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Risk spillovers in Chinese production network: A supply-side shock perspective

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Highly interconnected production network exists in one economy, and it is crucial to investigate how and why supply-side shocks spread across industries via the production network and cause systemic risks in the real sector. Based on input-output framework, this paper designed a model to simulate the propagation of risk spillovers along the production network given supply-side shocks. This paper defined the systemically important industries (SIIs) and systemically vulnerable industries (SVIs) according to the degree and direction of risk spillovers. Simulation results show that risk spillovers spread among industries via the production network, leading to systemic risk in the real sector. This paper also classified the important risk spillover paths "SVIs → SIIs → SVIs" in the model for risk regulation and prevention and identified 75 risk spillover paths and 9 closed-loop paths in 2018. Furthermore, key factors of systemic importance (vulnerability) included input-output relationships and production network centrality. This paper provides a scientific basis to strengthen the risk supervision of the real sector based on the supply chain.

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Introduction

The risk of global industrial chain breaking is continuously rising, posing a serious challenge to all countries. The 2011 earthquake in Japan, for example, disrupted local production network and even transnational supply chains. In modern economic patterns, industries are highly interconnected, and the shock from one industry can quickly spread to other industries and even lead to macroeconomic fluctuations (Acemoglu et al. 2016). Different from other countries, China has the most complete national industrial chain in the world and the output of more than 220 industrial products ranks first in the world, which features a complex system among chains in different industries. In this vein, each industry that suffers from a shock can affect another. Considering the advantages of the network model in portraying complex systems, compared to theoretical analysis (Acemoglu and Azar, 2020; Acemoglu et al. 2012; Carvalho, 2014; Elliott et al. 2022), a network model is crucial to simultaneously identify risk spillover paths from industrial chains and key industries that can enhance the resilience of China's industrial chains.

Current research extensively covers risk spillover in financial markets (Cao, 2022; Du and He, 2015; Wang and Xiao, 2023) and supply chain network (Inoue and Todo, 2019; Li and Zobel, 2020; Li et al. 2020). However, research on industry-level risk spillover based on production network is relatively lacking. Existing studies either analyse structural characteristics in production networks (Liu et al. 2020) or employ network cascade failure model (Wang and Zhang, 2018; Zeng and Xiao, 2014). The literature overlooks the crucial role of production network in the risk spillover and the indirect impact of supply-side effects on downstream industries, leading to an underestimated risk level in the real sector. Therefore, our goal is to fill this gap and construct a production network using input-output framework for a quantitative analysis of industry-level risk spillover.

This paper focuses on the shock from the supply side, which is a crucial part of the supply chain (Tang et al. 2020). If upstream industries face difficulties, they would be unable to fulfil supply contracts, leading to supply-side shocks for downstream industries and even further to the consumer industry. Consequently, these shocks can persistently propagate throughout the production network (Acemoglu et al. 2016; Acemoglu et al. 2012; Aobdia et al. 2014; Carvalho, 2014; Nguyen et al. 2020; Yang et al. 2023). This paper applies the Cobb-Douglas production function to explore how and why supply-side shocks can transmit widely to other industries within the production network, resulting in systemic risk to the real sector.

This paper constructs a directed production network based on the input-output framework and quantitatively analyses the risk spillovers of supply-side shocks in multiple rounds along this production network. First, this paper defines the round of risk spillover as the number of intermediate industries through which the risk spills from one industry to another industry. If the risk does not pass through the intermediate industry, it is one round of risk spillover; if it passes through an intermediate industry, it becomes two rounds of risk spillover, and so on. Second, this paper divides the spillovers of multiple rounds into two parts: direct and indirect spillovers. The former encompasses one round of risk spillover, while the latter is the sum of risk spillover via two or more rounds. This paper finds that, given the shock of a 10% loss to output, there is a maximum total reduction of approximately 6% in the output of one downstream industry, and the total reduction may be approximately 20% across the network. In addition, indirect spillovers are significant. The proportion of indirect spillover effects ranges from 30% to 50% in approximately one-third of the simulation cases. Therefore, there is a risk amplification effect within the production network.

Furthermore, this paper divides indirect spillovers into effects on direct downstream industries and indirect downstream industries. The former are the two or more rounds of effects on the industries directly connected to the initially shocked industry, and the latter are the two or more rounds of effects on the indirectly related industries. In most cases, the indirect effect on direct downstream industries accounts for over 20% of the total spillover effects, indicating the importance of focusing on not only the direct spillovers but also the risk amplification effects brought by the production network. Otherwise, systemic risk in the real sector may be underestimated.

Next, this paper investigates the spillover channel in the production network, which is defined as a chain comprised of "systemically vulnerable industries (SVIs) - systemically important industries (SIIs) - systemically vulnerable industries (SVIs)". The systemic vulnerability of one industry refers to the extent of risk spillover to this industry given a shock to other industries. The higher the degree of risk spillover is, the greater the industry's systemic vulnerability. The systemic importance of an industry refers to the extent of risk spillover to other industries given a shock to itself. The higher the degree of risk spillovers is, the greater the industry's systemic importance. The logic of this channel is that SVIs are vulnerable industries and are easily affected by external shocks, so this paper starts the chain using SVIs. Next, when SVIs suffered from negative shocks, risks spread to SIIs and then to the entire production network, ultimately increasing the risks for both SVIs and the real sector.

This paper identifies 75 risk spillover paths and 9 closed-loop paths during 2018. Taking the paths with higher risk as an example, this paper finds that risks in the three SVIs of "mining support service activities", "coke and refined petroleum products", and "other transport equipment" spread through multiple pathways to SIIs of "chemical and chemical products", "basic metals" and "wholesale and retail trade; repair of motor vehicles", triggering systemic risks in the enterprise sector. Moreover, there is a risk loop among the industries of "mining support service activities", "coke and refined petroleum products", and "water transport", etc., leading to risk amplification.

