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Research Article

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Tail-Risk Spillovers among Green Innovative Firms: A Dynamic Network Analysis Based on TENET

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Abstract

Amid the transition toward a green and low-carbon economy, green innovative firms have become important micro-level agents of industrial upgrading. However, limited attention has been paid to the network of extreme-risk spillovers among these firms. This study examines extreme-risk spillovers among 150 green innovative firms from a network perspective and investigates their dynamic evolution. Using firm-level financial data, we employ the TENET model with rolling-window estimation, LASSO, and univariate quantile regression to identify directional extreme-risk spillovers. We then examine network connectedness, node importance, cross-industry transmission, and the effects of external shocks. The results show that, first, extreme-risk spillovers among green innovative firms are significant and heterogeneous, indicating that systemic risk has a clear network structure. Second, the risk network evolves dynamically with market conditions, with both the scope and intensity of risk connections changing over time. Third, systemic importance is concentrated in a small number of core nodes, while centrality does not necessarily translate into stronger direct risk-transmission capacity. Fourth, cross-industry risk transmission is pronounced, with inter-industry spillovers accounting for 66.1% of total connectedness. Fifth, different external shocks induce distinct network restructuring, suggesting that extreme-risk spillovers are both shock-type dependent and structurally adaptive. This study develops an integrated framework linking green innovation, extreme risk, and industrial networks, thereby extending the literature. The findings suggest that risk governance in green industries should address key nodes, industrial linkages, and transmission pathways simultaneously. They also provide empirical evidence for promoting high-

quality development in green industries and strengthening systemic risk prevention and control.

Keywords Green innovation; Tail-risk spillovers; TENET; Cross-industry transmission; Systemic risk

1 Introduction

Enterprises are the micro-level foundation of industrial transformation toward a green and low-carbon economy. However, firms often face greater cash-flow pressures and tighter financing constraints when investing in green patents, expanding production capacity, and upgrading production lines (Gao et al., 2026). At the same time, firms are exposed to common shocks from macroeconomic interest rates, energy prices, and market sentiment in financial markets (Ramelli & Wagner, 2020). These shocks can propagate across firms through industrial linkages and financial channels, particularly under extreme market conditions. As external conditions become more complex, inter-firm risk connectedness may intensify, making systemic risk spillovers increasingly salient (Wang et al., 2025). Yet most existing studies examine firms in isolation, limiting their ability to capture system-wide risk dynamics (Zhang et al., 2026). Meanwhile, tail-risk network studies, including those based on the TENET framework, have paid limited attention to green innovative firms, which are characterized by both industrial transformation and technological innovation (Hu & Guo, 2024).

This study makes three main contributions to the literature. First, we move beyond the single-firm risk framework by shifting the focus from firm-level risk effects to the interconnected transmission and restructuring of tail risks across firms. This approach provides a multidimensional view of the dynamic evolution of the risk network. Second, using daily data for 150 green innovative firms from 2015 to 2024, we identify directional tail-risk spillovers and capture changes in both the breadth and intensity of risk connections. Third, we aggregate firm-level risk linkages to the industry level to identify within-industry and cross-industry transmission pathways. We further examine how different types of external shocks reshape the risk network. These findings provide empirical evidence for systemic risk prevention and control in green industries. They

also offer implications for regulators seeking to identify critical nodes and transmission pathways and to implement differentiated, dynamic oversight.

2 Literature review

2.1Green Innovation and Corporate Risk

Green innovation is a key technological pathway through which firms pursue low-carbon transformation and improve resource efficiency. Existing studies have examined its implications for operating performance, financial outcomes, and corporate risk-taking. On the one hand, green innovation may mitigate operating risk by improving resource allocation, reducing environmental risks, and strengthening firms' competitive positions (Hayat & Qingyu, 2024). On the other hand, its long development cycles and high technological uncertainty may increase firms' exposure to risk (Peng et al., 2025).

Recent research has increasingly examined the relationship between green innovation and corporate financial risk. Some studies find that green innovation reduces corporate default risk, partly by lowering cash-flow volatility and managerial risk-taking (Liu, 2024). Evidence from U.S. firms shows that greater green innovation is associated with lower default risk, although the relationship varies with firm characteristics (Chung et al., 2025). Evidence from China further suggests that green innovation can affect corporate risk by reducing financialization (Zhou & Qi, 2023). Related studies also show that financial-risk prevention policies can promote green innovation by curbing financial-asset investment and reducing managerial short-termism (Liang et al., 2025). However, green innovation does not necessarily have a risk-mitigating effect. Some studies argue that green innovation strategies may increase default risk because they require long investment horizons and substantial financing (Wang et al., 2024). Evidence from Chinese listed firms, for example, suggests that green innovation strategies can increase debt default risk, partly through overinvestment (Guo et al., 2023). Conversely, financial risk may constrain firms' green innovation, with the negative effect becoming stronger under greater economic policy uncertainty (Zhou et al., 2022). This evidence points to a potentially bidirectional relationship between green innovation and corporate risk.

Overall, the literature points to a complex relationship between green innovation and corporate risk. However, most studies adopt a single-firm perspective. Even when they identify risk-reducing or risk-enhancing effects, they do not fully capture how risks propagate across firms or become systemic. This limitation is particularly relevant for green innovative firms, whose investment activities, financing conditions, and technological transitions may create interconnected exposures across firms and industries. A network-based perspective is therefore needed to move beyond the effects of green innovation on individual firms and examine the transmission and evolution of tail risks across the broader green industrial system.

2.2 Corporate Tail Risk and Risk Network Research

Unlike conventional corporate risk research, systemic risk research emphasizes the interdependence and transmission of risk across multiple entities. Against this background, Härdle et al. (2016) developed the Tail-Event driven NETwork (TENET) approach, which integrates tail events with network dynamics to identify tail-risk dependence among financial institutions in high-dimensional settings. It also distinguishes major risk transmitters from risk receivers. The approach has since been applied to financial-market and industry-level risk analysis, showing that tail-risk networks can reveal directional transmission patterns that aggregate risk measures may overlook (Li et al., 2025). Subsequent studies further show that risk networks are not static. Instead, they can be substantially reconfigured following major shocks (Domínguez-Monterroza et al., 2026).

However, most existing studies remain focused on markets or industries and have yet to examine the underlying mechanisms at the firm level (Väyrynen et al., 2025). Thus, the risk transmission chain linking markets and firms within green industries remains insufficiently understood. This gap motivates our firm-level network approach, in which green innovative firms serve as nodes and TENET is used to identify directional tail-risk linkages among them.

Taken together, the literature on green innovation and corporate risk, as well as that on tail-risk networks, has generated substantial insights. Yet several important gaps

remain. First, the unit of analysis is often limited to individual firms. Existing studies on green innovation and corporate risk primarily analyze firms in isolation, making it difficult to capture how risk propagates to other firms through industrial linkages and market connections. Second, the characterization of risk remains limited. Most studies rely on measures such as default probabilities and pay limited attention to the direction and network structure of tail-risk transmission under extreme market conditions. Third, inter-industry linkages are insufficiently captured. Industries are connected through multiple channels, yet existing firm-level risk studies often treat firms as relatively independent risk entities. As a result, cross-industry tail-risk transmission within green industries remains underexplored. Fourth, external-shock scenarios remain relatively narrow. Although previous studies recognize that major events can strengthen market-wide risk connectedness, less is known about whether different types of shocks produce distinct patterns of network restructuring (Mo et al., 2025).

3 Research Methods

3.1 Sample Selection

We examine listed firms to investigate the dynamic tail-risk spillovers among green innovative firms. The sample is identified in two stages. In the first stage, following Hunjra (2025), we identify firms operating in industries covered by the Green Industry Guidance Catalogue. In the second stage, following Sartirana (2025), we further identify green innovative firms using green patent application data. Green innovation activity is measured by the total number of green invention and utility model patent applications filed independently or jointly by firm i in year t, denoted as $GreenApply_{i,t}$, We then construct green innovation intensity as: $GI_{i,t}=ln(1+GreenApplyi,t)$To distinguish innovation quality, we further construct a high-quality green innovation measure:$GIQ_{i,t}=ln(1+GreenInventionApply_{i,t})$Compared with green utility model patents, green invention patents generally reflect greater technological sophistication. After screening for green-industry status, green innovation activity, and the completeness of trading and financial data, 337 firms remain for the initial TENET estimation. Given the computational burden of high-

dimensional risk-network estimation and the need to retain market-representative nodes, we further select 150 firms based on data completeness, market representativeness, and the persistence of green innovation to construct the baseline risk network.

3.2 Data Sources

Following Zhou et al. (2025), we construct the dataset from two sources: daily stock-trading data and annual firm-level financial data. The sample consists of A-share listed firms in green industries over the period 2015–2024. Following the classification criteria of the 2019 edition of the Green Industry Guidance Catalogue and firms' primary business activities, we identify firms operating in seven major green-industry segments: new-energy vehicles; photovoltaic and wind power; energy conservation and environmental protection; energy storage; resource recycling; transmission and distribution equipment manufacturing; and other green industries. Daily stock-trading data, including daily returns with cash dividends reinvested and the circulating market capitalization of individual stocks, are obtained from the CSMAR China Stock Market Trading Database. Annual firm-level financial data are obtained from the CSMAR China Listed Companies Financial Statements Database.

