing literature relevant to this study can be broadly divided into three strands. The first examines connectedness and risk spillovers across financial, energy, and carbon markets. The second focuses on the effects of major policy, geopolitical, and technological events on market linkages. The third considers how digital technologies and artificial intelligence reshape industrial structures, resource allocation, and infrastructure demand.

The first strand focuses on market connectedness and cross-sectoral risk transmission. Existing studies have provided important evidence on spillovers across financial, energy, and carbon-related markets [16,17]. These studies show that shocks in one market can be associated with changes in the intensity and direction of connectedness in other markets and have contributed to a better understanding of how risk is distributed across interconnected market systems. However, much of this literature has concentrated on energy markets themselves or on the relationship between energy and financial markets [18,19]. Less attention has been given to the direct relationship between technology and energy, even though the rapid development of artificial intelligence and digital infrastructure is making the two sectors increasingly interdependent.

The second strand examines how major events reshape market relationships. Previous research has shown that policy changes, geopolitical uncertainty, financial crises, and technological developments can alter both the strength and direction of market linkages [20,21]. These studies demonstrate that major events can generate substantial adjustments in market expectations and connectedness. Nevertheless, different types of events are often treated as broadly comparable shocks. Limited attention has been paid to whether policy-driven events, external technological shocks, and domestic innovation breakthroughs operate through different mechanisms or produce different patterns of risk reconfiguration [22,23]. This distinction is important because policy events may primarily affect expectations and resource allocation, while technological breakthroughs may influence markets through information updating, industrial repricing, and changes in infrastructure demand.

The third strand concerns the economic implications of digital technologies and artificial intelligence. A growing body of research has emphasized that technological progress does not merely improve productivity or create new growth opportunities. It can also reshape real economic systems through industrial revaluation, resource reallocation, and infrastructure expansion [24]. Much of the existing literature has focused on productivity, innovation, and industrial upgrading. However, less attention has been given to the implications of artificial intelligence for energy-related financial risk, particularly the possibility that domestic large language model breakthroughs may alter the risk structure of energy security through expanding computing demand and increasing dependence on electricity [25,26]. As artificial intelligence becomes more deeply embedded in domestic production and infrastructure systems, this relationship deserves more systematic examination.

2.2. Research Gap and Purpose of the Study

Despite the growing literature on market connectedness, energy risk, and technological transformation, several gaps remain in understanding the changing relationship between technology and energy. These gaps have become increasingly relevant as artificial intelligence, computing infrastructure, and electricity systems have become more closely connected. Existing studies provide an important foundation for examining financial and energy market spillovers, but they do not fully explain how major technological and policy developments reshape the risk structure linking technology and energy sectors.

First, previous studies on cross-sectoral risk transmission have paid relatively limited attention to the direct relationship between technology and energy. This limitation

has become increasingly important with the rapid development of artificial intelligence. Computing intensive activities, such as large language models, increasingly depend on energy infrastructure. At the same time, the energy sector has become more reliant on digital technologies for system operation and related activities. The relationship between technology and energy has therefore developed into a more complex form of interdependence, in which changes in one sector may be associated with changes in the risk structure of the other. However, this emerging form of connectedness has not yet been sufficiently examined from the perspective of systemic risk spillovers.

Second, the existing event-related literature often treats major events as broadly comparable shocks. In practice, different types of events may affect markets through distinct channels. External technological breakthroughs may initially influence domestic markets through shifts in expectations and asset repricing, whereas domestic technological breakthroughs may operate through more direct linkages with production activities and industrial coordination. Treating these events as equivalent shocks may therefore obscure important differences in the intensity, direction, and persistence of predictive spillovers. A comparative framework that distinguishes among different types of events is needed to determine whether they generate similar or heterogeneous patterns of connectedness between the technology and energy sectors.

Third, artificial intelligence has attracted extensive attention in studies of productivity, innovation, and industrial upgrading. However, its implications for energy-related financial risk remain less well understood. In particular, domestic advances in large language models may have different implications from external technological shocks. This distinction is especially relevant in China, where digital infrastructure expansion and the low-carbon transition are developing simultaneously. The interaction between these two processes raises an important question. Domestic artificial intelligence breakthroughs may lead to deeper and more persistent changes in the risk network between technology and energy.

Therefore, the purpose of this study is to examine how different types of major events reshape predictive risk spillovers between technology and energy sectors. The study focuses on changes in overall connectedness, directional predictive spillovers, and the relative positions of firms and sectors within the spillover system. In this study, directional spillovers are interpreted as predictive relationships based on forecast error variance contributions. The study addresses three related questions. First, do policy-driven events strengthen the existing connectedness between technology and energy and increase the overall intensity of spillovers? Second, do external technological shocks primarily alter the direction of predictive spillovers and the relative roles of the two sectors rather than generating a persistent increase in overall connectedness? Third, do domestic technological breakthroughs produce stronger and more persistent changes in the technology and energy risk network because of their closer links with domestic computing demand, electricity requirements, infrastructure investment, and industrial coordination?

To address these questions, the study places policy-driven events, external technological shocks, and domestic technological breakthroughs within a unified comparative framework. The analysis combines firm-level event spillover estimation with sector-level dynamic connectedness analysis. This design makes it possible to distinguish short-term changes around individual events from broader structural adjustments in sectoral relationships. The study therefore aims to provide a more differentiated understanding of how major events reconfigure technology and energy connectedness and how these changes may relate to the broader issue of energy security.

2.3. Research Hypotheses and Conceptual Framework

Major events do not usually affect technology and energy markets in the same way. Their effects depend on how new information enters the system. They also depend on whether the event mainly changes expectations, resource allocation, or real industrial links. Existing research on policy shocks, technology news, and market connectedness suggests that these channels can produce different responses in asset prices and cross-sector relationships, providing a theoretical basis for distinguishing policy-driven events, external technology shocks, and domestic technological breakthroughs. Policy-driven events mainly work through expectations and resource allocation [27]. Clear policy signals reduce uncertainty about future industrial priorities. They can also redirect investment and infrastructure development. When a policy simultaneously affects technology development, energy transition, and infrastructure planning, firms in both sectors respond to a common change in expectations and resource allocation, which can strengthen their existing connectedness and raise the overall level of predictive spillovers [28]. The Dual Carbon goals and the East Data and West Computing project follow this logic. Both provide strong signals about future development priorities. Both also involve investment and infrastructure adjustment. The former links low-carbon transition with energy restructuring, while the latter connects computing capacity with electricity supply and regional infrastructure, so both events are expected to strengthen the existing relationship between technology and energy rather than simply affect one sector in isolation.

H1. *Policy-driven events strengthen connectedness between technology and energy and increase overall spillovers.*

External technology shocks work through a different channel. Their immediate effect is mainly informational. Markets may respond before domestic production and infrastructure fully adjust [29]. When a major technology emerges outside the domestic industrial system, investors first reassess future technology demand, firm value, and sector exposure, which can change directional connectedness and the relative positions of sectors without necessarily producing an immediate and persistent increase in aggregate spillovers [30,31]. The release of ChatGPT 3.5 represents this type of shock. It changed expectations about the development of generative artificial intelligence [32]. Its initial effect on China was largely reflected in market reassessment. Changes in domestic computing capacity and electricity demand required more time. The short-term response is therefore expected to appear more clearly in directional predictive spillovers and sectoral roles than in a sustained increase in overall connectedness.

H2. *External technology shocks mainly change directional connectedness and the relative roles of the two sectors.*

Domestic technological breakthroughs are more deeply embedded in the domestic industrial system [33]. They affect market expectations and real economic links at the same time. Their development can increase demand for computing capacity, electricity, and related infrastructure. When a domestic breakthrough is supported by local supply chains, industrial coordination, infrastructure investment, and policy response, its influence can extend from financial market expectations to actual technology and energy interactions, creating stronger conditions for a broader and more persistent reconfiguration of the connectedness network [34]. DeepSeek R1 represents this type of event. Its development is closely linked to domestic computing resources. It also increases attention to electricity supply and digital infrastructure. These links make the technology and energy sectors

more closely connected. A domestic technological breakthrough is therefore expected to produce a deeper structural adjustment than an external technology shock.

H3. *Domestic technological breakthroughs produce stronger and more persistent changes in the technology and energy risk network.*

Figure 1 summarizes the conceptual framework. It links each event type with its main economic channel and expected spillover pattern. Policy-driven events operate mainly through common expectations and resource allocation, external technology shocks operate mainly through information and market repricing, while domestic technological breakthroughs combine expectation effects with changes in computing demand, electricity requirements, and domestic industrial links. These differences provide the theoretical basis for examining heterogeneous changes in overall spillovers, directional connectedness, and network structure across the four major events.

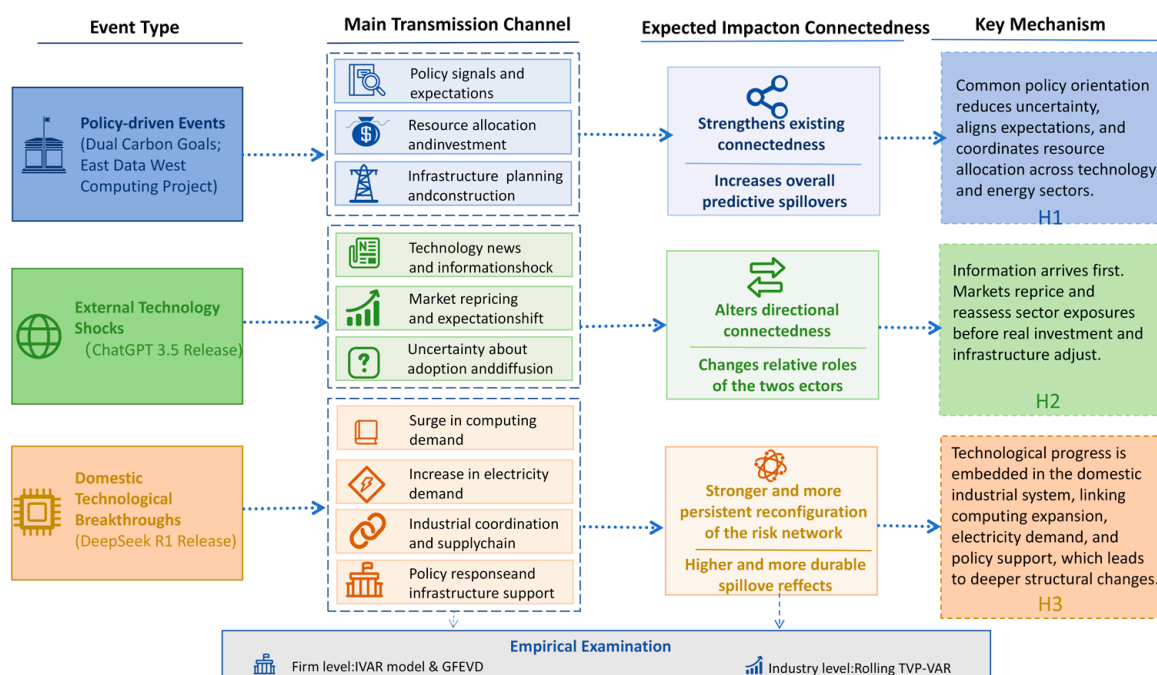


Figure 1. Conceptual framework.