This conclusion indicates that upstream industries are critical, systemically important sectors. These industries are highly prone to triggering risk spillovers across other sectors within the production network. Other industries are heavily influenced by the performance of upstream industries. This phenomenon is also why this paper investigates risk spillovers from the perspective of supply-side shocks.

Finally, this paper empirically analyses the factors of SIIs and SVIs using data from Chinese A-share listed companies and the OECD input-output tables for the 2006–2018 period. The results reveal that the key factors for SVIs and SIIs include input-output relationships and network centrality. Specifically, industries offering more intermediate input exhibit greater systemic importance, while industries receiving more intermediate input have higher systemic vulnerability. Additionally, industries with higher degree (or out-degree) centrality and betweenness centrality exhibit greater systemic importance, while industries with higher degree (or in-degree) centrality, betweenness centrality, eigenvector centrality, and closeness centrality display higher systemic vulnerability.

The marginal contributions of this paper may include the following three points. First, this paper extends the literature in the field of risk spillovers among supply chains. The literature mostly focuses on firm-level supply chain networks (Barrot and Sauvagnat, 2016; Diem et al. 2022; Elliott et al. 2022), given negative shocks such as natural disaster risk (Barrot and Sauvagnat, 2016; Boehm et al. 2019; Carvalho et al. 2021), import tariff risk (Demir et al. 2022), network attack (Crosignani et al. 2023), tail risk (Yang et al. 2023), or zombie risk (Dai et al. 2021). However, not all listed companies reveal their suppliers or customers, so there may be a problem of selection bias.

Several papers primarily analyse the structural characteristics of the production network and industry-specific risk spillovers, such as the real estate industry chain (Chen et al. 2023) or cascading failure models in a network (Wang and Zhang, 2018; Zeng and Xiao, 2014). However, existing studies overlook the risk spillover between industries in the supply network over multiple rounds, which may result in an underestimation of the degree of risk spillover. In fact, indirect risk spillover analysis is more common in research on the financial sector (Duarte and Eisenbach, 2021). To fill this gap, this paper studies risk spillovers using the production network, which can avoid selection bias, and investigates the spillovers over multiple rounds, which can obtain a more precise measure of the risks in the industrial chain.

Second, this paper quantitatively identifies risk spillover paths through the transmission of shocks in the industrial chain. Theoretically, production networks can provide a reliable network foundation for studying the key transmission paths of risk spillover through input-output linkages (Liu et al. 2020). However, Liu et al. (2020) only predicts the possible paths of epidemic shock transmission, such as path centrality. Different from the paper above, this paper simulates the occurrence of risk spillover in the industrial chain, depicting the complete risk spillover path of "SVIs→SIIs→SVIs", which can show more information about risk spillovers in the production network. This paper could provide policy recommendations for relevant regulatory agencies to formulate risk monitoring and early warning measures focusing on key paths, enabling timely intervention and assistance at the next industry of the risk spillover path when shocks occur.

Finally, this paper identified key factors of critical industries. The literature has mostly focused on systemically important and systemically vulnerable financial institutions (Bao et al. 2020; Brownlees and Engle, 2017), with less emphasis on SIIs and SVIs in the real economy. Zhai (2019) identified SIIs and SVIs through the risk spillover relationship between the banking industry and the real sector. Bu and Liu (2021), Li et al. (2019) and Song et al. (2022) identify them using the TENET and LOO.

However, these studies did not consider the role of input-output linkages between industries. To fill this gap, this paper chooses several key factors based on the Cobb-Douglas production function and empirically investigates the driving factors of SIIs and SVIs. This paper finds that systemic importance and systemic vulnerability are essentially determined by input-output relationships and network centrality. Therefore, this finding could help deepen the understanding of the formation of SIIs and SVIs in China and provide empirical evidence for relevant regulatory agencies to focus on weak and important links in risk spillover.

The remaining structure of this paper is as follows. Section 2 constructs a risk spillover model based on a production network and uses a three-layer production network as an example to show the intuitive analysis of risk spillover from upstream industries to downstream industries. Section 3 introduces the data sample and parameter settings and analyses the simulation results, including the basic analysis, the identification and decomposition of SIIs and SVIs, the portrayal of risk spillover paths, and robustness tests. Section 4 analyses the formation of systemic importance and systemic vulnerability and provides robustness analysis. Section 5 and Section 6 presents economic implications and conclusions.

Production network and risk spillover model

When a certain industry faces a shock that disrupts its normal transactions, it can have a cascading impact on industries downstream, leading to a reduction in their production activities. This section constructs a directed and weighted production network to illustrate this spillover effect. In addition, we use a three-layer production network as an example to provide an intuitive analysis of how upstream industries generate risk spillover to downstream industries.

Production network. We consider an economic system consisting of N industries, and the production of each industry j follows a Cobb-Douglas production function.

$$y_j = e^{z_j} l_j^{\alpha_j} \prod_i x_{ij}^{\beta_{ij}}. \tag{1}$$

where j represents the downstream industry and i represents the upstream industry. z_j denotes the total factor productivity, l_j represents the labor input, and x_{ij} represents the intermediate input provided by upstream industry i to downstream industry j. α_j represents the output elasticity of labor, and β_{ij} represents the output elasticity of intermediate input, indicating the share of intermediate input upstream in downstream output in the equilibrium state of the economy (Acemoglu et al. 2016).