3. 3TENET-Based Tail-Risk Spillover Network Construction

3.3.1 Stage 1: Estimation of Conditional Tail Risk

The first stage estimates firms' conditional tail risk using linear quantile regression under common macro-financial conditions. For firm i, the model is specified as follows (Zhou et al., 2025):

$$R_{i,t} = \alpha_i(\tau) + \gamma_i(\tau)' M_{t-1} + \varepsilon_{i,t}(\tau) \quad (1)$$

Where R_{it} denotes the log return of firm i on trading day t, and M_{t-1} is a vector of lagged macro-financial variables. The term $\alpha_i(\tau)$ is the intercept, $\gamma_i(\tau)$ captures firm i's sensitivity to common macro-financial factors at quantile τ, and $\varepsilon_{i,t}(\tau)$ is the error term. By controlling for common macro-financial risk factors, the model separates firm-specific tail risk from shocks shared across the market.

At quantile τ, the conditional tail risk of firm i is defined as:

$$\widehat{VaR}_{i,t}(\tau) = \hat{\alpha}_{i,\tau} + \hat{\gamma}_{i,\tau}' M_{t-1} \quad (2)$$

The baseline specification sets τ=0.01, corresponding to the first percentile of the firm's return distribution and capturing severe downside risk. Because risk spillovers are time-varying, we use a rolling-window estimation procedure. The baseline window contains 250 trading days, corresponding to approximately one year. The window is shifted forward by one trading day at a time, and the model is re-estimated to obtain a new conditional VaR. This produces a time-varying series of firm-level tail-risk measures.

3.3.2 Stage 2: Estimation of Inter-Firm Tail-Risk Spillovers

The second stage identifies directional tail-risk transmission across firms. Let firm *j* denote the target firm. The information set consists of the conditional tail risks of all other firms, common macro-financial variables, and the lagged characteristics of firm *j*:

$$\mathcal{R}_{j,t} = \{\Phi_{-j,t,\tau},\ M_{t-1},\ B_{j,t-1}\} \tag{3}$$

where $\Phi_{-j,t,\tau}$ denotes the conditional tail risks of all firms except *j*, M_{t-1} is the vector of lagged macro-financial variables, and $B_{j,t-1}$ represents the lagged characteristics of firm *j*.

$$\Phi_{j,t,\tau} = g\left(\beta_{j|\mathcal{R}_{i,t}}'\right) + \varepsilon_{j,t} \tag{4}$$

We then employ a single-index quantile regression model:

$$D_{j|i,t} = g'\left(\beta_{j|\mathcal{R}_{i,t}}'\right) \cdot \beta_{j|i} \tag{5}$$

where $g(\cdot)$ is an unknown single-index function and $\beta_j|\mathcal{R}_{j,t}$ is the parameter vector associated with the information set. With 150 firms in the network, the information set is high-dimensional: each target firm may, in principle, be affected by the tail risks of the other 149 firms. To remove spurious connections and identify economically meaningful transmission links, we use LASSO for variable selection. This procedure retains the most informative risk sources from the high-dimensional set of candidate links. Given the estimated parameters of the single-index model, the marginal tail-risk spillover from firm *i* to target firm *j* is defined as:

where $D_{j|i,t}$ measures the marginal effect of a change in firm i's tail risk on the tail

risk of firm j. A positive value, $D_{j|i,t}$>0, indicates a directional spillover from firm i to firm j, denoted by $i \rightarrow j$. Importantly, $D_{j|i,t}$ is not equivalent to a quantile regression coefficient. Instead, it combines the local marginal effect of the single-index function with the corresponding parameter. It therefore captures how the magnitude of risk spillovers varies with market conditions.

3.3.3 Dynamic Tail-Risk Spillover Network Construction

Following Li et al. (2025), we organize the marginal tail-risk spillovers between all firm pairs into an adjacency matrix for each rolling window:

$$P_t = \left[\left|D_{j|i,t}\right|\right]_{N\times N}, \quad N = 150 \tag{6}$$

where N denotes the number of firms in the baseline network and the diagonal elements are set to zero. Following the direction of risk transmission, rows represent risk-receiving firms, whereas columns represent risk-transmitting firms. Thus, $D_{j|i,t}$ measures the intensity of the tail-risk spillover from firm i to firm j.

Because the model is re-estimated over rolling windows, a sequence of networks can be obtained for different points in time:

$$P_{ji,t} = \left|D_{j|i,t}\right| \tag{7}$$

These networks constitute the dynamic tail-risk spillover network among green innovative firms.

3. 3.4 System-Wide Tail-Risk Connectedness

To measure the overall level of tail-risk connectedness among green innovative firms, following Liu et al. (2026), we use system-wide connectedness, denoted by Q_t:

$$Q_{t=\sum_{j=1}^{N}\sum_{i=1,j\neq 1}^{N}\times}\left|D_{j|i,t}\right| \tag{8}$$

A larger Q_t indicates stronger overall tail-risk spillovers among firms, whereas a smaller Q_t indicates weaker network connectedness.

3.3.5 Firm-Level Risk Inputs, Outputs, and Net Spillovers

To identify the roles played by different firms in the risk network, following Zhang et al. (2020), we calculate three measures: outgoing spillovers, incoming spillovers, and net spillovers. Outgoing spillovers are defined as:

$$OUT_{i,t} = \sum_{i\neq i}\left|D_{j|i,t}\right|$$

and measure the total amount of tail risk transmitted from firm i to other firms. Incoming spillovers are defined as:

and measure the total amount of tail risk received by firm i from other firms. Net

$$IN_{i,t} = \sum_{i \neq i} \left| D_{i|j,t} \right|$$

spillovers are defined as:

$$NET_{i,t} = OUT_{i,t} - IN_{i,t}$$

A positive $NET_{i,t}$ indicates that firm i is a net risk transmitter, whereas a negative value indicates that it is a net risk receiver. Together, these measures help identify major risk sources and risk-absorbing nodes in the network.

3.3.6 Systemic Importance and PageRank

We use PageRank to measure firms' systemic importance. PageRank assigns greater importance to firms that are connected to more influential nodes in the network. Thus, firms with stronger connections to highly ranked nodes have greater systemic importance (Deng et al., 2023).

3.3.7 Industry-Level Risk Spillovers

Building on the firm-level network, we aggregate firm-to-firm risk linkages to the industry level according to firms' green-industry classifications (Chaney, 2018). This allows us to identify risk transmission pathways across green industries. Let I_a and I_b denote the sets of firms belonging to industries a and b, respectively. The risk spillover from industry a to industry b is defined as:

$$Spill_{a \to b,t} = \sum_{i \in I_a} \sum_{i \in I_b} | \left| D_{j|i,t} \right|$$

We further decompose the network into within-industry and cross-industry spillovers. Specifically, $Within_t$ captures risk spillovers among firms within the same industry, whereas $Between_t$ measures spillovers across different industries. By comparing the two, we assess whether tail risks among green innovative firms are transmitted primarily within industries or diffuse across industry boundaries.

3.3.8 Identification of Key Risk Pathways

The full network of 150 firms is highly connected, and displaying all links would create substantial visual clutter while obscuring its key structure (Nobre et al., 2019).

We therefore apply the Planar Maximally Filtered Graph (PMFG) to sparsify the full network. PMFG retains the most informative risk linkages while removing a large number of weaker connections. This makes it possible to identify key nodes and core pathways of tail-risk transmission.

4. Empirical Results and Analysis

4.1 Dynamic Evolution of Conditional Tail Risk among Green Innovative Firms

In the first stage, we estimate conditional quantile regressions of firms' daily returns on lagged macro-financial variables. The conditional tail-risk measure is estimated at the 1% quantile using a 250-trading-day rolling window to capture its time-varying behavior. The resulting measure captures firms' downside tail risk conditional on the prevailing macro-financial environment. As shown in Figure 1, conditional tail risk among green innovative firms exhibits pronounced variation across different periods of the sample.