3. Research Design, Data and Methodology

3.1. Research Design

This study investigates how major events reshape risk spillovers between the technology and energy sectors in China. The empirical strategy is designed to capture both immediate event-related changes and broader structural adjustments in cross-sectoral risk transmission. To do so, the analysis proceeds at two levels. At the firm level, the study uses daily interval data for 16 representative listed firms in the technology and energy sectors to estimate changes in risk spillovers before and after major events. This part of the design focuses on short-term responses and allows the analysis to identify how predictive spillover intensity, directional connectedness, and firm-level network positions change under different types of shocks. The firm-level framework is based on an interval vector autoregressive model combined with generalized forecast error variance decomposition, from which pairwise spillover matrices and aggregate spillover measures are derived.

At the sector level, the study conducts a robustness analysis using three broad-sector indices representing traditional energy, new energy, and technology. This second step is intended to assess whether the event-related patterns observed at the firm level are consistent with longer-term changes in sectoral connectedness. For this purpose, a rolling time varying parameter vector autoregressive framework (TVP-VAR) is used to trace the evolution of spillovers and net transmission directions over time. In this way, the empirical design moves beyond short-term event responses and examines whether major events contribute to more persistent structural asymmetries. This design constitutes one methodological contribution of the study. Existing research often focuses either on firm specific spillover responses or on broad sectoral connectedness. By linking the two, the present analysis captures both micro-level event sensitivity and macro-level structural persistence. It is therefore better suited to examining how policy shocks, external technology shocks, and domestic technological breakthroughs reshape the relationship between technology and energy in different ways. Figure 2 shows the corresponding mechanism diagram of the study.

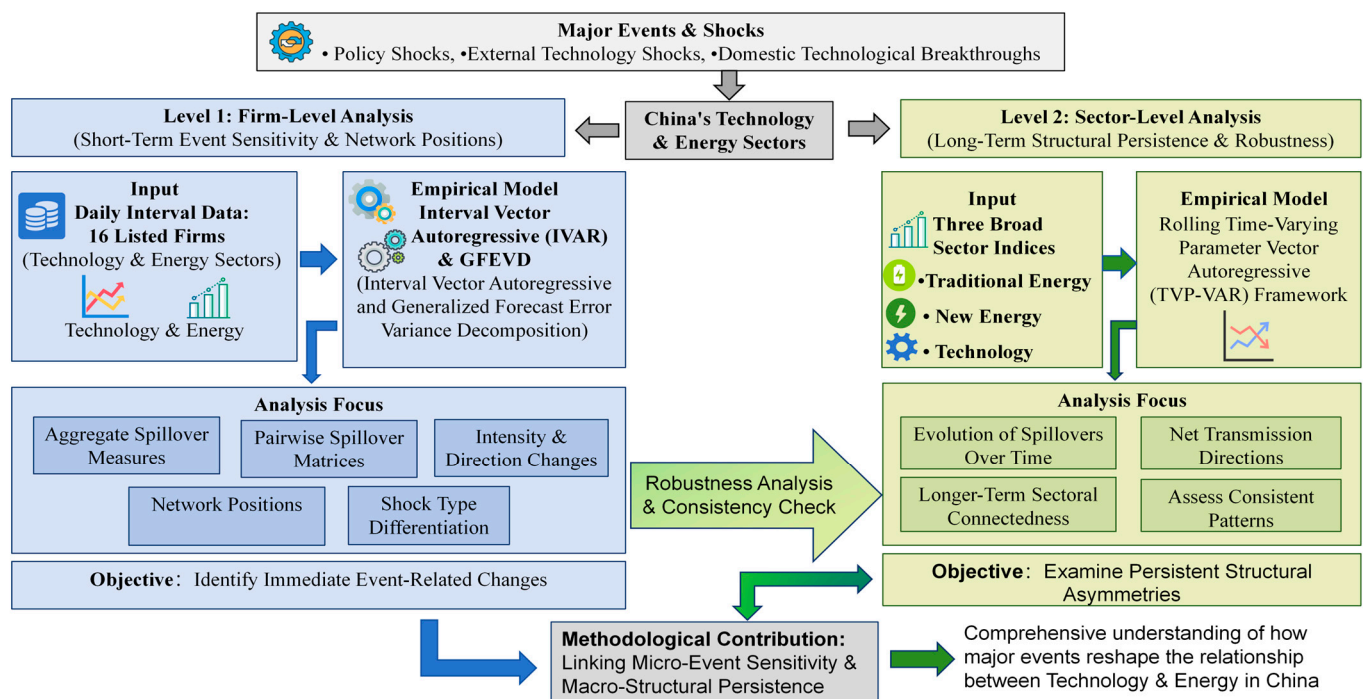


Figure 2. Two-level research design for risk spillovers. Note: the design combines firm-level event analysis with sector-level dynamic connectedness analysis.

3.2. Data and Sample Selection

This study selects representative technology and energy firms listed in China's A share market to examine risk spillovers between the two sectors. The sample period runs from 1 January 2021 to 30 September 2025 and covers four key events during the development of large language models. Daily data on high prices, low prices, and closing prices are obtained from the Choice Financial Terminal. To preserve information on intraday price movements, the analysis constructs interval log returns and uses them as the input for the subsequent interval model. The final sample consists of 16 listed firms, including 9 technology firms and 7 energy firms. Sample selection is based on three criteria: industry representativeness, relevance to national strategies such as the carbon peaking and carbon neutrality agenda and the East Data and West Computing project, and the completeness and continuity of the data. Table 1 shows the overview of sample enterprises.

Table 1. Overview of sample enterprises.

Category	Stock Code	Company Name	Introduction
Technology Industry	688256.SH	Cambricon Technologies Corporation Limited (Beijing, China)	A global pioneer in the field of intelligent chips, focusing on the R&D and sales of AI chips.
	688111.SH	Kingsoft Office Software Co., Ltd. (Beijing, China)	China's leading office software and service provider, deeply applying AI technology.
	002230.SZ	iFlytek Co., Ltd. (Hefei, China)	A leading AI company in China, specializing in speech and natural language processing.
	000977.SZ	Inspur Electronic Information Industry Co., Ltd. (Jinan, China)	A leading cloud computing and big data service provider in China, and a core supplier of AI servers.
	600588.SH	Yonyou Network Technology Co., Ltd. (Beijing, China)	China's leading enterprise cloud service and software provider.
	603019.SH	Sugon Information Industry Co., Ltd. (Beijing, China)	China's leading enterprise in high-performance computing, deeply involved in data center construction.
	688981.SH	Semiconductor Manufacturing International Corporation (Shanghai, China)	China's most technologically advanced and largest integrated circuit manufacturing enterprise.
	000063.SZ	ZTE Corporation (Shenzhen, China)	A global leader in comprehensive communication solutions, and a core provider of 5G and computing power.
Energy Industry	000938.SZ	Unisplendour Corporation Limited (Beijing, China)	A leading provider of digital solutions in China, focusing on cloud computing and IT services.
	600011.SH	Huaneng Power International, Inc. (Beijing, China)	One of China's largest listed power generation companies, primarily focused on thermal power.
	601012.SH	LONGi Green Energy Technology Co., Ltd. (Xi'an, China)	The world's most valuable solar technology company and a leader in the photovoltaic industry chain.
	600438.SH	Tongwei Co., Ltd. (Chengdu, China)	A leading Chinese enterprise developing dual businesses in photovoltaic new energy and green agriculture.
	600900.SH	China Yangtze Power Co., Ltd. (Beijing, China)	China's largest listed power company and the world's largest hydropower company.
	600028.SH	China Petroleum & Chemical Corporation (Sinopec) (Beijing, China)	A leading oil and gas producer and distributor in China.
	601857.SH	PetroChina Company Limited (Beijing, China)	China's largest crude oil and natural gas producer.
	002202.SZ	Xinjiang Goldwind Science & Technology Co., Ltd. (Beijing, China)	A leading wind turbine manufacturer and comprehensive wind power solution provider in China.

Data source: Choice Financial Terminal.

The final number of firms was determined by the intersection of these three screening criteria rather than by imposing a predetermined sample size. The technology group was constructed to cover the major segments associated with artificial intelligence and computing infrastructure, including AI chips, cloud computing, big data processing, enterprise software, high-performance computing, communications infrastructure, and integrated circuits. The energy group was selected to capture both conventional and transition-related energy activities, including thermal power, oil and gas, hydropower, photovoltaic energy, and wind power. Firms were retained when they simultaneously exhibited clear sectoral relevance, close connection with the technological or energy channels examined in this study, and complete daily high, low, and closing price data over the required event windows. The purpose of the firm-level sample is therefore not to reproduce the complete population of listed companies in the two sectors, but to construct a functionally representative network spanning the main technology–energy transmission channels relevant to the research question. The selected technology firms cover upstream computing hardware, semiconductor manufacturing, computing infrastructure, software, and digital applications, while the energy firms cover both conventional energy supply and major renewable-energy segments. This functional coverage allows the network analysis to capture heterogeneous transmission channels between technological expansion and energy constraints.