Then, this paper constructs a production network $G = (V, E)$ among industries. Here, $V = \{v_1, v_2, \cdots, v_n\}$ represents the set of n nodes, and $E = \{e_1, e_2, \cdots, e_m\}$ represents the set of m directed edges. Nodes represent various industries in the economic system, and directed edges represent intermediate input from one industry i to another industry j. The n × n adjacency matrix B of G is defined as $[\beta_{ij}]$, where β_{ij} represents the share of upstream industry i's intermediate input in downstream industry j's output (Acemoglu et al. 2016), serving as the weight of the directed edge. β_{ij} is as follows:

$$\beta_{ij} = \begin{cases} \frac{IO_{ij}}{Output_j} & i \neq j \\ 0 & i = j \end{cases}. \tag{2}$$

In the input-output table (see Supplementary Table S1 online), IO_{ij} represents the direct consumption of output from upstream industry i by downstream industry j. $Output_j$ represents the output of downstream industry j. β_{ij} measures the proportion of direct consumption of output from upstream industry i by downstream industry j relative to the output of downstream industry j, reflecting the intermediate input link between upstream industry i and downstream industry j.

Risk spillover path analysis based on a three-layer production network. This section uses a three-layer production network as an example to illustrate the risk spillover paths. In Fig. 1, there might be multiple production networks, including but not limited to Networks (a)-(c), each with its unique risk spillover path. We will then describe three representative scenarios in detail. In addition, different from traditional literature which uses volatility to measure risk, production losses are regarded as a proxy variable for risk referring to Inoue and Todo (2019) and Duarte and Eisenbach (2021). The greater the prosduction losses, the higher the risk for the industry.

Risk spillover in a single path. In subfigure (a), industry A is the sole upstream industry for industry B and industry C, while industry B is the sole upstream industry for industry D. Industry A provides intermediate inputs as proportions to industries B and C, denoted as x_{AB}/y_A and x_{AC}/y_A, respectively, and these ratios remain unchanged throughout the risk spillover process. The Cobb-Douglas production function for industries B to D is represented by Eq. (3).

$$y_B = e^{z_B} l_B^{\alpha_B} x_{AB}^{\beta_{AB}}, y_C = e^{z_C} l_C^{\alpha_C} x_{AC}^{\beta_{AC}}, y_D = e^{z_D} l_D^{\alpha_D} x_{BD}^{\beta_{BD}}. \tag{3}$$

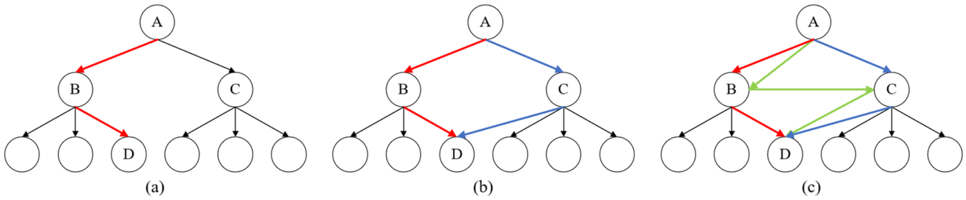

Fig. 1 Three-layer production network. When industry A is subjected to a certain degree of external shock, the risk spills over to industry D, showing single, double and triple spillover paths in the three different production network structures in **a**, **b** and **c**, respectively. In subfigure **a**, the red path represents the "A → B → D" single risk spillover path. In subfigure **b**, the red and blue paths represent the two "A → B → D" and "A → C → D" risk spillover paths. In subfigure **c**, the red path, blue path and green path represent the three "A → B → D", "A → C → D" and "A → B → C → D" risk spillover paths. Three-layer production network is used as an example to provide an intuitive analysis, the simulation model in this paper is based on the production network of the whole industry in the economy, for example, Supplementary Fig. S1.

where z represents total factor productivity, l represents labor input, and x represents intermediate input. α represents the output elasticity of labor, and β represents the output elasticity of intermediate input.

The transmission process of risk shown in Fig. 1 is as follows: (1) In stage $t = 0$, industry A experiences an initial shock $\rho(0 \le \rho < 1)$, leading to a reduction in its output to ρy_A. (2) In stage $t = 1$, the risk is transmitted to the midstream industries through paths "A → B" and "A → C". Assuming that industry A reduces its intermediate input to industries B and C by ρx_{AB} and ρx_{AC}, the outputs of industries B and C will decrease to $\widetilde{y_B} = \rho^{\beta_{AB}} y_B$ and $\widetilde{y_C} = \rho^{\beta_{AC}} y_C$, respectively. (3) In stage $t = 2$, the risk propagates along the "B → D" path to industry D, causing the output of industry D to change to $\widetilde{y_D} = \rho^{\beta_{AB}\beta_{BD}} y_D$.

In subfigure (a), the risk spillover exhibits a single path of "A → B → D". We refer to Inoue and Todo (2019) and use the proportional change in output before and after the shock to indicate the risk level of a certain industry. The higher the proportion of output changes, the greater the risk for the industry. The risk levels for industries B, C, and D are obtained as follows:

$$Risk_B = \left(y_B - \widetilde{y_B}\right)/y_B = 1 - \rho^{\beta_{AB}}. \tag{4}$$

$$Risk_C = \left(y_C - \widetilde{y_C}\right)/y_C = 1 - \rho^{\beta_{AC}}. \tag{5}$$

$$Risk_D = \left(y_D - \widetilde{y_D}\right)/y_D = 1 - \rho^{\beta_{AB}\beta_{BD}}. \tag{6}$$

Risk spillover in a dual path. In subfigure (b), industries B and C are both upstream industries for industry D. The Cobb-Douglas production function for the B-D industries is represented by Eq. (7).

$$y_B = e^{z_B} l_B^{\alpha_B} x_{AB}^{\beta_{AB}}, y_C = e^{z_C} l_C^{\alpha_C} x_{AC}^{\beta_{AC}}, y_D = e^{z_D} l_D^{\alpha_D} x_{BD}^{\beta_{BD}} x_{CD}^{\beta_{CD}}. \tag{7}$$

In subfigure (b), the spillover of risk in stages $t = 0$ and $t = 1$ is consistent with that in subfigure (a). However, in stage $t = 2$, both industries B and C will impact industry D, and the risk propagates along two pathways, "B → D" and "C → D". As a result, the output of industry D changes to $\widetilde{y_D} = \rho^{\beta_{AB}\beta_{BD} + \beta_{AC}\beta_{CD}} y_D$.