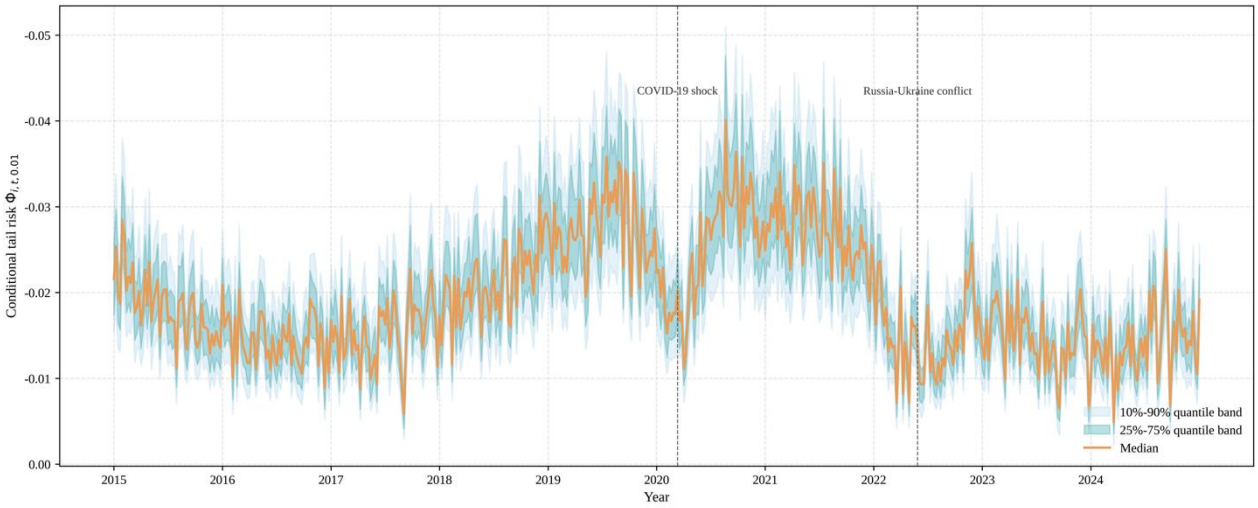


Fig 1. Time-Varying Conditional Tail Risk (VaR) of Green Innovative Firms

During 2015–2016, market expectations were relatively stable and tail risk remained contained. Tail-risk volatility increased sharply in 2018 amid China–U.S. trade tensions and domestic deleveraging. In 2020, the COVID-19 shock drove a broad-based increase in tail risk across industries, marking the first sample-period peak. Tail risk declined in 2021 as pandemic conditions eased, but rose again in 2022 amid the

Russia–Ukraine conflict and higher global energy costs. During 2023–2024, tail risk returned to a moderate level as energy prices eased and industry policies stabilized. Across industries, new-energy vehicle and clean-energy firms exhibit substantially greater tail-risk volatility than green service firms, while considerable heterogeneity also exists across firms. These patterns highlight strong time variation and cross-firm heterogeneity and provide the basis for identifying risk transmitters, receivers, and systemically important nodes. Because firm-level tail-risk measures alone cannot capture how risk propagates across firms, the second-stage TENET analysis focuses on directional tail-risk spillovers.

Beyond aggregate connectedness, we use network reciprocity to measure the symmetry of risk transmission. Reciprocity rises from 0.194 in normal periods to 0.495 during the pandemic and 0.586 during the extreme-market period, indicating stronger bidirectional dependence under stress. Stability selection further reveals a highly dynamic network: only 6.8% of LASSO-selected edges persist across all three periods, whereas 52.9% appear in only one period. The number of risk connections increases from 4,288 in normal periods to 11,116 during the pandemic and 12,990 during the extreme-market period, but only 1,248 edges persist across periods, while 943 normal-period edges disappear during shocks. Network restructuring therefore reflects both the emergence and breakdown of risk linkages. Persistent and shock-sensitive edges display a similar industry composition, with cross-industry and within-industry edges accounting for roughly 80% and 20%, respectively, confirming that cross-industry transmission is a stable structural feature. However, the specific firm-level linkages are highly shock-dependent: among 14,164 shock-sensitive edges, 5,140 are unique to the extreme-market period. The pandemic generates broader diffusion-oriented linkages, whereas the extreme-market shock produces a more selective set of panic-transmission channels.

4.2 System-Wide Tail-Risk Connectedness

We calculate system-wide connectedness from the dynamic spillover matrices of the 150 firms. For comparability across time, Q_t is normalized using the min–max method. Figure 2 presents the evolution of system-wide tail-risk connectedness among green innovative firms over the sample period.

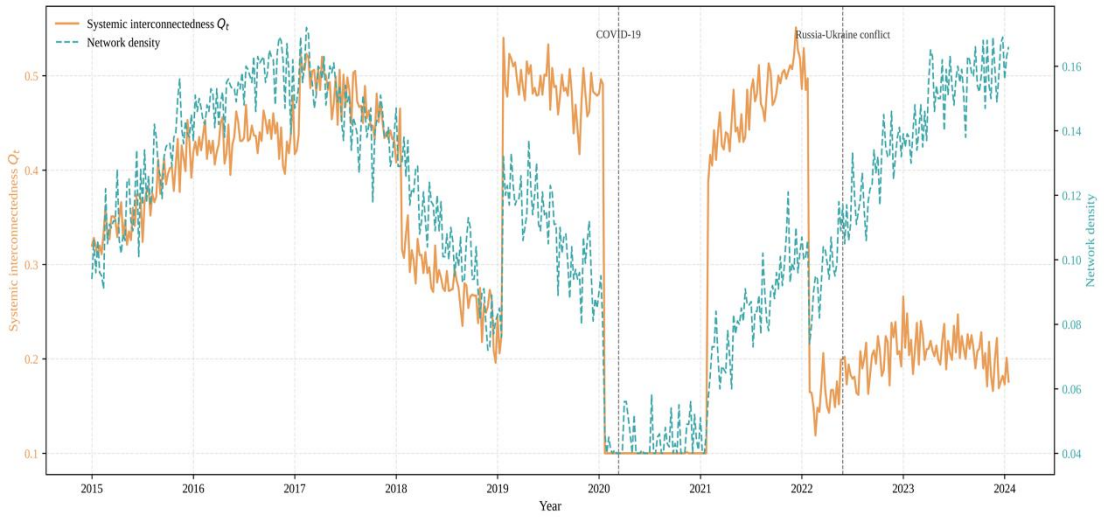


Fig 2. Dynamic Evolution of System-Wide Tail-Risk Connectedness

Q_t exhibits pronounced cyclical variation, indicating that inter-firm tail-risk connectedness differs across market states and that risk transmission is state dependent. During 2015–2017, Q_t remained within a narrow range of 0.0227–0.0233, indicating relatively limited inter-firm connections and moderate tail-risk transmission within the system. During the 2019 trade tensions, Q_t fell sharply to 0.0097, while network density declined to its sample-period low of 0.0572. This indicates a broad contraction in network connectedness. This pattern does not, by itself, imply stronger firm-level risk transmission. In 2020, system-wide connectedness increased to 0.0140 amid the COVID-19 shock, indicating stronger inter-firm linkages. It rose again to 0.0230 during the Russia–Ukraine conflict in 2022. During 2023–2024, system-wide connectedness fluctuated between 0.013 and 0.024.Changes in system-wide connectedness do not necessarily imply a uniform strengthening of risk linkages across all firms. In particular, an increase in Q_t does not mean that all pairwise risk linkages become stronger. System-wide connectedness alone cannot distinguish between these two mechanisms. A more complete assessment therefore requires network density and firm-level measures of

outgoing and incoming spillovers.

To assess whether firms' tail-risk linkages form local clusters, we calculate the weighted average clustering coefficient. The results show that local clustering in the risk network varies with market shocks. The coefficient fell to 0.254 in 2019, rose to 0.266 during the COVID-19 period, and increased further to 0.345 during the Russia–Ukraine conflict in 2022. This suggests that extreme shocks can concentrate risk linkages within local groups rather than spread them uniformly across the network.

The two shocks also produced different patterns of network restructuring. During the pandemic period (2019–2020), the clustering coefficient increased by only 4.7% (0.254 to 0.266). Although the number of risk connections increased substantially, local clustering changed only modestly. This pattern is consistent with broad-based network expansion. During the Russia–Ukraine conflict (2021–2022), the coefficient increased from 0.310 to 0.345, a rise of 11.3%. Risk linkages therefore became more concentrated within specific industrial chains and local clusters.

This finding is consistent with the PMFG results. The "new-energy vehicles–energy storage–clean energy" cluster identified in the PMFG network corresponds to stronger local clustering. The risk network is therefore not uniformly connected. Instead, it exhibits localized structures in which risk linkages are denser within certain industrial chains, while connections across clusters are relatively weaker.We further use betweenness centrality to identify bridge nodes. Some firms, such as Weiming Environmental Protection and Yanghe Distillery, have moderate PageRank but relatively high betweenness centrality. These firms are not major risk transmitters. However, they serve as bridges connecting different industries and core nodes. This finding highlights that systemic importance, direct risk-transmission capacity, and network brokerage are distinct dimensions of firms' roles in the risk network.

4.3 Firm-Level Risk Spillover Analysis

4.3.1 Risk Outputs and Inputs

Figures 3 and Figures 4 present dynamic heat maps of firm-level risk-output and risk-input intensity across industries, illustrating how firms' capacities to transmit and receive tail risk evolve over time. Darker shades indicate higher risk intensity, whereas lighter shades indicate lower intensity. To prevent a small number of extreme observations from distorting the overall color distribution, the data are winsorized, and the color scale is restricted to 0.003–0.010. Only 1.2% of observations have risk-output intensity above 0.010, while 1.4% have risk-input intensity above 0.010. Thus, the winsorization has only a limited effect on the distribution of the main body of the observations.