The technology sample covers key segments of large language model development and application, including AI chips, cloud computing, big data processing, software services, and communications infrastructure. The energy sample includes both traditional and new energy firms, covering thermal power, oil and gas, solar power, and wind power. The two types of samples correspond to the technological impact and energy constraints brought about by the development of large language models, respectively. Therefore, they can better support the subsequent identification of cross industry risk transmission. Figure 3 presents the descriptive statistics. The descriptive statistics show that the interval returns of technology firms exhibit greater fluctuation and dispersion than those of energy firms, indicating higher overall volatility in the technology sector. At the same time, energy firms display more pronounced extreme downside movements. This suggests substantial heterogeneity in the structure of risk exposure across the two sectors and provides a basis for the subsequent analysis of risk spillovers under major event shocks.

The four focal events are the announcement of the Dual Carbon goals on 24 October 2021, the launch of the East Data and West Computing project on 17 February 2022, the release of ChatGPT 3.5 on 30 November 2022, and the release of DeepSeek R1 on 20 January 2025. For each event, the baseline analysis uses three-month pre-event and post-event windows, with the event date itself excluded from both periods. The baseline event windows are designed to balance two considerations. First, a sufficiently long pre- and post-event period is required to provide adequate observations for stable estimation of the 16-variable IVAR system. Second, the event horizon should remain sufficiently concentrated around the focal event to reduce contamination from unrelated market developments occurring further away from the event date. The original event windows therefore represent a medium-short horizon for identifying changes in technology and energy spillover structures. Because the estimated effects may depend on the selected horizon, alternative symmetric event windows are examined as a sensitivity test below.

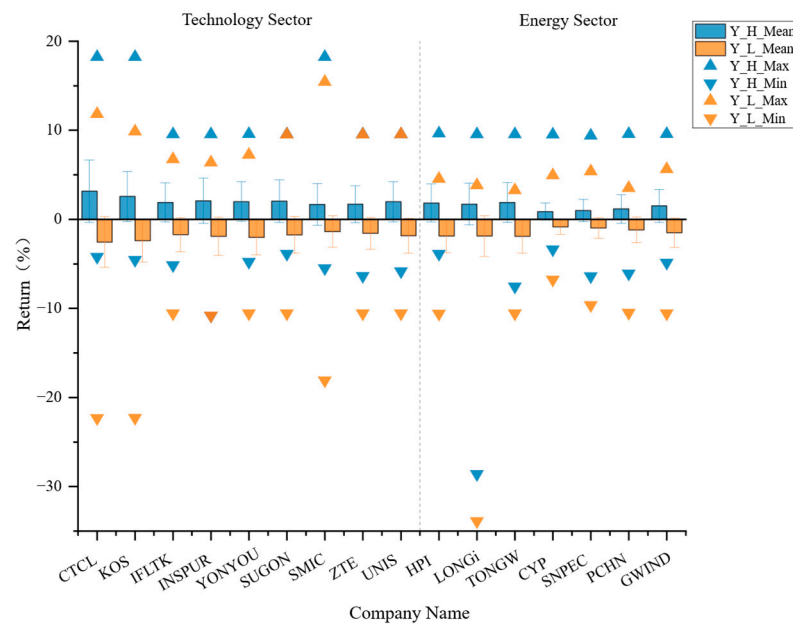


Figure 3. Descriptive statistics of sample enterprises. Note: The node abbreviations in the figure correspond as follows: Cambricon Technologies Corporation Limited (CTCL), Kingsoft Office Software Co., Ltd. (KOS), iFlytek Co., Ltd. (IFLTK), Inspur Electronic Information Industry Co., Ltd. (INSPUR), Yonyou Network Technology Co., Ltd. (YONYOU), Sugon Information Industry Co., Ltd. (SUGON), Semiconductor Manufacturing International Corporation (SMIC), ZTE Corporation (ZTE), Unisplendour Corporation Limited (UNIS), China Yangtze Power Co., Ltd. (CYP), Tongwei Co., Ltd. (TONGW), Xinjiang Goldwind Science & Technology Co., Ltd. (GWIND), LONGi Green Energy Technology Co., Ltd. (LONGi), Huaneng Power International, Inc. (HPI), China Petroleum & Chemical Corporation (SNPEC), PetroChina Company Limited (PCHN).

3.3. Methodology

To identify the dynamic evolution of risk spillovers between the technology and energy sectors in the context of large language model development, this study develops an interval data framework to capture intraday price variation and changes in intersectoral risk transmission under major event shocks [35]. The study first employs an interval vector autoregressive model to characterize the dynamic dependence between the technology and energy sectors. On this basis, generalized forecast error variance decomposition is used to assess the contribution of shocks from different sources to sectoral fluctuations. It further constructs the total spillover index and related measures to characterize the overall intensity, directional structure, and predictive connectedness patterns within the system. This framework provides a progressive analytical structure that moves from the identification of dynamic dependence to the measurement of risk contributions and, ultimately, to the characterization of systemic transmission patterns. It offers a unified methodological basis for comparing how different major events reshape the risk relationship between technology and energy.

3.3.1. Interval Vector Autoregressive (IVAR) Model

To capture more fully the market response to major events, this study uses interval log returns rather than conventional point returns [36]. Compared with point-valued data, interval data retain richer information on daily price variation, including the lower and upper bounds of intraday movements, and are therefore better suited to identifying changes in volatility and cross-sectoral risk transmission under event shocks. The analysis adopts an interval vector autoregressive framework to characterize the dynamic dependence among firms in the technology and energy sectors. Recent developments in interval-valued time

series analysis have further extended the use of interval information in dynamic modelling and forecasting, highlighting its value when conventional point observations cannot fully represent within period variation [37,38]. These advances provide additional support for the use of an IVAR framework in the present study. The model is specified as follows:

$$Y_t = (\alpha + \beta I_0) + \sum_{k=1}^q \Gamma_k Y_{t-k} + \varepsilon_t, t = 1, \dots, T, \quad (1)$$

where $Y_t = (Y_{1t}, \dots, Y_{nt})'$ is an n dimensional interval time series vector. Equation (1) describes the dynamic dependence among the interval returns of the 16 sample firms. For asset i on day t , the interval log return is defined as

$$Y_{it} = [Y_{it}^L - Y_{i,t-1}^c, Y_{it}^H - Y_{i,t-1}^c] \quad (2)$$

where $Y_{it}^L = \ln(\text{low}_{i,t})$, $Y_{it}^H = \ln(\text{high}_{i,t})$, and $Y_{i,t-1}^c = \ln(\text{close}_{i,t-1})$.

As shown in Equation (2), the interval log return measures the daily return range relative to the previous closing price and preserves the lower and upper bounds of intra-day price movements. In the model, α and β are n -dimensional parameter vectors, and $I_0 = [-\frac{1}{2}, \frac{1}{2}]$ is a fixed interval introduced to capture the central shift of interval data. Γ_k denotes the autoregressive coefficient matrix at lag k , with each element reflecting the lagged effect of one variable on another. The disturbance term ε_t is an interval residual vector with zero mean and weak dependence, and q denotes the lag order. To formally verify this specification, we conducted additional lag order selection tests using both the Akaike information criterion (AIC) and Bayesian information criterion (BIC). The tests were performed for the full firm-level sample and separately for all eight pre- and post-event windows. Both criteria consistently selected $p = 1$ in all cases. The first-order specification is therefore supported by formal information criteria rather than imposed solely for model parsimony. The results are summarized in Appendix A Table A1.

Model parameters are estimated using the minimum DK distance [39,40]. This approach is appropriate for interval-valued time series because it preserves the geometric structure of interval observations. For an interval $E = [a, b]$, the support function $s_E(u)$ is defined as follows:

$$s_E(u) = \begin{cases} au, & u < 0, \\ bu, & u \geq 0. \end{cases} \quad (3)$$

Based on the support function, interval-valued observations can be mapped into the real domain while preserving endpoint information, thereby providing an operational distance metric for parameter estimation. Let $s_E(u)$ and $s_F(u)$ denote the support functions of two intervals E and F , respectively. The DK distance between them is defined as follows:

$$d_{DK}(E, F) = \left[\sum_{i=1}^2 \sum_{j=1}^2 (s_E(u_i) - s_F(u_i))(s_E(u_j) - s_F(u_j)) K(u_i, u_j) \right]^{1/2} \quad (4)$$

where $S_0 = \{-1, 1\}$ is the set of support points, $u_i, u_j \in S_0$, and $K(u_i, u_j)$ denotes the DK kernel matrix. In this study, the kernel matrix is specified as follows:

$$K = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix} \quad (5)$$

The kernel matrix in Equation (5) is used to capture the dependence structure between the interval endpoints. For interval vectors $E = (E_1, \dots, E_n)$ and $F = (F_1, \dots, F_n)$, the DK distance is further defined as follows:

$$d_{DK}(E, F) = \left[\sum_{i=1}^n d_{DK}(E_i, F_i)^2 \right]^{1/2} \quad (6)$$

On this basis, model parameters are estimated by minimizing the sum of squared DK distances between the observed interval vectors and their fitted counterparts:

$$\min_{\alpha, \beta, \Gamma, \{\epsilon_t\}_{t=q+1}^T} \sum_{t=q+1}^T d_{DK}(Y_t, \hat{Y}_t)^2 \quad (7)$$

where $\hat{Y}_t$ is generated by the interval vector autoregressive model. The key advantage of this estimation strategy is that parameter inference does not rely on reducing interval data to point values. Instead, estimation is conducted directly on the basis of interval distances, thereby preserving the structural information contained in the lower and upper bounds of returns. This feature is particularly important in the present setting, where major events may affect not only the level of returns but also the range within which market fluctuations unfold.