Therefore, the risk spillover exhibits a dual pathway of "A → B → D" and "A → C → D". The risk levels for industries B, C, and D are shown below:

$$Risk_B = \left(y_B - \widetilde{y_B}\right)/y_B = 1 - \rho^{\beta_{AB}}. \tag{8}$$

$$Risk_C = \left(y_C - \widetilde{y_C}\right)/y_C = 1 - \rho^{\beta_{AC}}. \tag{9}$$

$$Risk_D = \left(y_D - \widetilde{y_D}\right)/y_D = 1 - \rho^{\beta_{AB}\beta_{BD} + \beta_{AC}\beta_{CD}}. \tag{10}$$

Risk spillover in a triple path. In subfigure (c), both industries A and B serve as upstream industries for industry C. The Cobb-Douglas production function for industries B-D is given by Eq. (11).

$$y_B = e^{z_B} l_B^{\alpha_B} x_{AB}^{\beta_{AB}}, y_C = A_C l_C^{\alpha_C} x_{AC}^{\beta_{AC}} x_{BC}^{\beta_{BC}}, y_D = A_D l_D^{\alpha_D} x_{BD}^{\beta_{BD}} x_{CD}^{\beta_{CD}}. \tag{11}$$

In this case, the process of risk spillover at stages $t = 0$ and $t = 1$ is consistent with subfigure (a), but the difference lies in the following aspects: (1) At $t = 2$, the risk propagates along three paths: "B → D", "C → D", and "B → C". As a result, the output of industry C decreases to $\widetilde{y_C} = \rho^{\beta_{AC} + \beta_{AB}\beta_{BC}} y_C$, and the output of industry D decreases to $\widetilde{y_D} = \rho^{\beta_{AB}\beta_{BD} + \beta_{AC}\beta_{CD}} y_D$. (2) At $t = 3$, the risk further propagates along the "C → D" path, causing the output of industry D to decrease to $\widetilde{y_D} = \rho^{\beta_{AB}\beta_{BD} + \beta_{AC}\beta_{CD} + \beta_{AB}\beta_{BC}\beta_{CD}} y_D$.

In subfigure (c), the risk spillover presents a triple path of "A → B → D", "A → C → D", and "A → B → C → D". The risk levels of industries B, C, and D are as follows:

$$Risk_B = \left(y_B - \widetilde{y_B}\right)/y_B = 1 - \rho^{\beta_{AB}}. \tag{12}$$

$$Risk_C = \left(y_C - \widetilde{y_C}\right)/y_C = 1 - \rho^{\beta_{AC} + \beta_{AB}\beta_{BC}}. \tag{13}$$

$$Risk_D = \left(y_D - \widetilde{y_D}\right)/y_D = 1 - \rho^{\beta_{AB}\beta_{BD} + \beta_{AC}\beta_{CD} + \beta_{AB}\beta_{BC}\beta_{CD}}. \tag{14}$$

Risk spillover model based on the production network. Real-world production networks are more complex than the scenarios described above. Therefore, we conduct systematic simulations of risk spillover in the production network based on the following rules:

1. Build production network. Based on IO data, we construct an interindustry production network $G = (V, E)$, with the initial output of each industry as $y_i\,(i = 1, 2, 3, \ldots, n)$.
2. Set initial shock. Initially, industry k in the production network experiences a negative shock $\rho(1 > \rho \ge 0)$, causing its output to decrease to ρy_k and affecting its downstream industries. This constitutes the first round of risk spillover.
3. Simulate shock propagation. We traverse the network and identify the set of industries IS that received negative shocks in the previous round, and calculate the shock ρ_i for each industry i. Then, we identify the downstream industry DS of each industry in the set IS, confirm the input-output linkage β between the upstream and downstream, measure the impact of changes in intermediate inputs on the downstream output according to the Cobb-Douglas production function in Eq. (1), and update the output of the downstream industry $y_i{}'$. This constitutes the second round of risk spillover.
4. Set cycle termination conditions. We check whether the difference between the total output value of all industries in the previous round and the total output value of all industries in the current round is less than the threshold ε or whether the cycle round t has reached the upper limit T, i.e., $\left|\rho y_k + \sum_{i \neq k} y_i - \sum_i y_i{}'\right| \le \varepsilon$ or $t \le T$. If either condition is satisfied, the cycle is

terminated, and the current round t is the last round of the cycle; otherwise, we repeat step 3.

5. Export risk spillover results. We calculate the impact of risk spillover. Output $\left(y_k{}' - y_k\right)/y_k - \left(1 - \rho\right)$ is the spillover extent of the initial shocked industry k, excluding the specific shock ρ. Output $\left(y_i{}' - y_i\right)/y_i$ $(i \neq k)$ is the spillover extent of other industries.

Sample, parameters, and simulation results analysis

In this section, we first present the sample selection and parameter settings, followed by an analysis of the simulation results.