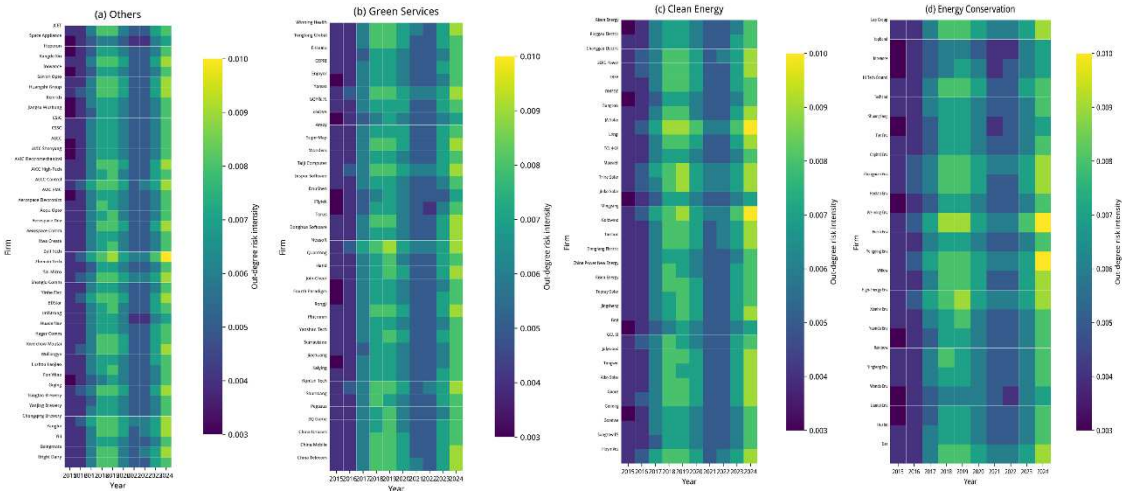


Fig 3. Dynamic Evolution of Firm-Level Risk-Output Intensity across Industries, 2015–2024

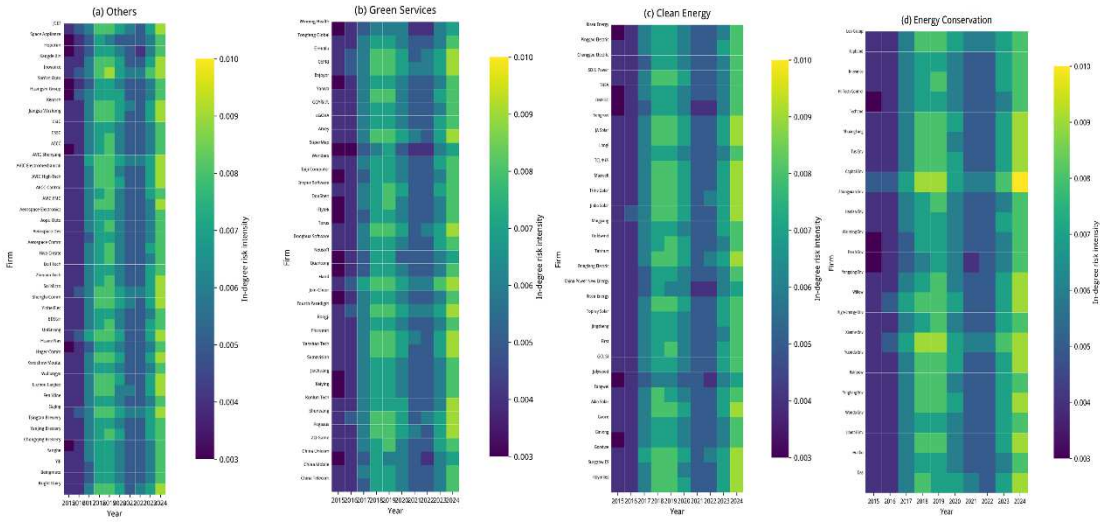


Fig 4. Dynamic Evolution of Firm-Level Risk-Input Intensity across Industries, 2015–2024

On the transmission side, outgoing spillovers display substantial temporal and cross-industry heterogeneity, with leading firms playing a more prominent role. During

2015 – 2016, leading firms across industries exhibited relatively high risk-output intensity. Under market stress, they became important sources of tail-risk spillovers. From 2017 to 2019, risk-output intensity declined overall, although some leading firms remained prominent. The decline was less pronounced in new-energy vehicle and photovoltaic and wind-power firms, but more evident in energy-conservation, environmental-protection, and power transmission and distribution firms. In 2020, the COVID-19 shock sharply increased inter-firm connectedness and risk-output intensity, extending the increase beyond leading firms to many small and medium-sized firms. In 2022, risk-output intensity rose markedly among upstream resource and new-energy supply-chain firms, suggesting stronger transmission along energy and commodity linkages. During 2023 – 2024, overall risk-output intensity declined, but growth-oriented sectors such as new-energy vehicles and energy storage remained important transmission nodes.On the receiving side, risk-input intensity also varies substantially across periods and industries. During the 2015–2016 market turbulence, risk-input intensity rose broadly, particularly among firms in the new-energy vehicle and photovoltaic and wind-power supply chains. This may reflect greater sensitivity to supply-chain price fluctuations and market sentiment. From 2017 to 2019, risk-input intensity declined across most industries as market conditions stabilized, with particularly pronounced declines in power transmission and distribution and environmental-protection equipment. Firms in energy storage and new-energy vehicles, however, continued to exhibit relatively high incoming spillovers. In 2020, the pandemic generated a broad-based increase in risk-input intensity as production and consumption disruptions strengthened cross-firm and supply-chain transmission. The increase was especially pronounced among downstream consumer-oriented firms. Incoming spillovers eased in 2021 but rose again in 2022, particularly among upstream resource- and energy-intensive firms and suppliers of new-energy materials. Consumer-facing and service-oriented firms showed a weaker rebound, indicating pronounced heterogeneity in risk exposure. During 2023 – 2024, risk-input intensity gradually

returned toward pre-pandemic levels as geopolitical pressures eased and market conditions stabilized..

4.3.2 Systemically Important Firms and Core Risk Nodes

OUT, IN, and NET measures alone cannot fully capture a firm's systemic importance in a complex risk network. We therefore use PageRank to measure each firm's structural position and systemic importance within the overall network. Figure 5 presents the green innovative firms with the highest PageRank values.

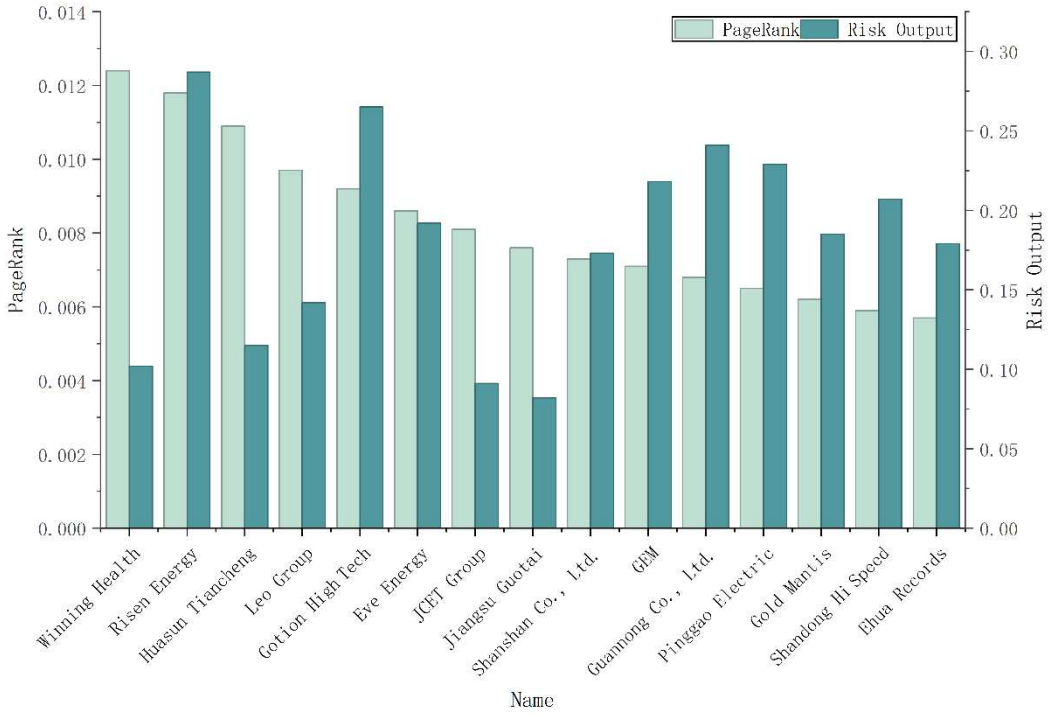


Fig 5. PageRank of Green Innovative Firms

Systemic importance is highly concentrated across the sample firms. The top 15 firms account for approximately 32.1% of total PageRank, while most firms have low to moderate values. Risk-transmission roles are therefore concentrated in a small number of core nodes. High-PageRank firms span multiple green-industry segments, with green services and other green industries accounting for a relatively large share. Systemic importance is thus not determined solely by industry affiliation, but by firms' structural positions and connections to influential nodes.