3.3.2. Parameter Initialization and Alternative Solutions

To improve numerical stability, the initial parameter values are constructed from the midpoint series of the interval data. The midpoint vector is defined as

$$M_t = \left(\frac{Y_1^L + Y_1^H}{2}, \dots, \frac{Y_n^L + Y_n^H}{2} \right), \quad (8)$$

and a conventional vector autoregressive model is first estimated as

$$M_t = \mu + \sum_{k=1}^q \Phi_k M_{t-k} + v_t \quad (9)$$

The resulting estimates are then used to initialize the interval model. The intercept term is taken from the midpoint VAR estimates, the scale parameter is calibrated according to the volatility of the midpoint series, and the autoregressive coefficient matrices are initialized using the corresponding VAR coefficients. This initialization procedure helps mitigate local instability in the estimation of a high dimensional interval system and improves the convergence performance of the optimization routine. Parameter estimation is implemented using the L-BFGS-B algorithm, with parameter bounds set to $[-10, 10]$. To strengthen the numerical reliability of the estimation and avoid premature termination, the maximum number of iterations was increased to 2000. We further conducted window-specific convergence diagnostics for all pre- and post-event estimations. All eight IVAR models converged successfully under the revised optimization setting, and none reached the maximum iteration limit. Detailed numerical diagnostics are summarized in Appendix A Table A1. The number of iterations required for convergence varied across event windows. Specifically, the pre- and post-event estimations required 505 and 618 iterations for the Dual Carbon event, 451 and 413 iterations for the East Data and West Computing project, 398 and 650 iterations for ChatGPT 3.5, and 700 and 706 iterations for DeepSeek R1, respectively. These results confirm successful numerical convergence across all event windows under a common IVAR estimation procedure. Detailed diagnostics are summarized in Appendix A Table A1. If the interval model fails to converge under

these constraints, the midpoint VAR specification is used as a fallback for the subsequent variance decomposition and spillover analysis. This treatment does not alter the overall empirical logic of the study; rather, it serves as a numerical robustness device to ensure the feasibility and consistency of the estimation framework in a high-dimensional setting. This procedure provides numerically stable starting values for the optimization, while the final IVAR estimates are determined by minimizing the DK-distance objective rather than by the midpoint VAR estimates themselves.

3.3.3. Generalized Forecast Error Variance Decomposition

Based on the estimated IVAR model, risk spillovers are quantified using generalized forecast error variance decomposition [41]. This approach measures the extent to which the forecast error variance of one sector can be explained by shocks originating from other sectors, and therefore provides a natural basis for evaluating cross-sectoral spillovers [42,43]. Accordingly, risk transmission in this study is interpreted as predictive spillover, measured by the contribution of innovations in one variable to the forecast error variance of another variable. To implement the decomposition, the IVAR system is first rewritten in companion form:

$$C = \begin{bmatrix} \Gamma_1 & \Gamma_2 & \cdots & \Gamma_q \\ I_n & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & I_n & 0 \end{bmatrix} \quad (10)$$

where I_n is the $n \times n$ identity matrix. Based on the estimated residuals, the covariance matrix Σ is obtained from the support function representation of the interval residuals. To ensure numerical stability, a small constant is added where necessary, and the matrix is factorized accordingly.

The generalized forecast error variance decomposition matrix is then constructed for an h step ahead forecast horizon [44]. Its (i, j) element measures the share of the forecast error variance of variable i attributable to shocks from variable j . It should be emphasized that the directional spillover measures derived from the generalized forecast error variance decomposition represent predictive connectedness rather than structural causal effects. Specifically, a directional spillover from variable j to variable i indicates the share of the forecast error variance of i associated with innovations in j , conditional on the estimated dynamic system. Accordingly, the direction of the spillover should be interpreted as a statistical predictive relationship and not as evidence of causal transmission. Following standard practice, each row is normalized so that the entries sum to 100. This normalized matrix provides the basis for all subsequent spillover measures.

Using the normalized variance decomposition matrix, the study constructs a set of spillover indicators to summarize the intensity and direction of risk transmission. First, the pairwise directional spillover matrix captures the bilateral spillover relationship between sectors, where off diagonal elements represent cross-sectoral risk transmission. On this basis, the total spillover index is defined as

$$TSI = \frac{\sum_{i \neq j} \bar{\xi}_{ij}}{n} \quad (11)$$

which measures the overall share of cross-sectoral spillovers in the system. In addition, the spillover received index for sector i is defined as

$$SRI_i = \sum_{j \neq i} \xi_{ij}, \quad (12)$$

and the spillover transmitted index is defined as

$$STI_i = \sum_{j \neq i} \xi_{ji}, \quad (13)$$

These measures identify whether a given sector mainly absorbs risk from others or serves as a source of outward transmission. Together, they provide a compact description of the overall level, directional structure, and local paths of spillovers within the system. This framework is implemented consistently across all event windows, ensuring comparability of the estimated spillover patterns under different major shocks. Relative to volatility measures, the total spillover index is more effective in capturing the transmission of event-driven shocks because it focuses directly on cross-sectoral risk propagation rather than isolated price fluctuations. To provide an explicit assessment of estimation uncertainty, we further conducted a residual-based Monte Carlo analysis using the fitted IVAR models. Residual variation was propagated through the generalized forecast error variance decomposition while retaining the estimated dynamic structure of each event window. This procedure yields simulation-based standard errors for the event-related changes in the total spillover index and complements the point estimates used in the baseline event analysis. An additional advantage of the generalized variance decomposition is that it does not require orthogonalization through a Cholesky decomposition and is therefore invariant to the ordering of variables, reducing dependence on arbitrary identification restrictions.

4. Empirical Results

Before examining the event-specific spillover effects, we conducted additional numerical diagnostics to evaluate the stability and comparability of the IVAR estimation across event windows. All eight pre- and post-event IVAR models converged successfully under the revised L-BFGS-B optimization setting. Importantly, none of the eight estimations required the midpoint VAR fallback. Therefore, all spillover measures reported across the four event windows are derived from the same IVAR framework, eliminating potential comparability concerns associated with the use of different estimators. Detailed estimation diagnostics are reported in Appendix A Table A1. The four major events did not reshape the risk relationship between the technology and energy sectors in the same way. Overall, policy-driven events and technology driven events followed clearly different shock mechanisms. These differences are reflected not only in changes in the overall intensity of risk spillovers, but also in the direction of risk transmission, the relative position of the two sectors, and the reorganization of network structures. The baseline estimates also suggest that technology breakthroughs, especially domestic large language model breakthroughs, are associated with more pronounced changes in the structure of the technology and energy risk network. The uncertainty assessment further shows that the changes in the total spillover index for the Dual Carbon, East Data and West Computing, ChatGPT 3.5, and DeepSeek R1 events are 4.33, 5.74, −6.92, and 17.01 percentage points, with corresponding simulation-based standard errors of 5.4524, 4.9417, 3.9726, and 8.6064, respectively. Full numerical diagnostics are reported in Appendix A Table A1. The uncertainty assessment also reveals differences in estimation precision across events. The Dual Carbon and East Data and West Computing estimates are accompanied by relatively large simulation-based standard errors, while the DeepSeek R1 estimate is comparatively larger in magnitude. The four events therefore show clear differences in the direction, magnitude, and precision of the estimated spillover changes.

To identify these heterogeneous effects, the analysis combines firm-level event comparisons with sector-level dynamic evidence. At the firm level, interval daily data for 16 leading technology and energy firms are used to compare changes in the spillover matrix and the total spillover index before and after each event, thereby capturing short term network reconfiguration. At the sector level, a further rolling dynamic analysis is conducted for the traditional energy, new energy, and technology sectors to examine whether these shocks evolved into more persistent structural adjustments. This design makes it possible to identify both the immediate market response to major events and their broader medium to long-term risk implications. Throughout the following analysis, directional spillovers are interpreted as differences in predictive connectedness and forecast error variance contributions. References to net transmitters and receivers therefore describe relative positions within the estimated spillover system.

4.1. Static Risk Spillover Effects Between the Technology and Energy Sectors

4.1.1. Effects of the Announcement of the Carbon Peaking and Carbon Neutrality Goals

Under the baseline event window, risk linkages between the technology and energy sectors became stronger following the announcement of the carbon peaking and carbon neutrality goals. As shown in Table 2, the total spillover index increased by 4.33 percentage points. The corresponding simulation standard error is 5.4524 percentage points, indicating relatively high uncertainty in the estimated magnitude. At the same time, the direction of risk transmission across sectors also changed. The average net risk change in the technology sector was negative, indicating that it acted as a net receiver of risk, whereas the average net risk change in the energy sector was positive, indicating that it acted as a net transmitter. This pattern suggests that, under the policy signal of the carbon peaking and carbon neutrality goals, which reinforced market expectations and industrial coordination, the directional connectedness measures indicate stronger net predictive spillovers from the energy sector toward the technology sector.

At the firm level, this change was not evenly distributed across all firms, but was concentrated in several key nodes. Within the energy sector, PetroChina recorded an increase of 29.59% in net risk transmission and emerged as an important source of risk within the system. Within the technology sector, Cambricon and Inspur Information recorded increases of 50.95% and 26.16%, respectively, in net risk transmission, indicating that firms related to communications networks and high-performance computing exhibited a stronger outward spillover capacity after the policy shock. At the same time, Kingsoft Office and SMIC experienced a further deepening of net risk reception, suggesting substantial heterogeneity in the way different segments of the technology sector responded to the policy signal. The baseline result is consistent with H1, although the estimated spillover change for the Dual Carbon event varies across alternative event windows.

4.1.2. Effects of the Launch of the East Data and West Computing Project

Following the launch of the East Data and West Computing project, the total spillover index increased by 5.74 percentage points under the baseline specification. The corresponding simulation standard error is 4.9417 percentage points, indicating uncertainty in the magnitude of the estimated change. Although the technology sector remained a net receiver of risk, with an average net risk change of -4.90% , its average spillover change reached $+8.53\%$, indicating a marked increase in its capacity to transmit risk outward. The energy sector continued to occupy a net transmitting position. Predictive spillover between the two sectors still ran from energy to technology, and the net value widened to -44.09 .

Table 2. Firm-level spillover changes before and after the release of the Dual Carbon targets.