Sample selection and parameter settings. The sample selection and parameter settings involve the process of choosing the data sample and determining the values of various parameters used in the simulation.

Sample selection. This paper analyses data from the OECD Input-Output Tables for China for the years 2006 to 2018. The 2021 version of the OECD Input-Output Tables provides input-output matrices for 45 industries (classified according to ISIC Rev.4) across 67 economies for the years 1995 to 2018. This dataset offers the advantage of temporal continuity and strong timeliness. Subsequently, this paper manually matched the Chinese National Economic Industry Classification with the OECD International Industry Classification (the detailed processing steps are outlined in Supplementary Discussion 1 online), resulting in a final set of 44 industries. Supplementary Table S2 presents the industry codes and names used in this paper.

Parameters. The initial parameters include the number of industries in the network, the number of edges, edge weights, and shock level. Leveraging the OECD Input-Output Tables data, this paper establishes the number of industries, denoted as n, and the number of edges, denoted as m, as outlined in Supplementary Table S3 online. The edge weights, represented by β, are computed according to Eq. (2). As indicated in Supplementary Table S3, the production network in this paper is essentially a fully connected network.

Supplementary Fig. S1 illustrates the production network based on the data from 2018. In the diagram, the industry labels represent industry numbers, and the thickness of the edges represents the magnitude of their weights. Thicker directed edges indicate a higher degree of input-output relationship between industries. To simplify the model, this paper uniformly sets the shock level as $\rho = 0.9$, indicating that the output of the industry affected by the initial shock will decrease to 0.9 times its original value.

Simulation results analysis. This paper conducts risk spillover model simulations using Python to ultimately derive the risk level caused by supply-side shocks from a specific industry within the production network. Given the assumption that each industry experiences one exogenous shock, this section conducts a total of 44 simulation experiments. In each experiment, the spillover situation for all 44 industries is obtained, leading to a total of 1936 risk spillover results for each year.

Baseline results. 1. Maximum spillover degree and single-industry spillover proportion

Firstly, two indicators are constructed: $\max\_spill_i$ and $spill\_to\_single_{ij}$. The former measures the maximum extent to which shocks from a specific industry spill over to other industries, while the latter gauges the ratio of spillover to a specific industry compared to all industries. The calculation

Table 1 Risk spillover results for 2018 (partial).

Initial shock industry *i*	Affected industry *j*	$spillover_{i\to j}$	$spill\_to\_single_{ij}$
TTL_05T06	TTL_19	0.0606	27.90%
TTL_01T02	TTL_10T12	0.0367	19.84%
TTL_20	TTL_22	0.0326	17.04%
TTL_24	TTL_25	0.0291	16.22%
TTL_10T12	TTL_55T56	0.0284	19.96%
TTL_19	TTL_50	0.0283	16.65%
TTL_05T06	TTL_35	0.0242	11.14%
TTL_21	TTL_86T88	0.0234	75.40%
TTL_01T02	TTL_16	0.0232	12.52%
TTL_24	TTL_27	0.0231	12.86%
TTL_23	TTL_41T43	0.0203	37.92%
TTL_24	TTL_28	0.0182	10.16%
TTL_01T02	TTL_55T56	0.0179	9.67%
TTL_19	TTL_52	0.0178	10.49%
TTL_19	TTL_51	0.0168	9.87%
TTL_05T06	TTL_50	0.0164	7.54%
TTL_24	TTL_30	0.0158	8.82%

The first two columns in Table 1 show the industry code. Please refer to Table S2 for the code and name comparison table.

formulas are as follows:

$$\max\_spill_i = \max_j spillover_{i\to j} \tag{15}$$

$$spill\_to\_single_{ij} = \frac{spillover_{i\to j}}{\sum_k spillover_{i\to k}} \tag{16}$$

where i represents the initially shocked industry and j represents the affected industry. $spillover_{i\to j}$ represents the extent of risk spillover from the initial shocked industry to the affected industry.

Table 1 presents 17 spillover results in 2018 where the risk level exceeds 1.5%[1]. In Table 1, initial shock industry i is initially shocked based on the model settings. Affected industry j is the industry affected by initial shock industry i. $spillover_{i\to j}$ represents the extent to which risks spill over from industry i to industry j, specifically, the proportional change in output in industry j under the supply shock of industry i. $spill\_to\_single_{ij}$ represents the ratio of industry i's risk spill over to industry j compared to all industries.

Taking the first row as an example, the first column represents the initially shocked industry as "mining and quarrying, energy producing products", the second column represents the affected industry subject to risk spillover as "coke and refined petroleum products", and the third column signifies that the latter is the industry most affected by the shock in the former, with a risk level of 0.0606. This conclusion indicates that if the "mining and quarrying, energy producing products" industry experiences a 10% output shock, it will lead to a 6% decrease in output for the "coke and refined petroleum products", highlighting the strong reliance on coke and refined petroleum product manufacturing on the extraction of crude oil, coal, and natural gas resources.