We further examine local clustering using the weighted average clustering coefficient. Local clustering varies markedly across shock periods. The coefficient

reached a sample-period low of 0.254 in 2019, increased to 0.266 in 2020, and rose further to 0.345 in 2022. The two shocks generated distinct forms of network restructuring. During the pandemic, clustering increased by only 4.7%, from 0.254 to 0.266, despite a substantial increase in the number of risk connections. This pattern is consistent with broad-based network expansion rather than local concentration. During the Russia–Ukraine conflict, clustering increased by 11.3%, from 0.310 to 0.345, indicating stronger concentration within specific industrial chains and local clusters. The PMFG results provide complementary evidence, with a "new-energy vehicles–energy storage–clean energy" cluster exhibiting dense local linkages. The network is therefore characterized by localized clustering and denser within-chain transmission, while cross-cluster connections remain relatively limited.Betweenness centrality further identifies bridge nodes that may have moderate PageRank but high brokerage centrality. Examples include Weiming Environmental Protection and Yanghe. These firms are not necessarily major risk transmitters, but they connect different industry segments and core nodes. Systemic importance, direct transmission capacity, and network brokerage therefore represent distinct dimensions of firms' network roles. The corresponding results are reported in Table 1.

Table 1. Top 10 Firms by Betweenness Centrality in the PMFG Network

Rank	Firm	Green-industry segment	Betweenness centrality
1	Risen Energy	Clean energy	1.005
2	TRS Information Technology	Green services	0.953
3	Doushen Education & Technology	Green services	0.913
4	Haige Communications	Other green industries	0.912
5	Tus Environmental Science and Technology	Energy conservation and environmental protection	0.907
6	Huace Navigation	Other green industries	0.907
7	eGOVA	Green services	0.906

8	Guizhou Space Appliance	Other green industries	0.903
9	Hangzhou First Applied Material	Clean energy	0.892
10	Zhejiang Weiming Environment Protection	Energy conservation and environmental protection	0.872

Comparing PageRank and betweenness rankings further reveals firms with moderate structural importance but pronounced brokerage roles. The results are reported in Table 2.

Table 2. Firms with High Betweenness Relative to PageRank

Firm	PageRank Rank	Betweenness Rank	Green-industry Segment
Inner Mongolia First Machinery Group	80	8	Other green industries (defense-related)
Beijing UniStrong Science & Technology	50	12	Other green industries (navigation)
Guangdong Shenglu Telecommunication Tech.	88	14	Other green industries (communications)
Shanghai Taisheng Wind Power Equipment	85	15	Clean energy (wind power)
China Aerospace Times Electronics	96	17	0Other green industries (defense-related)
CECEP Solar Energy	63	20	Clean energy

Inner Mongolia First Machinery ranks 80th by PageRank but eighth by betweenness centrality. Its moderate PageRank indicates a less central structural position, whereas its high betweenness identifies it as an important intermediary between the defense-related segment and other green-industry segments. Many transmission paths between these segments pass through this firm, highlighting its intermediary role in cross-sector risk transmission. Taisheng Wind Power ranks 85th by PageRank but 15th by betweenness centrality. As a wind-power equipment manufacturer, it bridges upstream inputs and downstream applications within the clean-energy supply chain. Similar patterns are observed for Aerospace Electronics and Shenglu Communication. Overall, the network exhibits a three-layer core–bridge–periphery structure. High-PageRank firms form the structural core, high-betweenness

firms serve as bridges across industries and transmission pathways, and the remaining firms occupy more peripheral positions.

4.4 Risk Transmission Across Industries

4.4.1 Within-Industry and Cross-Industry Tail-Risk Spillovers

Building on the firm-level risk network, we aggregate firm-level risk linkages to the industry level according to firms' green-industry classifications. This allows us to identify within-industry and cross-industry transmission pathways. Figure 6 shows pronounced directionality and asymmetry in tail-risk spillovers across green industries.

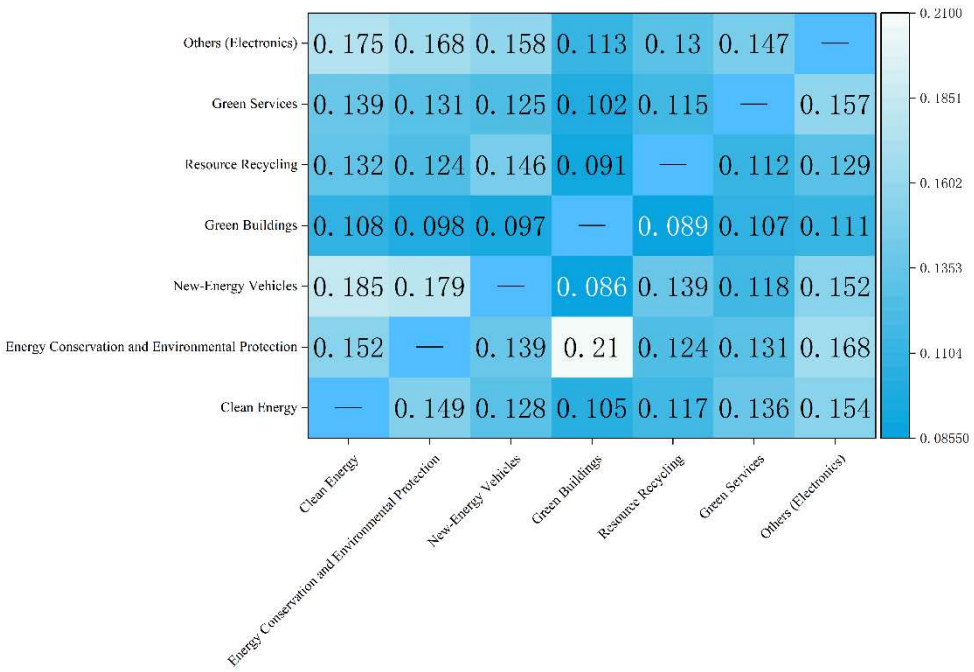


Fig 6. Heat Map of Inter-Industry Tail-Risk Spillovers

Within-industry spillovers account for 33.9% of total connectedness, compared with 66.1% for cross-industry spillovers. Cross-industry linkages therefore dominate the network. The green industrial system is not a set of parallel and independent sectors. Instead, industries occupy differentiated positions within the risk-transmission network. The industry-level spillover matrix also reveals pronounced asymmetry in transmission intensity. Spillovers from clean energy to new-energy vehicles are substantially stronger than those in the reverse direction, consistent with transmission from upstream energy-related sectors to downstream vehicle manufacturing along supply chains.

Spillovers from energy conservation and environmental protection to clean energy are also relatively strong, while resource recycling exhibits a relatively strong directional spillover toward new-energy vehicles. These findings indicate that industries play distinct roles in tail-risk transmission and highlight the need to complement firm-level risk management with attention to critical industry nodes. We further calculate IndustryNET, defined as total outgoing minus incoming spillovers, to characterize relative transmission positions across industries. Energy conservation and environmental protection (+4.2%), clean energy (+3.2%), and new-energy vehicles (+1.6%) are net risk transmitters, whereas green building (-3.9%), green services (-3.0%), and resource recycling (-2.5%) are net risk absorbers. The corresponding results are reported i**n Table 3.**

Table 3. Industry-Level Net Tail-Risk Spillovers

Rank	Industry	Total Outgoing Spillovers	Total Incoming Spillovers	Net Spillover (NET)	Risk-Transmission Role
1	Energy conservation and environmental protection	1.051	1.007	+0.044 (+4.2%)	Net-transmitting core
2	Clean energy	1.135	1.099	+0.036 (+3.2%)	Net-transmitting core
3	New-energy vehicles	1.096	1.079	+0.017 (+1.6%)	Weak net transmitter
4	Other green industries	1.077	1.090	−0.013 (−1.2%)	Weak net absorber
5	Resource recycling	0.935	0.958	−0.023 (−2.5%)	Net absorber
6	Green services	0.986	1.016	−0.030 (−3.0%)	Net absorber
7	Green buildings	0.789	0.820	−0.031 (−3.9%)	Net absorber at the downstream end

These relative positions are broadly consistent with an upstream–midstream–downstream pattern of risk transmission. However, net spillovers are modest, with all

values within ±5%. This suggests that inter-industry transmission is predominantly reciprocal rather than a one-way cascade. Industries both transmit and receive risk, while their net positions reflect the relative strength of these two processes.

4.4.2 Key Risk Transmission Paths and Network Structure

We apply the Planar Maximally Filtered Graph (PMFG) to sparsify the full risk network. The PMFG retains the most informative risk linkages while filtering out weaker connections. This allows us to identify the core nodes and key pathways of tail-risk transmission. As shown in Figure 7.