Category	Company Name	Stock Code	STI Change (%)	SRI Change (%)	Net Change (%)	Role (Post-Event)
Technology Industry	Cambricon Technologies Corporation Limited	688256.SH	9.18	−41.77	50.95	Net transmitter
	Kingsoft Office Software Co., Ltd.	688111.SH	−0.66	50.5	−51.16	Net receiver
	iFlytek Co., Ltd.	002230.SZ	0.34	26.31	−25.97	Net receiver
	Inspur Electronic Information Industry Co., Ltd.	000977.SZ	13.08	−13.08	26.16	Net transmitter
	Yonyou Network Technology Co., Ltd.	600588.SH	11.55	2.54	9.01	Net transmitter
	Sugon Information Industry Co., Ltd.	603019.SH	10.71	−1.47	12.18	Net transmitter
	Semiconductor Manufacturing International Corporation	688981.SH	−36.3	2.66	−38.96	Net receiver
	ZTE Corporation	000063.SZ	16.6	12.82	3.78	Net transmitter
	Unisplendour Corporation Limited	000938.SZ	−10.81	16.28	−27.09	Net receiver
Tech industry average	5 Transmitters, 4 Receivers		1.52	6.09	−4.57	Net receiver
Energy industry	China Yangtze Power Co., Ltd.	600900.SH	8.23	14.79	−6.56	Net receiver
	Tongwei Co., Ltd.	600438.SH	6.36	9.2	−2.84	Net receiver
	Xinjiang Goldwind Science & Technology Co., Ltd.	002202.SZ	6.18	9.15	−2.97	Net receiver
	LONGi Green Energy Technology Co., Ltd.	601012.SH	4.37	4.26	0.11	Net transmitter
	Huaneng Power International, Inc.	600011.SH	9.03	−1.09	10.12	Net transmitter
	China Petroleum & Chemical Corporation (Sinopec)	600028.SH	8.08	−5.56	13.64	Net transmitter
	PetroChina Company Limited	601857.SH	13.29	−16.3	29.59	Net transmitter
Energy industry average	4 transmitters, 3 receivers		7.93	2.06	5.87	Net transmitter
Key statistical facts	Overall spillover index change (full sample)				4.33	Positive baseline spillover change
	Cross industry net predictive spillover direction	Direction: energy → tech	Net value: −41.09	Energy industry is the dominant net spillover transmitter		

At the firm level, this adjustment was concentrated in several firms directly linked to computing capacity. In the technology sector, Unisplendour, Yonyou Network, and SMIC recorded substantial increases in net risk transmission, pointing to a reinforcing interaction between the hardware and software segments of the computing chain. In the energy sector, Sinopec registered a sharp increase of 68.50% in net risk transmission, suggesting that traditional energy firms became important spillover sources under the combined pressure of expanding computing demand and ongoing energy transition. The baseline results show stronger spillover linkages after the launch of the East Data and West Computing project. Firms related to computing also played a more important role in risk transmission. This pattern is consistent with H1. Table 3 summarizes the changes in firm-level spillover effects before and after the launch of the East Data and West Computing project, together with the key empirical facts.

4.1.3. Effects of the Release of ChatGPT 3.5

Under the baseline event window, the total spillover index declined by 6.92 percentage points after the release of ChatGPT 3.5. The corresponding simulation standard error is 3.9726 percentage points, indicating some uncertainty in the estimated change. The baseline result points to a temporary weakening of the risk relationship between the technology and energy sectors. According to Table 4, the direction of intersectoral risk transmission also changed markedly. The technology sector shifted from being a net receiver of risk to a weak net transmitter, whereas the energy sector moved from a net transmitting position to a net receiving position. As a result, the estimated directional connectedness was reversed, with net predictive spillovers becoming stronger from the technology sector toward the energy sector, reaching a net value of 3.97. This pattern shows that the technology sector acted as a net spillover transmitter under the baseline specification.

At the firm level, this adjustment was concentrated in several key firms closely associated with advances in artificial intelligence. Within the technology sector, iFlytek and Inspur Information recorded increases of 84.42% and 62.58%, respectively, in net risk transmission, indicating that the breakthrough in generative artificial intelligence strengthened the outward spillover capacity of related firms. Within the energy sector, the response was more heterogeneous. Sinopec recorded an increase of 36.88% in net risk transmission, whereas PetroChina experienced a 42.21% increase in net risk reception. This pattern suggests that the external technology shock did not generate a uniform response across the energy sector but instead produced differentiated changes in risk exposure and transmission positions across subsectors. These results indicate that the release of ChatGPT 3.5 did not lead to a uniform increase in systemic risk. Instead, its effects were reflected more clearly in a reorientation of risk transmission and a temporary reconfiguration of sectoral roles. Compared with the strengthening effect of policy events on existing linkages, the external technology shock was more likely to trigger a repricing of the relationship between technology and energy and to alter the direction of predictive spillover between the two sectors in the short run. The baseline pattern is consistent with H2. However, the estimated spillover change shows some sensitivity to the selected event window.

4.1.4. Effects of the Release of Deepseek R1

Among the four events, DeepSeek R1 shows the largest baseline increase in overall spillovers. The total spillover index increased by 17.01 percentage points. The corresponding simulation standard error is 8.6064 percentage points. The positive direction of this change remains relatively stable across alternative event windows. The average net risk change in the technology sector was -5.50% , indicating that it remained a net receiver of risk, while its average spillover change reached $+18.23\%$, suggesting that both

risk transmission and risk reception increased markedly. The energy sector recorded an average net risk change of +7.07% and remained a net transmitter of risk. As a result, the estimated net predictive spillover shifted back toward a stronger direction from the energy sector to the technology sector, with the net value widening to −49.46. This indicates that the position of the energy sector as the main source of risk in the system became even more pronounced.

Table 3. Firm-level spillover changes before and after the release of the East Data and West Computing project.

Category	Company Name	Stock Code	STI Change (%)	SRI Change (%)	Net Change (%)	Role (Post-Event)
Technology industry	Cambricon Technologies Corporation Limited	688256.SH	−22.12	119.10	−141.22	Net receiver
	Kingsoft Office Software Co., Ltd.	688111.SH	14.21	26.11	−11.90	Net receiver
	iFlytek Co., Ltd.	002230.SZ	−5.47	29.04	−34.51	Net receiver
	Inspur Electronic Information Industry Co., Ltd.	000977.SZ	6.18	30.38	−24.20	Net receiver
	Yonyou Network Technology Co., Ltd.	600588.SH	20.85	−38.48	59.33	Net transmitter
	Sugon Information Industry Co., Ltd.	603019.SH	6.97	−13.48	20.46	Net transmitter
	Semiconductor Manufacturing International Corporation	688981.SH	18.05	−10.70	28.75	Net transmitter
	ZTE Corporation	000063.SZ	7.35	−21.89	29.24	Net transmitter
	Unisplendour Corporation Limited	000938.SZ	30.74	0.78	29.96	Net transmitter
Tech industry average	5 Transmitters, 4 Receivers		8.53	13.43	−4.90	Net receiver
Energy industry	China Yangtze Power Co., Ltd.	600900.SH	−8.52	19.34	−27.86	Net receiver
	Tongwei Co., Ltd.	600438.SH	3.78	−14.59	18.37	Net transmitter
	Xinjiang Goldwind Science & Technology Co., Ltd.	002202.SZ	18.15	17.44	0.71	Net transmitter
	LONGi Green Energy Technology Co., Ltd.	601012.SH	5.12	−8.59	13.71	Net transmitter
	Huaneng Power International, Inc.	600011.SH	−9.85	−10.51	0.66	Net transmitter
	China Petroleum & Chemical Corporation (Sinopec)	600028.SH	21.95	−46.55	68.50	Net transmitter
	PetroChina Company Limited	601857.SH	−15.59	14.42	−30.01	Net receiver
Energy industry average	5 transmitters, 2 receivers		2.15	−4.15	6.30	Net transmitter
Key statistical facts	Overall spillover index change (full sample)				5.74	Positive baseline spillover change
	Cross industry net predictive spillover direction	Direction: energy → tech	Net value: −44.09	Energy industry is the dominant net spillover transmitter		

Table 4. Firm-level spillover changes before and after the release of ChatGPT 3.5.

Category	Company Name	Stock Code	STI Change (%)	SRI Change (%)	Net Change (%)	Role (Post-Event)
Technology industry	Cambricon Technologies Corporation Limited	688256.SH	0.94	−6.92	7.86	Net transmitter
	Kingsoft Office Software Co., Ltd.	688111.SH	5.67	5.48	0.19	Net transmitter
	iFlytek Co., Ltd.	002230.SZ	10.60	−73.83	84.42	Net transmitter
	Inspur Electronic Information Industry Co., Ltd.	000977.SZ	−5.48	−68.06	62.58	Net transmitter
	Yonyou Network Technology Co., Ltd.	600588.SH	−14.38	44.91	−59.28	Net receiver
	Sugon Information Industry Co., Ltd.	603019.SH	−17.69	6.10	−23.79	Net receiver
	Semiconductor Manufacturing International Corporation	688981.SH	−17.39	−57.26	39.88	Net transmitter
	ZTE Corporation	000063.SZ	−12.61	14.90	−27.51	Net receiver
	Unisplendour Corporation Limited	000938.SZ	−38.30	42.08	−80.38	Net receiver
Tech industry average	5 Transmitters, 4 Receivers		−9.85	−10.29	0.44	Net transmitter
Energy industry	China Yangtze Power Co., Ltd.	600900.SH	11.95	6.11	5.84	Net transmitter
	Tongwei Co., Ltd.	600438.SH	−3.24	−21.86	18.62	Net transmitter
	Xinjiang Goldwind Science & Technology Co., Ltd.	002202.SZ	−10.94	−3.75	−7.19	Net receiver
	LONGi Green Energy Technology Co., Ltd.	601012.SH	−3.63	−12.42	8.78	Net transmitter
	Huaneng Power International, Inc.	600011.SH	−22.58	30.86	−53.44	Net receiver
	China Petroleum & Chemical Corporation (Sinopec)	600028.SH	13.81	−23.07	36.88	Net transmitter
	PetroChina Company Limited	601857.SH	−7.45	6.01	−13.46	Net receiver
Energy industry average	4 transmitters, 3 receivers		−3.16	−2.59	−0.57	Net receiver
Key statistical facts	Overall spillover index change (full sample)				−6.92	Negative baseline spillover change
	Cross industry net predictive spillover direction	Direction: tech → energy	Net value: 3.97	Technology industry is the dominant net spillover transmitter		

At the firm level, the release of DeepSeek R1 led to a more differentiated pattern of risk reorganization. Within the technology sector, Sugon and Inspur Information, both closely associated with computing infrastructure, recorded sharp increases in net risk transmission and became major nodes of outward risk propagation. By contrast, AI algorithm-related firms such as Cambricon and iFlytek experienced a further deepening of net risk reception, indicating that different segments of the technology sector were exposed to risk pressures of different directions and intensities under the shock of a domestic large language model breakthrough. A similar differentiation emerged within the energy sector. New energy firms such as Tongwei and Goldwind registered clear increases in net risk transmission, whereas traditional energy firms such as PetroChina showed a further increase in risk reception. This suggests that the domestic technological breakthrough did not generate a uniform effect across the energy sector but instead produced a more complex adjustment shaped by differences in sectoral function and market expectations.