The fourth column represents the spillover level from the "mining and quarrying, energy producing products" industry to the "coke and refined petroleum products" industry, accounting for approximately one-fourth of the total spillover level to the 44 industries. In other words, the mining industry's shock will lead to systemic effects across all industries in the economic system through the production network, resulting in an amplified risk level of 21.7%. This paper finds that the ratio of spillover to a specific industry compared to all industries is below 20%,

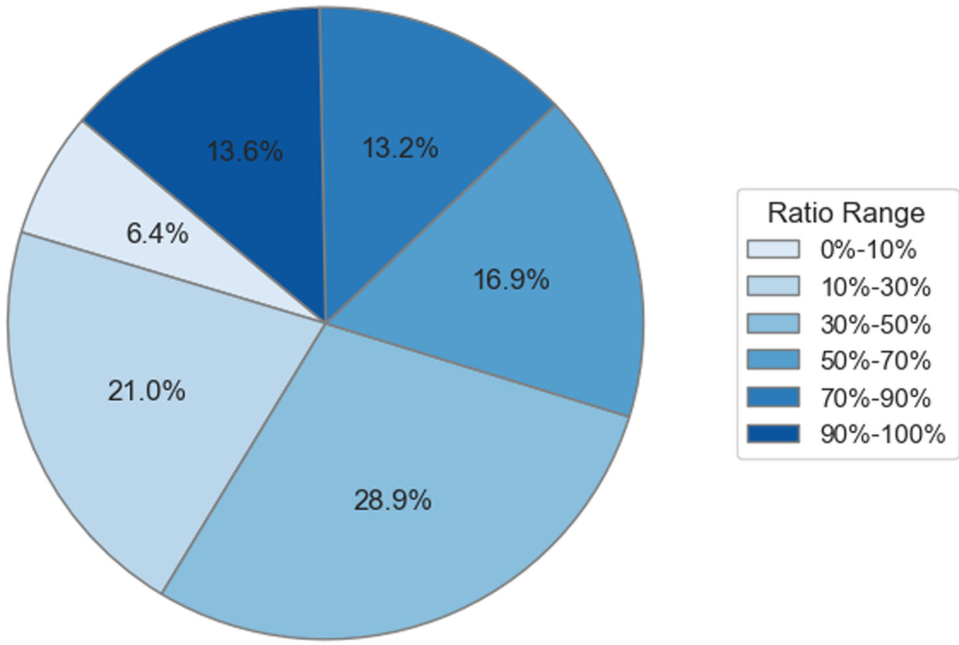

Fig. 2 Frequency distribution of the indirect spillover ratio. The indirect spillover ratio is calculated based on the simulation results of 2018. The majority of industries have a proportion of indirect spillover between 30% and 50%, with 13.58% of samples exceeding 90% and only 6.45% of samples falling below 10%. In other words, in most cases, 30–50% of the risk does not originate directly from the initially impacted industry but results from the mutual spillover among other industries in the production network.

confirming the significance of researching the systemic risks of entity sectors based on production networks.

Indirect spillover ratio

Secondly, this paper distinguishes direct and indirect spillovers and calculates $indirect\_spill_{ij}$. The specific construction process is: (1) We define industries directly connected to the initially shocked industry as direct downstream industries, while other industries without direct connections are regarded as indirect downstream industries. (2) We define the round of risk spillover as the number of intermediate industries through which the risk spills from one industry to another industry. If the risk does not pass through the intermediate industry, it is one round of risk spillover; if it passes through an intermediate industry, it becomes two rounds of risk spillover, and so on. (3) We divide the spillovers of multiple rounds into two parts: direct and indirect spillovers. The former is one round of risk spillover, and the latter are the sum of two or more rounds of risk spillover. Thus, $indirect spill_{ij}$ represents the ratio of total spillovers from one industry to another minus direct spillovers to total spillovers, emphasizing the significance of indirect spillover within the production network. The calculation formulas are as follows:

$$indirect\_spill_{ij} = \frac{spillover_{i\to j} - spillover_{i\to j(direct)}}{spillover_{i\to j}} \tag{17}$$

where $spillover_{i\to j(direct)}$ represents the direct spillover degree to industry j when it is a direct downstream industry of industry i.

For instance, in Fig. 1(c), A is the initially shocked industry, and C is both a direct downstream industry and an indirect downstream industry of A. "A → C" indicates direct spillover, and "A → B → C" indicates indirect spillover. Now we can calculate $indirect\_spill_{AC} = spillover_{A\to B\to C}/\left(spillover_{A\to B\to C} + spillover_{A\to C}\right)$.

Figure 2 presents the frequency distribution of the $indirect\_spill_{ij}$ based on the simulation results of 2018. It is evident that the majority of samples have a proportion of indirect spillover between 30% and 50%, with 13.58% of samples exceeding 90% and only 6.45% of samples falling below 10%. In other words, in most cases, 30%–50% of the risk does not originate directly from the initially shocked industry but results from the spillovers among other industries in the production network over multiple rounds. It emphasizes that indirect spillover is a significant aspect of systemic risk in entity sectors and underscores the importance of this paper's approach through production networks for investigating systemic risks. To gain a deeper understanding of indirect spillovers, we distinguish between the indirect spillovers to direct downstream and indirect downstream industries in the next section, providing further insights into the risk amplification effects within the production network.

SIIs and SVIs. Referencing Duarte and Eisenbach (2021), the systemic importance of an industry refers to the extent to which it transmits risks to other industries after being affected by shocks. The greater the extent of transmitting risk spillover is, the higher the systemic importance of that industry. The systemic vulnerability of an industry refers to the extent to which it is affected by risks from other industries after they are affected by shocks. The greater the extent of receiving risk spillover is, the higher the systemic vulnerability of that industry.

This paper calculates the systemic importance and systemic vulnerability of industries using the following method. Based on the simulation model, negative shocks with a magnitude of $\rho = 0.9$ are sequentially applied to the $n = 44$ industries. First, concerning the initially shocked industry, the summation of the changes in output proportionally influenced across all industries represents the systemic importance of the initially shocked industry. Second, for the industries affected by the spillover, the changes in output proportionally influenced by each of the 44 industry shock scenarios are sequentially summed, signifying the systemic vulnerability of each respective industry. Finally, this paper individually ranks the industries based on their systemic importance and systemic vulnerability, ordering them from highest to lowest. The top ten industries in each ranking are designated SIIs and SVIs, respectively.