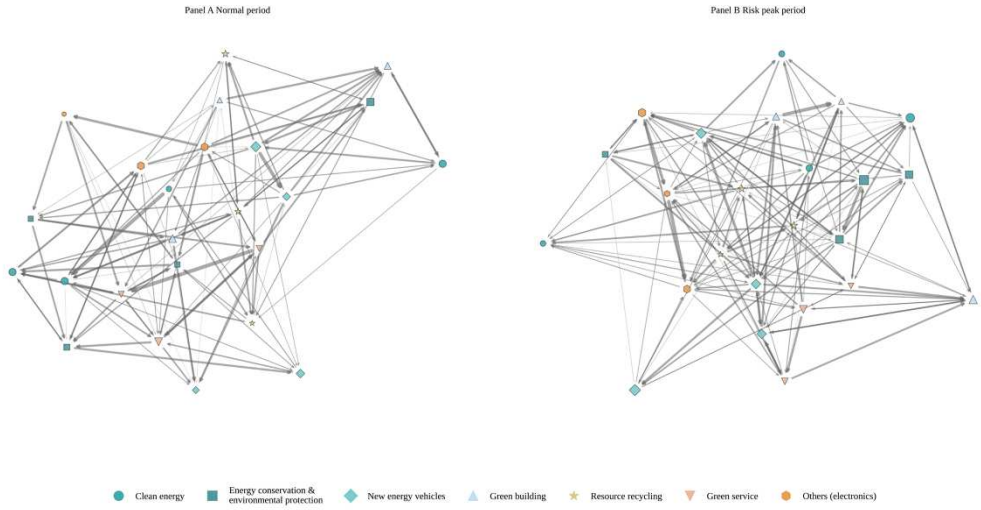


Fig 7. PMFG-Based Network of Key Tail-Risk Transmission Paths

Several high-PageRank firms in the new-energy vehicle and clean-energy sectors occupy the intersection of multiple transmission pathways and form core risk nodes. Firms in resource recycling and energy conservation and environmental protection generally have lower systemic importance but serve as bridges across industries and core nodes. The network therefore exhibits a hierarchical structure with distinct brokerage roles. High-intensity linkages further reveal several major transmission pathways, including Enjoyor Technology → JA Solar and TCL Zhonghuan → Hwa Create. These paths suggest that firm-level shocks may propagate through a small number of central nodes rather than directly across the entire network.

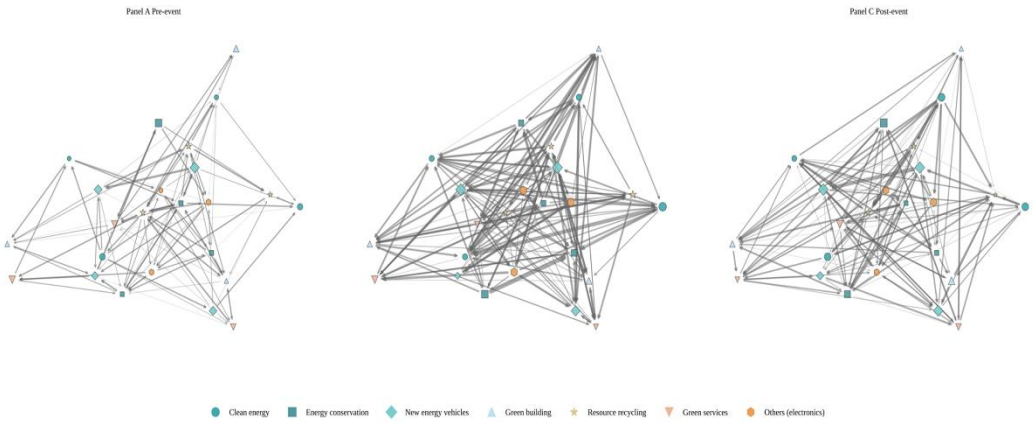
Edge betweenness centrality further identifies critical transmission channels. Most of the top 10 channels are cross-industry bridge edges. Examples include Shenglu

Communication → Taisheng Wind Power and Inner Mongolia First Machinery → Weiming Environmental Protection. These edges need not have the highest direct spillover intensity to be structurally important, as they connect otherwise weakly linked industry clusters and facilitate cross-industry transmission. Table 4 reports the top 10 critical risk-transmission channels.Starting from Ganfeng Lithium, the highest-PageRank node, we trace the strongest outgoing links to identify major transmission chains. The resulting paths indicate that tail risk often reaches distant nodes through one or two intermediaries. Risk from the lithium-resource node first reaches software and information-service firms such as Weining Health and GQY Video, then extends to GEM, Taiji Computer, and CECEP Geo-environmental, before reaching downstream firms such as LONGi Green Energy, China Solar Energy, iFlytek, and Huibop. This suggests a three-stage structure: core node → intermediary nodes → downstream nodes. The structure illustrates how firm-level tail risk can reach broader green industries through a limited number of strategically positioned intermediaries.

4.5 Risk Network Restructuring under Extreme Shocks

4.5.1 Risk Network under the COVID-19 Shock

The COVID-19 pandemic, which emerged as a global public-health crisis in 2020, had substantial effects on China's real economy and financial markets. It therefore provides a useful setting for examining how risk networks are reconfigured following an extreme shock. We use 2019 as the pre-pandemic benchmark and 2020 as the core shock period to compare changes in the size and structure of the tail-risk spillover network before and during the event. Figure 8 presents the network structure before,



during, and after the pandemic shock.

Fig 8. Changes in Risk Network Structure before and after the Extreme Shock

To examine how the pandemic shock altered the risk network, we conduct an event study using January 23, 2020, the date of the Wuhan lockdown, as the event date. Using [-4,+4] event window with biweekly observations, we examine changes in system-level risk measures around the event. The results show that system-wide connectedness Δ Q increased by 29.8%, while network density $\Delta Density$ also rose by 29.8%. Weighted clustering $\Delta Clustering$ increased by 4.9%, and PageRank concentration $\Delta PageRank$ rose by 15.2%. At the firm level, both ΔOUT and ΔIN increased markedly, indicating stronger risk transmission and risk exposure. Overall, the pandemic expanded both the intensity and breadth of tail-risk connectedness, making the network substantially denser. Annual data further indicate that these effects persisted beyond the immediate shock. Mean system-wide connectedness Q_t rose from 0.0108 in 2019 to 0.0208 in 2020, an increase of 92.6%. Network density increased from 0.111 to 0.152, or 36.9%. The much larger increase in connectedness than in density suggests that existing risk linkages intensified more strongly than the network expanded in breadth. Both measures declined after 2021 but remained above pre-pandemic levels. Together, the event-study and annual evidence indicate that COVID-19 generated both immediate and persistent restructuring of the tail-risk network. Tail-risk transmission is therefore strongly event-driven and cannot be fully captured by static firm-level risk measures.

4.5.2 Risk Network under the Russia–Ukraine Conflict

The Russia–Ukraine conflict, which began in 2022, represents a distinct type of external geopolitical shock. Its transmission channels to domestic markets differ fundamentally from those associated with the COVID-19 pandemic. As shown in Figure 9.

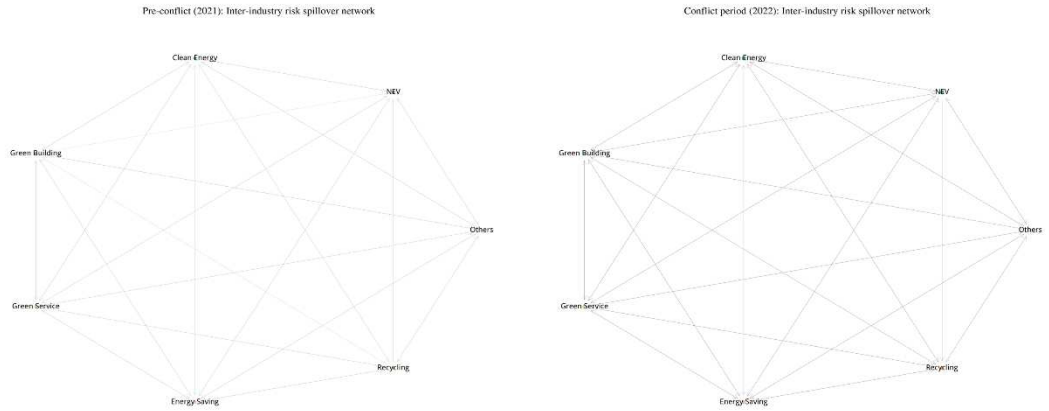


Fig 9. Industry-Level Tail-Risk Spillover Networks before and after the Russia–Ukraine Conflict

We conduct a similar event study using February 24, 2022, as the event date for the Russia–Ukraine conflict. Using a [-4,+4] window with biweekly observations, we examine changes in network indicators around the shock. System-wide connectedness ΔQ and network density $\Delta Density$ both increased by 25.3%, while weighted clustering $\Delta Clustering$ and PageRank concentration $\Delta PageRank$ rose by 11.3% and 22.7%, respectively. Compared with COVID-19, density increased by a similar magnitude, but clustering and PageRank concentration rose much more sharply. This pattern suggests that risk became more concentrated around core nodes and local industrial chains rather than spreading uniformly across the network.Annual dynamics further indicate selective network restructuring. Mean Q_t rose from 0.0168 in 2021 to 0.0230 in 2022, while network density increased from 0.108 to 0.142. Unlike COVID-19, the conflict did not produce broad-based network expansion but stronger linkages within selected parts of the network. The industry-level spillover matrix shows the same pattern. Average cross-industry spillover intensity nearly doubled relative to the pre-conflict period, but the increase was concentrated in the core resource-to-manufacturing

chain. Spillovers from new-energy vehicles to resource recycling rose to 0.00207, while the reverse linkage fell to nearly zero, highlighting strong directionality and asymmetry. By contrast, linkages involving consumer services and pharmaceuticals and biotechnology generally weakened, with some disappearing altogether.