These results indicate that DeepSeek R1 was associated with a higher aggregate level of spillovers and a deeper restructuring of the technology and energy risk network. Compared with the preceding events, the network adjustment was more pronounced, with stronger net predictive spillovers from energy toward technology and greater internal differentiation within both sectors. Table 5 summarizes the changes in firm-level net spillovers before and after the release of DeepSeek R1. The larger baseline spillover change and the broader network reconfiguration are consistent with H3.

4.2. Spillover Network Analysis of the Technology and Energy Sectors

Based on the risk spillover matrix, this study constructs a directed network framework to examine how the four events differently affected the structure of the risk network linking the technology and energy sectors. By applying a threshold and retaining only spillover paths with weights above 10, the framework identifies the main risk hubs and the most important transmission channels in each period. This makes it possible to show more clearly how the network responded differently to policy shocks and technology shocks. In the network, nodes represent leading firms, node size reflects total predictive spillover, node color distinguishes sectoral affiliation, and edge thickness and direction indicate the strength and direction of risk transmission, respectively.

As shown in Figure 4, before the announcement of the carbon peaking and carbon neutrality goals, the risk network displayed a clear pattern of sectoral segmentation. Within the technology sector, risk transmission had already formed around computing equipment firms, whereas the energy sector remained characterized by a relatively independent internal circulation. Only a few cross-sectoral links were observed, suggesting that risk transmission was still limited at the early stage of the transition. After the policy announcement, the network structure changed. Within the technology sector, software service firms replaced hardware firms as the new risk hubs. Within the energy sector, risk linkages between hydropower and thermal power firms strengthened markedly, and solar power firms became more active in transmitting risk. In addition, cross-sectoral risk transmission increased substantially. Green energy firms formed multiple transmission paths toward the technology sector, indicating that the carbon peaking and carbon neutrality goals had evolved from a source of sector-specific pressure into an important driver of cross-sectoral risk transmission.

Table 5. Firm-level spillover changes before and after the release of DeepSeek R1.

Category	Company Name	Stock Code	STI Change (%)	SRI Change (%)	Net Change (%)	Role (Post-Event)
Technology industry	Cambricon Technologies Corporation Limited	688256.SH	−9.41	182.53	−191.94	Net receiver
	Kingsoft Office Software Co., Ltd.	688111.SH	24.57	44.52	−19.95	Net receiver
	iFlytek Co., Ltd.	002230.SZ	17.09	91.52	−74.44	Net receiver
	Inspur Electronic Information Industry Co., Ltd.	000977.SZ	32.43	−47.00	79.44	Net transmitter
	Yonyou Network Technology Co., Ltd.	600588.SH	11.84	−28.69	40.53	Net transmitter
	Sugon Information Industry Co., Ltd.	603019.SH	23.40	−59.40	82.79	Net transmitter
	Semiconductor Manufacturing International Corporation	688981.SH	16.43	44.41	−27.98	Net receiver
	ZTE Corporation	000063.SZ	21.59	−11.92	33.51	Net transmitter
	Unisplendour Corporation Limited	000938.SZ	26.13	−2.43	28.56	Net transmitter
Tech industry average	5 Transmitters, 4 Receivers		18.23	23.73	−5.50	Net receiver
Energy industry	China Yangtze Power Co., Ltd.	600900.SH	2.05	3.46	−1.41	Net receiver
	Tongwei Co., Ltd.	600438.SH	30.49	−20.23	50.72	Net transmitter
	Xinjiang Goldwind Science & Technology Co., Ltd.	002202.SZ	26.09	−4.74	30.83	Net transmitter
	LONGi Green Energy Technology Co., Ltd.	601012.SH	15.87	7.43	8.44	Net transmitter
	Huaneng Power International, Inc.	600011.SH	9.14	19.94	−10.80	Net receiver
	China Petroleum & Chemical Corporation (Sinopec)	600028.SH	19.75	5.86	13.89	Net transmitter
	PetroChina Company Limited	601857.SH	4.75	46.97	−42.21	Net receiver
Energy industry average	4 transmitters, 3 receivers		15.45	8.38	7.07	Net transmitter
Key statistical facts	Overall spillover index change (full sample)				17.01	Positive baseline spillover change
	Cross industry net predictive spillover direction	Direction: energy → tech	Net value: −49.46	Energy industry is the dominant net spillover transmitter		

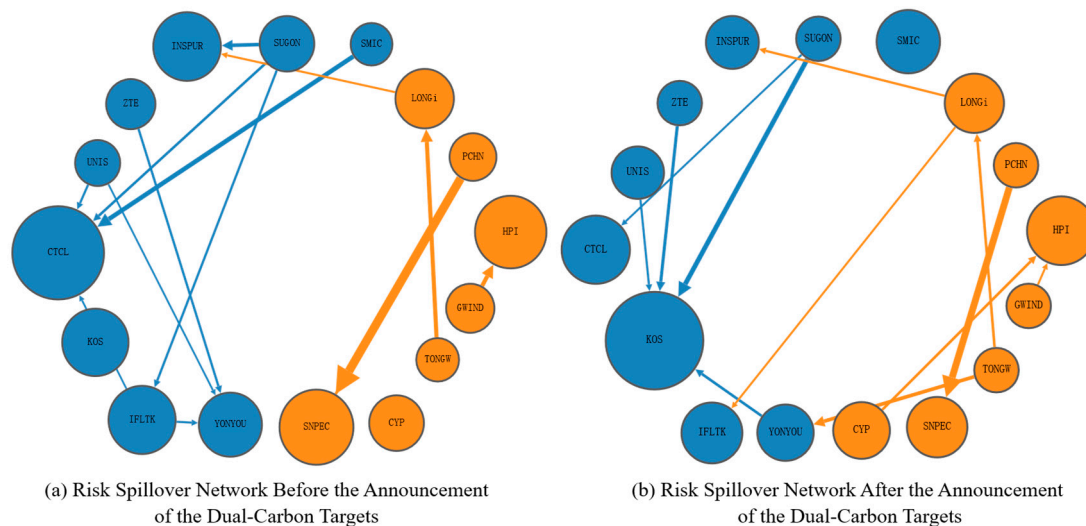


Figure 4. Short-term risk spillover networks before and after the Dual Carbon target announcement.

According to Figure 5, before the launch of the East Data and West Computing project, the risk network had already begun to display a technology-led structure, with cloud computing and semiconductor firms forming two major centers of risk absorption. Although the energy sector remained relatively independent as a whole, it had already started to transmit risk selectively to technology firms, suggesting that the relationship between the two sectors was shifting from weak linkage to a more functional form of coupling. After the full implementation of the project, the network became more integrated, and the concentration of risk within the technology sector increased markedly. AI chip firms in particular emerged as key nodes of risk accumulation, absorbing risk fluctuations from multiple segments, including servers and software services. At the same time, the scale of cross-sectoral risk transmission expanded substantially, with both traditional energy and renewable energy firms exhibiting stronger directional spillover contributions toward the core nodes of the technology sector. These patterns suggest that the East Data and West Computing project not only intensified the linkage between technology and energy, but also restructured the pattern of risk transmission between the two sectors through the national allocation of computing infrastructure, thereby reflecting the systemic effects of digital infrastructure expansion on the integrated technology energy ecosystem.

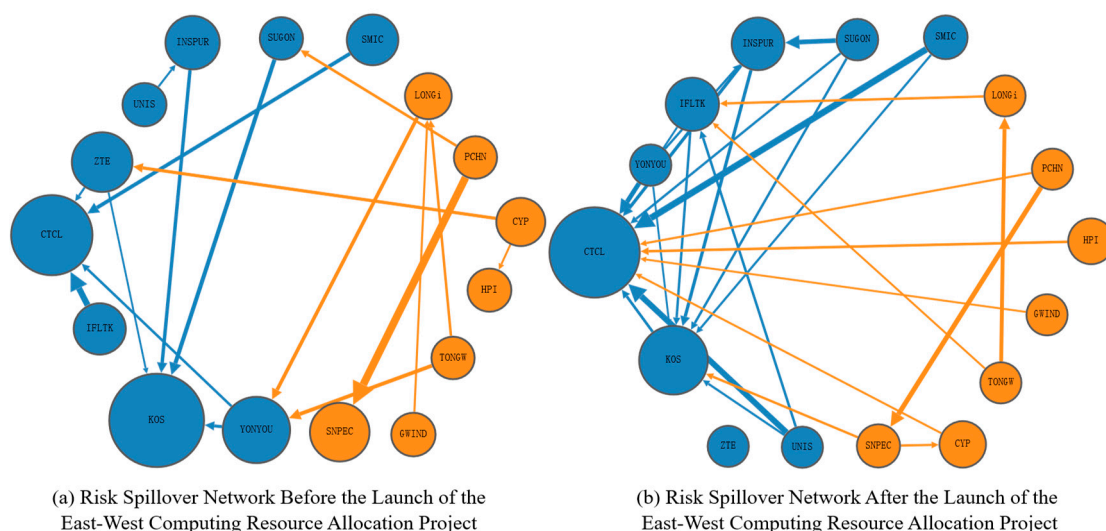


Figure 5. Short-term risk spillover networks before and after the East Data and West Computing project.

Figure 6 shows that the risk network had already displayed an active structure shaped by the global wave of technological change before the release of ChatGPT 3.5. Within the technology sector, a relatively dense pattern of risk transmission had emerged, with firms related to data infrastructure and chip manufacturing playing prominent roles in the transmission process. After the release of ChatGPT 3.5, the network structure adjusted further. Risk transmission paths within the technology sector were reconfigured, and communications equipment firms gradually became the new centers of risk transmission. At the same time, cross-sectoral risk transmission became more selective. Rather than diffusing risk broadly across the technology sector, the estimated network shows stronger directional spillover contributions from energy firms toward specific technology nodes. This suggests that the external technology shock did not simply expand the risk network as a whole, but instead reshaped cross-sectoral risk transmission in a more targeted manner by altering key nodes and transmission paths.