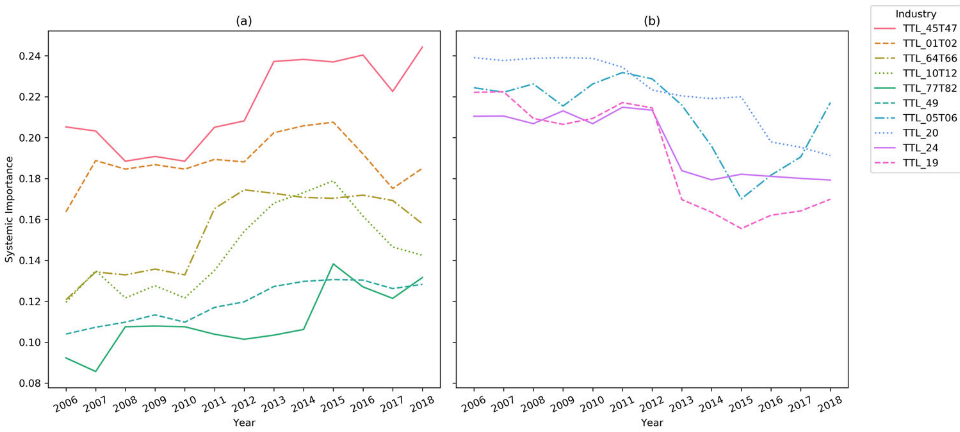

Fig. 3 Trend of SIIs. The graph shows the trend of SIIs from 2006 to 2018. Six industries show a fluctuating upwards trend. Four industries exhibit a fluctuating downwards trend.

Supplementary Table S4 presents the top five industries ranked by systemic importance during the period from 2006 to 2018. Throughout the sample period, SIIs in China remain relatively stable. Notably, four out of the top five industries are upstream industries that provide raw materials and engage in component manufacturing and production ("agriculture, hunting, forestry", "mining and quarrying, energy producing products", "basic metals", and "chemical and chemical products"). This observation underscores that upstream industries in the supply chain serve as the origin and starting point, determining the development potential of other industries. It also highlights the rationale for this paper's approach of investigating industrial chain risk spillover from the supply side.

Figure 3 shows the trend of SIIs from 2006 to 2018. Six industries show a fluctuating upwards trend: "wholesale and retail trade; repair of motor vehicles", "agriculture, hunting, forestry", "financial and insurance activities", "food products, beverages and tobacco", "administrative and support services", and "land transport and transport via pipelines". The majority of these industries are characterized by essential demand, contributing to their sustained high systemic importance. The finance industry, on the other hand, is a significant service sector that also plays a crucial role in influencing the development of the real economy.

Four industries exhibit a fluctuating downwards trend: "chemical and chemical products", "basic metals", "mining and quarrying, energy producing products", and "coke and refined petroleum products". Considering the context, it is evident that the worsening global climate crisis has had a significant impact on the economic development of various countries, including China. In recent years, the Chinese government has been actively promoting low-carbon transformation, leading to a gradual decline in the importance of the aforementioned four industries.

Supplementary Table S5 presents the top five industries in terms of systemic vulnerability from 2006 to 2018. In comparison to SIIs, SVIs exhibit more significant fluctuations. Among them, "coke and refined petroleum products", "electrical equipment", "manufacturing nec; repair and installation of machinery and equipment" and "construction" industries have consistently been identified as China's SVIs. Notably, the "coke and refined petroleum products" industry is both an SII and an SVI, highlighting the need for attention and oversight from relevant regulatory authorities.

Figure 4 illustrates the changing trends in SVIs from 2006 to 2018. "Manufacturing nec; repair and installation of machinery and equipment" and "construction" industries have consistently demonstrated elevated levels of systemic vulnerability. The "mining and quarrying, nonenergy producing products", "mining support service activities", and "other transport equipment" industries have all experienced substantial fluctuations, and the systemic vulnerability of the first two industries shows a fluctuating upwards trend over time.

Comparative analysis of direct and indirect spillovers in key industries. In this section, the indicators of SIIs and SVIs are broken down to provide a deeper analysis of direct and indirect spillovers, investigating the risk amplification effects of indirect spillovers in production network. We can divide the SIIs and SVIs into three parts according to the spillover round and whether the spillover industry is directly related to the industry. First, according to Fig. 5(a), the systemic importance of industry A can be decomposed into three components: (1) Direct_on_direct: The direct impact on its direct downstream industries is reflected as "Industry itself→Direct Downstream" ($A \rightarrow B$, $A \rightarrow C$). (2) Indirect_on_direct: The indirect impact on its direct downstream industries is reflected as "Industry itself→Other Industries→Direct Downstream" ($A \rightarrow B \rightarrow C$). (3) Indirect_on_other: Other indirect impacts (including impacts on indirect downstream industries and impacts on itself) are reflected as "Industry itself→Direct Downstream→Indirect Downstream" ($A \rightarrow B \rightarrow D$, $A \rightarrow C \rightarrow D$, $A \rightarrow B \rightarrow C \rightarrow D$) and "Industry itself→Direct Downstream ($\rightarrow$ Indirect Downstream)→Industry itself" ($A \rightarrow B \rightarrow A$, $A \rightarrow B \rightarrow D \rightarrow B \rightarrow A$, $A \rightarrow B \rightarrow C \rightarrow D \rightarrow B \rightarrow A$, $A \rightarrow C \rightarrow D \rightarrow B \rightarrow A$).