Overall, the conflict restructured the network by strengthening linkages among core industries and nodes rather than broadening risk coverage. The resulting structure was therefore more selective and concentrated than that observed during COVID-19.

4.6 Robustness test

4.6.1 X Sample Selection Robustness

To assess whether the baseline findings are robust to sample selection, we randomly draw 150 firms without replacement from the 337 eligible firms and re-estimate the key risk-network measures for each subsample. We repeat this procedure 50 times to obtain empirical sampling distributions. The results are reported in Table 5.

Table 5. Robustness of Network Measures to Random Sample Selection

Indicator	Baseline Value	Random Resampling Range (5th–95th Percentiles)
Mean Q_t	0.0162	[0.0151, 0.0173]
Mean Density	0.095	[0.089, 0.102]
Top-10 PageRank Overlap	—	7/10–9/10
Cross-Industry Spillover Share	66.1%	[64.0%, 68.0%]

The cross-industry spillover share remains between 64% and 68% across the 50 random draws and is closely centered on the baseline estimate of 66.1%. This indicates that the dominance of cross-industry transmission is not driven by the particular composition of the baseline sample. The overlap between the top 10 systemically important firms and those identified in the baseline sample exceeds 70%, indicating substantial stability in the identification of core nodes across alternative samples. Overall, the main structural features of the risk network—including system-wide connectedness, network density, the dominance of cross-industry transmission, and the identification of core nodes—remain robust to alternative firm selections.

4.6.2 Robustness of the TENET Estimation

The baseline specification sets the quantile at τ=0.01, uses a 250-trading-day rolling window, and applies LASSO for variable selection in the second stage. To assess whether the main findings are sensitive to these modeling choices, we conduct robustness checks by varying the quantile level and rolling-window length.

The baseline value of τ=0.01 corresponds to the lower 1% tail of the return distribution. To assess the sensitivity of the results to the tail threshold, we re-estimate conditional tail risk and reconstruct the risk network using τ=0.025 and τ=0.05. The

results are reported in Table 6.

Table 6. Robustness to Alternative τ

τ	Mean Q_t	Mean Network Density	Top-10 Core Node Overlap	Cross-Industry Spillover Share
τ=0.01	0.0162	0.095	—	66.1%
τ=0.025	0.0187	0.108	9/10	65.4%
τ=0.05	0.0224	0.126	8/10	64.8%

As the quantile increases from 0.01 to 0.05, both system-wide connectedness Q_t and network density increase gradually, indicating a broader set of identified risk linkages under less restrictive tail thresholds. More importantly, the main structural findings remain stable. Cross-industry spillovers consistently account for the majority of network connectedness, at around 65%, while the overlap rate among the top 10 systemically important firms exceeds 80%. These results indicate that the main conclusions regarding system-wide connectedness, the dominance of cross-industry transmission, and the identification of core nodes are robust to the choice of the tail threshold.

The rolling-window length determines the amount of historical information used to estimate the network at each point in time and affects the smoothness and time-varying sensitivity of network measures. The baseline specification uses a 250-trading-day window. To assess the sensitivity of the results to this choice, we further evaluate 200-, 300-, and 500-trading-day windows. The results are reported in Table 7.

Table 7. Robustness to Alternative Rolling Window Lengths

Rolling Window Length	Mean (Q_t)	(Q_t) Time-Series Correlation	Top-10 Node Ranking Spearman Correlation	Mean Network Density
200 days	0.0168	0.92	0.89	0.098
250 days (Baseline)	0.0162	1.00	1.00	0.095
300 days	0.0157	0.95	0.91	0.092
500 days	0.0142	0.87	0.78	0.084

The time path of system-wide connectedness Q_t is highly stable across specifications. The correlations with the baseline series all exceed 0.87. The timing and direction of the peaks associated with the COVID-19 pandemic and Russia–Ukraine conflict are also consistent across specifications. The ranking of core nodes is similarly stable. The Spearman correlations between the top-10 rankings under the 200- and 300-day windows and the baseline exceed 0.90. The 500-day window produces a modest smoothing effect because it incorporates a longer history. As a result, the volatility of network measures is somewhat reduced, and the correlation in core-node rankings declines to 0.78. Nevertheless, the main structural features, including the share of cross-industry spillovers and the core–periphery structure, remain intact. Overall, the main findings are robust to the choice of rolling-window length. The 250-day baseline

window therefore provides a reasonable balance between sufficient observations for high-dimensional network estimation and sensitivity to time variation.

5. Discussion

5.1 From Firm-Level Risk to Networked Tail Risk

Previous studies provide mixed evidence on the relationship between green innovation and corporate risk. Rekabder et al. (2026), using U.S. firms, find that green innovation is associated with lower default risk through lower cash-flow volatility and managerial risk-taking. In contrast, Wang et al. (2024), using Chinese listed firms, find that green innovation strategies can increase debt default risk through overinvestment. These findings suggest that the risk implications of green innovation are context dependent.

Our results add a network dimension to this debate. Rather than asking only whether green innovation increases or reduces a firm's own risk, we show that tail risk is also transmitted across firms. Green innovative firms exhibit heterogeneous individual risk exposure, but they are interconnected through market conditions, supply chains, and financial linkages. Thus, firm-level vulnerability and systemic importance are not necessarily equivalent. A firm with moderate individual tail risk may still occupy a central position in the transmission network, while a highly exposed firm may have limited systemic relevance when its network connections are weak. This perspective extends the existing literature from the determinants of corporate risk to the organization and transmission of risk across firms.

5.2 Dynamic and Cross-Industry Tail-Risk Transmission

Our finding of substantial time variation in tail-risk connectedness is consistent with the original TENET framework of Härdle et al. (2016), which emphasizes systemic interconnectedness generated by tail-driven spillovers. Subsequent applications also document strong time variation during crisis periods. For example, TENET-based evidence for Eurozone firms shows that total connectedness reached its highest level during the early COVID-19 period (Jareño et al., 2023). Our results confirm this crisis sensitivity at the firm level in green industries, but also show that changes in overall connectedness and network breadth need not move proportionally.

A more distinctive finding is the dominance of cross-industry spillovers. In our sample, cross-industry spillovers account for 66.1% of total connectedness. This result is consistent with recent research emphasizing strong cross-sectoral spillovers among green, brown, and financial industries under the low-carbon transition (He et al., 2024). It also complements evidence from China's energy markets showing time-varying and heterogeneous spillovers among new-energy and related sectors (Niu & Cao, 2024). Our results suggest that such inter-industry dependence extends from sector-level markets to firm-level risk networks. The reason may lie in the production structure of green industries. New-energy vehicles, clean energy, energy storage, and resource recycling share upstream inputs, energy markets, technologies, and downstream demand. Risk transmission can therefore cross conventional industry boundaries rather than remain confined within individual sectors.

The asymmetric spillover patterns further indicate that these linkages are directional. Stronger transmission from upstream or supply-side sectors toward downstream industries suggests that firms occupy different positions within the production network. This finding implies that systemic risk in green industries is shaped not only by the magnitude of individual risk but also by firms' locations in interconnected industrial chains.

5.3 Structural Importance Beyond Direct Risk Transmission

The concentration of PageRank among a relatively small number of firms provides another important insight. Existing systemic-risk research emphasizes that systemic importance depends on network structure rather than exposure alone. The TENET framework itself identifies systemically important institutions conditional on their interconnectedness structure (Wang et al., 2018). Our evidence extends this argument to green innovative firms. Importantly, direct risk output and structural importance capture different dimensions of systemic relevance. OUT measures the amount of tail risk transmitted directly to other firms, whereas PageRank also reflects the importance of the nodes to which a firm is connected. A firm can therefore be structurally important without having the largest direct spillover volume. The PMFG results further reveal

core and bridge nodes around which high-intensity transmission pathways are concentrated. This suggests that systemic vulnerability has a hierarchical structure, with a small number of nodes linking otherwise less-connected parts of the network. Such a structure cannot be fully identified by ranking firms according to their own risk levels.