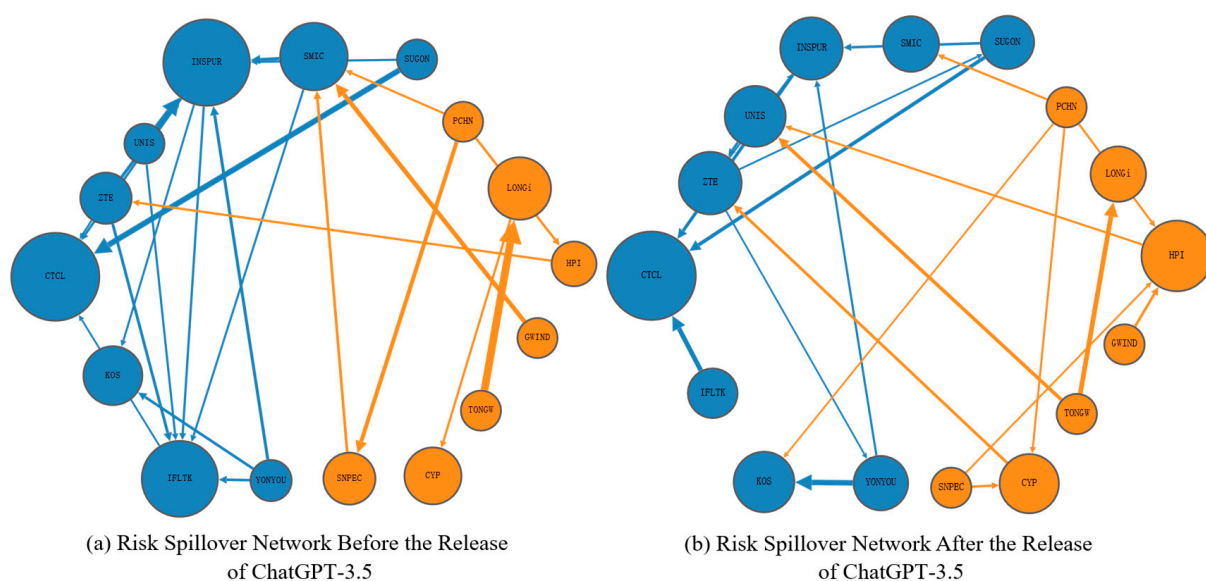


Figure 6. Short-term risk spillover networks before and after the ChatGPT-3.5 release.

According to Figure 7, before the release of DeepSeek R1, the risk network reflected a preparatory stage of domestic technological innovation. Within the technology sector, a dual structure of risk absorption had emerged, with both software and hardware firms playing important roles. The estimated network contained a limited number of directional spillover links from the energy sector toward the technology sector. After the release of DeepSeek R1, the network changed markedly. Risk polarization within the technology sector became more pronounced, with AI chip firms emerging as the main centers of risk accumulation, while application software firms shifted from net receivers to net transmitters of risk. Cross-sectoral risk transmission also expanded substantially. Both traditional power firms and renewable energy firms exhibited stronger directional spillover contributions toward core technology nodes. These patterns indicate that the domestic technological breakthrough represented by DeepSeek R1 produced a substantial reconfiguration of the risk network linking energy and technology.

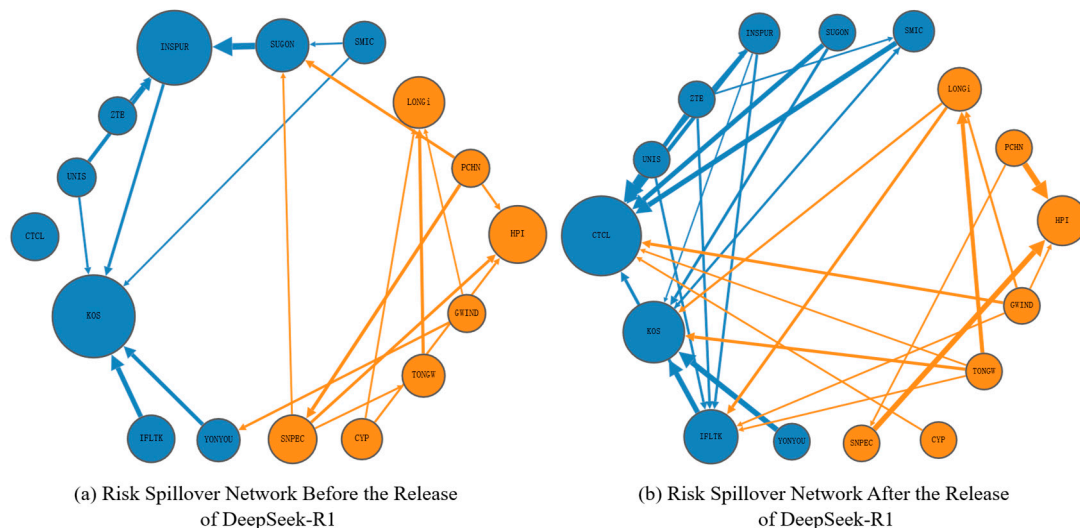


Figure 7. Short-term risk spillover networks before and after the DeepSeek R1 release.

4.3. Robustness Analysis

To further assess whether the firm-level findings also hold at the sector level, and to examine the overall mechanism of risk transmission among traditional energy, new energy, and technology from a broader perspective, this section uses three sectoral indices: the CSI Energy Index for traditional energy, the CSI Carbon Neutrality Index for new energy, and the CSI Technology 50 Index for the technology sector. A rolling window time varying parameter vector autoregressive model is constructed, and systemic risk spillovers are re-estimated using generalized forecast error variance decomposition. This robustness analysis serves three purposes. In the sector-level analysis, the rolling window covers 200 trading days, while the lag order is set to one, consistent with the firm-level IVAR specification. First, sectoral indices reduce the influence of firm-specific heterogeneity and provide a clearer picture of aggregate sectoral risk. Second, the three indices correspond to key industrial chains within China's energy security strategy and therefore carry clear policy relevance. Third, the time varying parameter framework captures structural changes in risk transmission and provides dynamic evidence on the different effects of policy events and technology events.

Figure 8 presents the time-varying pattern of risk spillovers among the three sectoral indices. The results show that the total spillover index varied substantially over time. Its average level was 31.55%, and its peak reached 51.87%. After each of the four major events, the spillover index rose markedly. Following the announcement of the carbon peaking and carbon neutrality goals, the index increased rapidly from around 30% to above 40% and remained at a high level. After the launch of the East Data and West Computing project, the level of risk contagion increased further. Around the release of ChatGPT 3.5, the index exceeded 45%. Following the release of domestic large language models, including DeepSeek R1, the index rose above 50%, reaching its highest level in the sample period.

The net spillover results also reveal a clear directional pattern. The new energy sector remained the main net transmitter of risk throughout the sample period. The technology sector remained a net receiver of risk. The traditional energy sector showed only a weak positive net spillover. The estimated connectedness network indicates that the directional predictive spillover from new energy toward technology was the strongest. It was much stronger than the spillover from traditional energy to new energy. Spillovers from technology to the other two sectors remained below 4%. Together, these results point to an asymmetric structure in which new energy plays the leading role, while the technology sector passively absorbs risk. The sector-level results are broadly consistent with the firm-level evidence. The degree of consistency, however, varies across events.

Both analyses show stronger connectedness after the two policy-driven events. Both also show a pronounced adjustment around DeepSeek R1. The main difference appears around ChatGPT 3.5. The firm-level analysis shows a temporary decline in overall spillovers, while the sector-level analysis shows stronger aggregate connectedness during the same period. This difference may reflect the different time scales of the two approaches. The firm-level analysis captures short-term event responses, whereas the rolling sector-level model reflects broader dynamic changes.

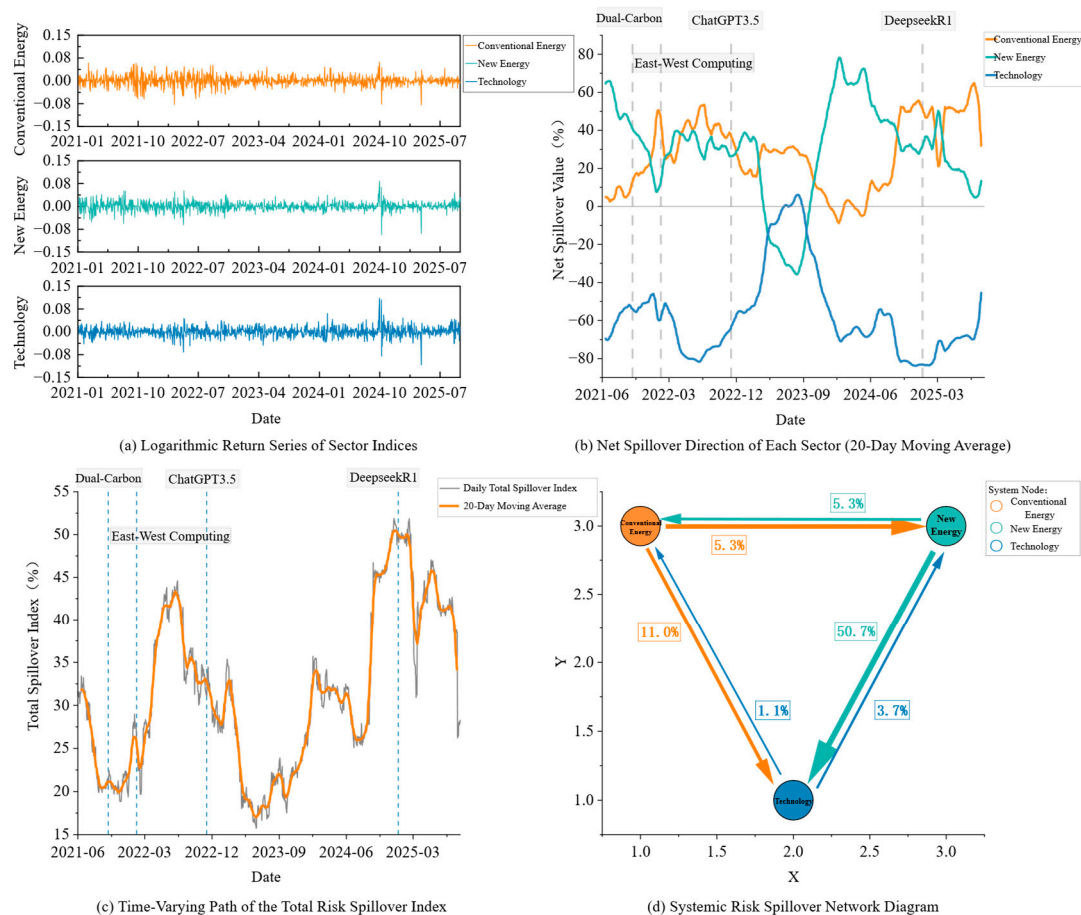


Figure 8. Systemic risk spillover among three major sector indices: Evidence from TVP-VAR. Note: Panel (a) shows the logarithmic return series of the three sector indices. Panel (b) presents the 20-day moving average of net directional spillovers. Panel (c) reports the time varying total spillover index, with the four major events marked for reference. Panel (d) summarizes the average directional spillover network among the three sectors. The results are estimated using the time varying parameter vector autoregressive (TVP-VAR) framework.

To examine whether the firm event results are sensitive to the choice of event horizon, we re-estimate the pre- and post-event spillover changes using symmetric windows of 30, 60, and 120 calendar days around each event. The event date itself is excluded from both windows. Except for the event-window length, the firm composition, interval-return construction, lag specification, forecast horizon, and spillover-measure calculation are kept unchanged. The original event-specific windows are retained as the baseline specification. Figure 9 reveals clear heterogeneity in window sensitivity across the four events. The positive spillover effect associated with the East Data and West Computing project remains unchanged in direction across all alternative specifications, with the overall spillover index change ranging from 1.19 percentage points under the 30-day window to 24.34 percentage points under the 120-day window.

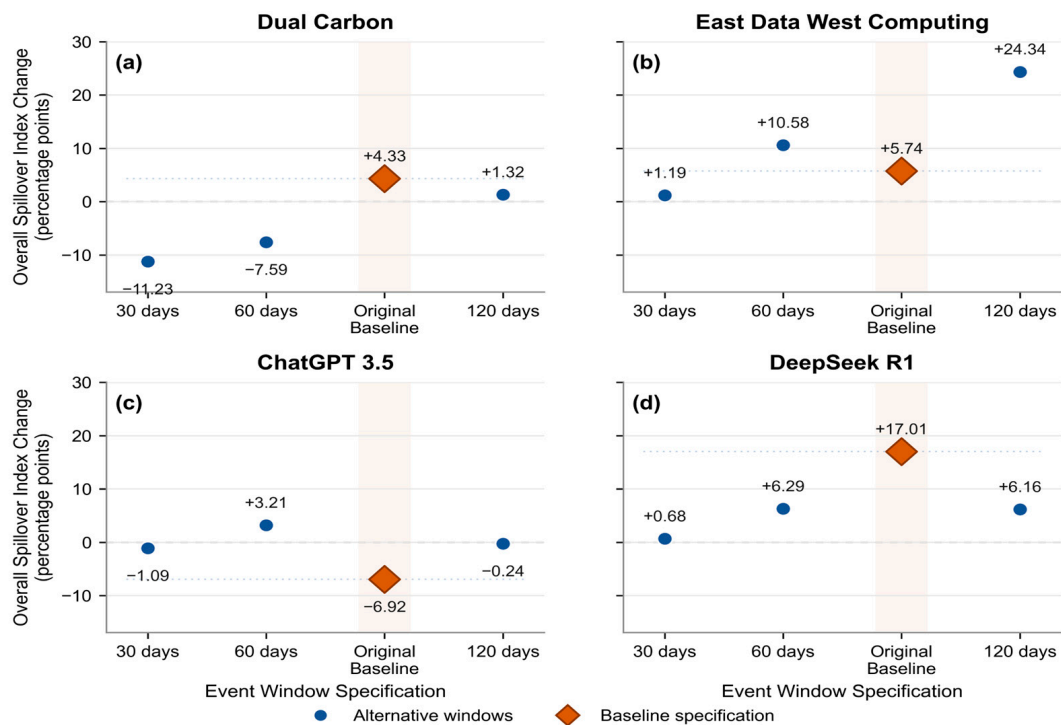


Figure 9. Event window sensitivity analysis. (a) sensitivity results for the Dual Carbon event; (b) sensitivity results for the East Data West Computing event; (c) sensitivity results for the ChatGPT 3.5 event; (d) sensitivity results for the DeepSeek R1 event.

A similarly stable positive pattern is observed for DeepSeek R1, for which the corresponding changes remain positive at 0.68, 6.29, 17.01, and 6.16 percentage points under the 30-day, 60-day, original baseline, and 120-day specifications, respectively. These two events therefore display relatively strong directional robustness to the choice of event horizon. By contrast, the results for the Dual Carbon event vary more noticeably with the choice of event window. The spillover change is negative over 30 and 60 days, whereas positive values are observed under the baseline and 120 days. The ChatGPT 3.5 event also shows some sensitivity to window length, as the direction changes only with the 60-day window. The results for East Data and West Computing and DeepSeek R1 remain positive across all event windows. The results for Dual Carbon and ChatGPT 3.5 are more sensitive to window length, with greater sensitivity observed for the Dual Carbon event.

5. Conclusions and Policy Implications

5.1. Main Conclusions

The rapid development of artificial intelligence is reshaping the relationship between technology and energy. As large language models continue to evolve, computing infrastructure expands, and energy transition advances in parallel, the link between the two sectors is no longer a conventional industrial relationship. It is increasingly becoming a deeper form of systemic coupling. This study examines how four key events restructured the risk relationship between technology and energy at both the firm level and the sector level. The results show different patterns across the four events. Under the baseline specification, the two policy events are associated with higher overall spillovers and stronger net predictive spillovers from energy toward technology. The positive pattern is stable across event windows for East Data and West Computing, while the Dual Carbon result is more sensitive to window length. ChatGPT 3.5 is associated with a temporary decline in overall spillovers and a reversal in directional connectedness under the baseline window, although this result also varies across event horizons. DeepSeek R1 shows the largest baseline increase in overall spillovers, and

its positive direction remains stable across the alternative event windows. The simulation standard errors also show differences in estimation precision across the four events.

These findings suggest that the risk relationship between technology and energy is not fixed. It is continuously reorganized under different types of major events. The sector-level robustness results further show that the new energy sector remained the main net transmitter of risk, while the technology sector consistently acted as the main net receiver. This produced an asymmetric structure in which new energy led and technology absorbed risk. Artificial intelligence creates new growth opportunities. Its expansion may also be associated with greater systemic pressure as the interdependence between technology and energy deepens.

5.2. Policy Recommendations

Based on the results at the firm and sector levels, this study proposes policy recommendations in three areas. These areas include energy planning, policy coordination, and financial stability monitoring. First, energy planning should take greater account of the electricity demand created by the expansion of artificial intelligence and computing infrastructure. The rapid growth of data centers, large language models, and computing activities that require very high processing capacity has increased the dependence of the technology sector on a stable supply of energy. Regions with large concentrations of computing resources should improve their forecasts of electricity demand over the medium and long term. The location of computing facilities should also be coordinated with grid capacity, the supply of clean energy, and the ability to transmit electricity across regions. Such coordination can reduce the pressure that rapid digital development may place on local energy systems. Second, stronger coordination is needed between digital policy and energy policy. The results show that major policy events are associated with changes in the connectedness between technology and energy sectors. Policies for artificial intelligence, digital infrastructure, and computing capacity should therefore consider energy supply and energy security from the early stages of policy design. At the same time, plans for digital infrastructure should be coordinated with renewable energy development, power grid construction, and regional energy planning. This can improve consistency between different policy areas and reduce potential risks across sectors. Third, the connectedness between technology and energy sectors should receive greater attention in financial stability monitoring. Regulators can use measures such as total spillovers, directional spillovers, and net spillovers as supplements to traditional indicators of market risk. Particular attention should be given to changes in the risk structure after major policy events or technological developments. Financial institutions should also monitor their exposure to technology and energy industries more closely. These measures can provide additional information for stress testing and the monitoring of risks under macroprudential policy.

5.3. Limitations and Future Research

This study also has several limitations. First, the analysis is based on China's A share market, and the extent to which the findings apply to other countries and market settings remains to be examined. In addition, the firm analysis focuses on representative listed companies with continuous trading data and therefore may underrepresent smaller or non-listed firms. Future research could extend the network to a broader cross-section of firms when comparable high-frequency data become available. Second, the analysis focuses on four key events, but discrete event windows cannot fully capture the longer process through which artificial intelligence diffuses and energy transition unfolds. The spillover changes across events also differ in estimation precision, and some results are sensitive to the event horizon. This sensitivity is most evident for the Dual Carbon event and is also present for ChatGPT 3.5. Third, the study examines risk spillovers at the firm level and the sector

level, but does not yet extend to more detailed parts of the value chain, such as computing equipment, data centers, power grids, and energy storage systems. Future research may therefore extend the analysis through cross country comparison, longer time horizons, and finer identification of transmission mechanisms along the technology and energy value chains. A further limitation concerns the interpretation of directional connectedness. The IVAR and generalized forecast error variance decomposition framework identifies predictive dependence and the relative contribution of shocks to forecast error variance, but it does not establish structural causality. The estimated direction of spillovers may reflect common information, omitted market factors, or simultaneous responses to broader shocks. Future research could combine connectedness measures with identification strategies such as structural models, external instruments, or quasi experimental designs to distinguish predictive spillovers from causal transmission more explicitly.

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Data Availability Statement: The data and materials supporting the findings of this study have been made available for peer review. These include the raw datasets used in the analysis, consisting of three sectoral indices and raw daily trading data for listed firms, together with the processed analytical datasets and the Python 3.7 scripts used for data processing, spillover estimation, event analysis, network analysis, and empirical analysis. The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to the applicable licensing restrictions.

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Appendix A

Table A1. IVAR estimation diagnostics and uncertainty assessment across event windows.

Event	Iterations Pre/Post	Converged Pre/Post	AIC Lag	BIC Lag	Fallback Used	ΔTSI	Simulation SE
Dual Carbon	505/618	Yes/Yes	1	1	No	4.33	5.4524
East Data and West Computing	451/413	Yes/Yes	1	1	No	5.74	4.9417
ChatGPT 3.5	398/650	Yes/Yes	1	1	No	−6.92	3.9726
DeepSeek R1	700/706	Yes/Yes	1	1	No	17.01	8.6064

Note: All eight pre- and post-event IVAR estimations converged successfully, and no midpoint VAR fallback was required. Both AIC and BIC selected $p = 1$ for the full sample and all event windows. Simulation SE denotes the residual Monte Carlo standard error associated with the event change in the total spillover index.

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