5.4 Shock-Specific Network Restructuring

The contrasting responses to COVID-19 and the Russia–Ukraine conflict provide evidence that systemic risk is not reshaped uniformly by external shocks. The broad increase in connectedness during COVID-19 is consistent with previous TENET evidence showing a sharp increase in firm-level tail-risk connectedness during the pandemic (Huynh et al., 2022). In our sample, both connectedness and network density increased, indicating a broad expansion of inter-firm risk linkages. The Russia–Ukraine conflict generated a different response. Overall connectedness increased, but network density did not expand in the same way. Instead, risk transmission became more concentrated within resource-, energy-, and manufacturing-related pathways. This pattern is consistent with research showing that the systemic role of energy-related sectors changes across major shocks and that energy and commodity exposures became particularly important during the Russia–Ukraine conflict. It is also consistent with recent evidence of heterogeneous risk spillovers across China's energy sectors. The comparison between the two shocks suggests that an increase in aggregate systemic risk can arise through different network mechanisms. Broad-based shocks may activate a large number of previously weak connections, whereas structural shocks may strengthen a smaller set of economically important pathways. The key issue is therefore not only how much systemic risk increases, but also how the network is reorganized in response to the shock. Overall, our findings extend the literature in two ways. First, they connect the green innovation–corporate risk literature with the systemic-risk network literature by shifting attention from individual risk exposure to inter-firm tail-risk transmission. Second, they show that firm position, cross-industry linkages, and shock characteristics jointly shape the evolution of systemic risk. This suggests that the financial risks associated with green transformation should be understood as both firm specific and network dependent.

6. Conclusions and Policy Implications

6.1 Conclusions

6.1.1 Formation and Structural Characteristics of the Tail-Risk Network among Green Innovative Firms

The empirical results show that green innovative firms are not independent risk entities. Instead, they form a directional, heterogeneous, and dynamic network of tail-risk spillovers. The first-stage estimates show that firms exhibit common fluctuations under extreme market conditions, while their exposure to tail risk remains heterogeneous. The second stage reveals how firm-level tail risk propagates through the network. The risk associated with green innovative firms is therefore not defined solely by changes in their own risk levels. It also depends on how risk is transmitted and reorganized across firms. A shared exposure to industrial transformation provides a common basis for risk exposure. However, differences in supply-chain position, business structure, and market linkages lead to asymmetric exposure to the same external shocks. Some firms transmit risk outward, others primarily absorb it, and some both transmit and receive risk. Tail risk is therefore not distributed uniformly across the network; differentiated firm roles are a fundamental feature of its transmission.

At the system level, network evolution involves changes in both the breadth and intensity of risk connections. Q_t varies markedly across market states, and weak inter-firm linkages can become active channels of risk transmission under extreme conditions. A firm's systemic importance depends not only on its own risk level, but also on the number and structure of its network connections. Systemic risk therefore reflects the interaction between firm-level vulnerability and network connectedness.

The reciprocity analysis further suggests that extreme shocks strengthen not only risk connectedness but also the bidirectional dependence between firms. The stability-selection analysis further shows that most risk linkages are shock-sensitive and transient rather than persistent features of the network.

6.1.2 Cross-Industry Transmission as a Key Feature of Risk Diffusion

Tail risk exhibits substantial cross-industry diffusion. Cross-industry spillovers account for approximately 66.1% of total connectedness and constitute the dominant component of the network. The green industrial system is not a collection of independent sectors but an interconnected production network. Strong linkages connect

upstream resource and energy supply, midstream manufacturing, and downstream markets. These linkages can transmit tail risk across successive stages of the supply chain when external shocks occur.

The industry-level spillover matrix further reveals pronounced directionality and asymmetry. Spillovers from clean energy to new-energy vehicles are stronger than those in the opposite direction. This suggests a stronger outward spillover role for upstream sectors. Risk transmission therefore follows directional pathways across interconnected industries. Risk governance should consequently extend beyond within-industry controls to supply-chain and network-based monitoring, with particular attention to critical nodes within the green industrial network.

Industry-level net spillovers further reveal a differentiated hierarchy of risk transmission. Energy conservation and environmental protection and clean energy are net risk transmitters, whereas green building and green services are net risk absorbers. Overall, the pattern is broadly consistent with risk transmission along an upstream–midstream–downstream chain from materials and equipment to manufacturing and downstream services..

6.1.3 Network Centrality and the Emergence of Core Nodes

Firms occupy markedly different structural positions in the network. Importantly, PageRank shows that a firm's systemic importance is not equivalent to the magnitude of its direct risk output. Centrality and transmission volume capture distinct dimensions of network influence. A firm that transmits a large amount of risk does not necessarily occupy a central position in the network. This distinction reveals a clear core–periphery structure, in which a small number of key nodes perform a disproportionate share of the network's connecting functions. A firm's structural importance depends not only on how much risk it transmits, but also on which firms it connects and the structural importance of those connected firms.

The PMFG provides further evidence of this structure. The filtered network preserves the concentration of core nodes, multiple transmission pathways, and

brokerage positions. High-intensity links form distinct paths around a small number of firms. Examples include Enjoyor Technology → JA Solar and TCL Zhonghuan → Hwa Create. This pattern suggests that tail risk rarely propagates from a single firm directly to the entire system. Instead, it tends to diffuse through a limited number of intermediary nodes. From a risk-monitoring perspective, identifying structurally critical nodes and their transmission paths may provide earlier signals of systemic vulnerabilities than ranking firms solely by their own risk levels.

Betweenness centrality further reveals the existence of bridge nodes. Some firms have only moderate PageRank rankings but substantially higher betweenness centrality. For example, Zhejiang Weiming Environment Protection exhibits this pattern. Such firms are not necessarily the largest risk transmitters, but they play critical brokerage roles in connecting otherwise less integrated industry clusters.

Edge-betweenness analysis identifies the most critical risk channels, many of which are cross-industry bridge edges connecting otherwise weakly integrated industry clusters. Taken together, OUT, PageRank, Betweenness, and PMFG provide a multidimensional framework for identifying structurally important sources and channels of tail-risk transmission. OUT captures direct risk-output capacity, PageRank measures structural importance, Betweenness captures brokerage and intermediary transmission capacity, and PMFG identifies the key transmission.

6.1.4 Risk Network Restructuring under Different Types of Extreme Shocks

External shocks do not reshape risk networks in the same way. The COVID-19 pandemic and the Russia–Ukraine conflict represent two distinct types of shocks and trigger markedly different patterns of network change. Differences in shock transmission channels lead to different changes in the breadth and intensity of risk connections. The COVID-19 pandemic is characterized by broad-based network expansion. The pandemic not only increased risk for individual firms, but also strengthened many previously weak tail-risk linkages. Both the number and intensity of connections increased, shifting the network from a relatively sparse structure toward much greater interconnectedness. The Russia – Ukraine conflict, by contrast, is

associated with structural network reconfiguration. The expansion in network breadth was less pronounced than during the pandemic. Instead, transmission within core industrial chains intensified, while peripheral connections less directly related to the shock weakened.

These two events therefore reveal two distinct mechanisms of network restructuring. Broad-based shocks tend to expand the network more widely, whereas structurally concentrated shocks related to resources, energy, and industrial linkages tend to concentrate risk connections around specific value chains and critical nodes. This implies that systemic risk concerns not only how much risk increases, but also how risk is reconnected across the network. The same increase in aggregate risk can therefore correspond to very different network structures. Dynamic network analysis helps distinguish whether risk connections expand broadly, contract locally, or become concentrated within a limited number of industrial chains. The value of a risk network lies precisely in its ability to reveal how shocks reshape the structure of risk transmission.

6.2 Policy Implications

The findings point to a clear shift in risk governance. Risk management in green industries should move beyond isolated firm-level monitoring toward an integrated framework spanning firms, industries, and networks. Systemic importance reflects the combined effects of risk transmission, net spillovers, and network centrality rather than a firm's absolute risk level alone. At the firm level, regulators should establish dynamic monitoring lists and increase monitoring frequency and early-warning requirements for firms that combine strong outward spillover capacity with central network positions. Shocks to these firms may propagate through multiple channels and affect a broader set of connected firms. They should therefore receive priority in systemic risk surveillance. At the industry level, risk governance should move from fragmented sector-based regulation toward coordinated supply-chain monitoring. Cross-industry spillovers account for more than 60% of total connectedness, indicating that regulatory systems organized strictly around administrative or industry boundaries may overlook important

transmission pathways. For closely connected sectors such as clean energy, new-energy vehicles, and resource recycling, regulators should strengthen upstream–downstream information sharing and joint risk monitoring. Particular attention should be paid to chain reactions associated with raw-material prices, energy supply, critical technologies, and market demand. Risk management should also become more shock specific. Broad-based shocks, such as pandemics, can generate sharp increases in the number and breadth of network connections. Monitoring should therefore expand rapidly when such shocks emerge. By contrast, structural shocks involving energy markets or geopolitical conflicts may concentrate risk within specific industrial chains and critical nodes. In these cases, early-warning systems should focus on upstream resources, energy supply, and critical manufacturing links. Distinguishing between different network responses to external shocks can improve the targeting of regulatory measures and the allocation of monitoring resources. Finally, risk surveillance should shift from static assessment toward dynamic network monitoring. Green industries are characterized by rapid technological change, ongoing supply-chain restructuring, and strong capital-market attention. Their risk structures can therefore change substantially with market conditions. Dynamic tail-risk measures, network density, system-wide connectedness, and changes in key nodes should be incorporated into continuous monitoring systems. Moving beyond static, firm-specific warning indicators can improve the early identification of tail-risk transmission and network restructuring.

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