Based on Fig. 5b, the systemic vulnerability of industry D can be decomposed into three components. (1) Direct_from_direct: The direct impact from its direct upstream industries is reflected as "Direct Upstream→Industry Itself" ($B \rightarrow D$, $C \rightarrow D$). (2) Indirect_from_direct: The indirect impact from its direct upstream industries is reflected as "Direct Upstream→Other Industries→Industry Itself" ($B \rightarrow C \rightarrow D$). (3) Indirect_from_other: Other indirect impacts (including impacts from indirect upstream industries and impacts from itself) are reflected as "Indirect Upstream→Direct Upstream→Industry Itself" ($A \rightarrow B \rightarrow D$, $A \rightarrow C \rightarrow D$, $A \rightarrow B \rightarrow C \rightarrow D$) and "Industry Itself ($\rightarrow$ Indirect Upstream)→Direct Upstream→Industry Itself" ($D \rightarrow B \rightarrow D$, $D \rightarrow B \rightarrow C \rightarrow D$, $D \rightarrow B \rightarrow A \rightarrow C \rightarrow D$, $D \rightarrow B \rightarrow A \rightarrow B \rightarrow D$, $D \rightarrow B \rightarrow A \rightarrow B \rightarrow C \rightarrow D$).

Based on the simulation results, we calculate the decomposition results for systemic importance and systemic vulnerability in 2018, and the decomposition ratios are shown in Figs. 6 and 7[2] (see Supplementary Tables S6 and S7 for decomposition results of

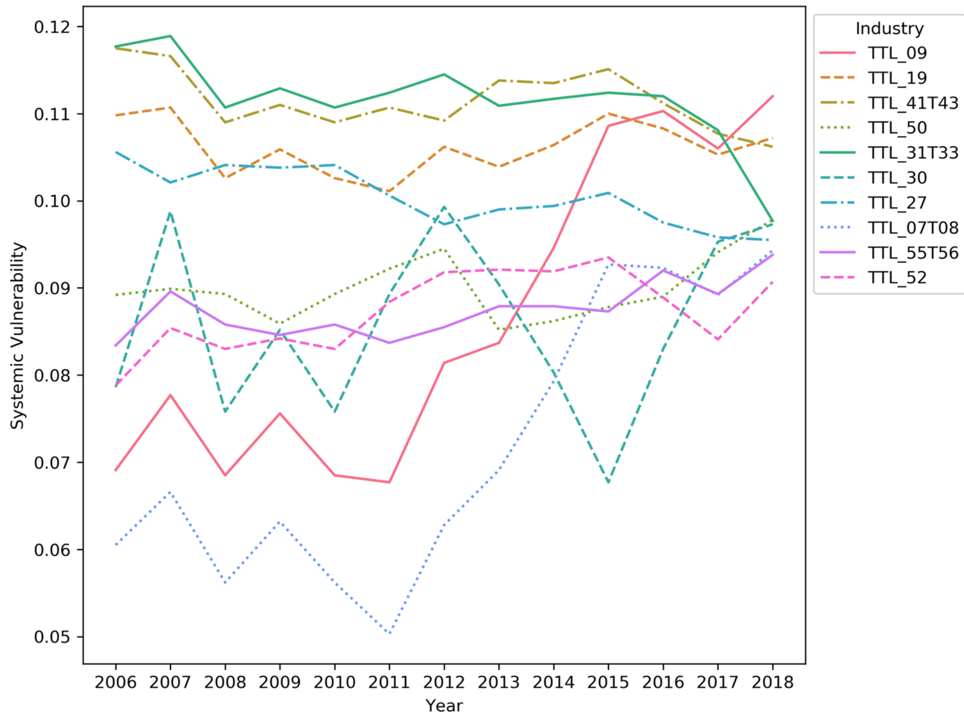

Fig. 4 Trend of SVIs. The graph illustrates the changing trends in SVIs from 2006 to 2018. “Manufacturing nec; repair and installation of machinery and equipment” and “construction” industries have consistently demonstrated elevated levels of systemic vulnerability.

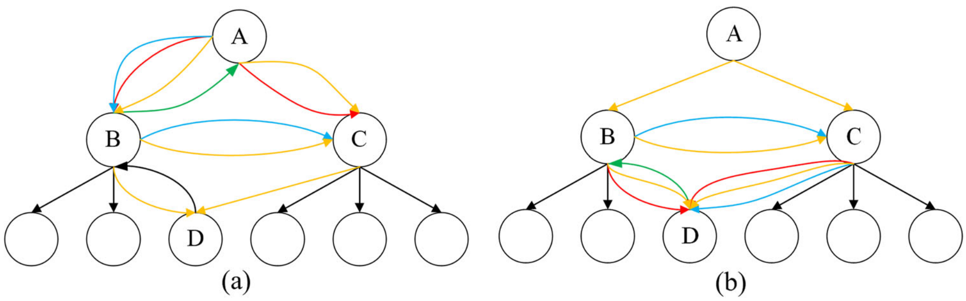

Fig. 5 Decomposition of SIIs and SVIs. Considering the bidirectional input-output relationship between industries in real economy, we add the bidirectional spillover relationship of “A ↔ B” and “B ↔ D” on the basis of Fig. 1. Subfigure **a** represents the decomposition path of systemic importance, and subfigure **b** represents the decomposition path of systemic vulnerability. In subfigure **a**, the red path represents the direct impact of industry A on the direct downstream industries, the blue path represents the indirect impact of industry A on the direct downstream industries, the yellow path represents the impact of industry A on the indirect downstream industries, and the green path represents the impact of industry A on itself. In subfigure **b**, the red path represents the direct impact of industry D from the direct downstream industries, the blue path represents the indirect impact of industry D from the direct downstream industries, the yellow path represents the impact of industry D from the indirect downstream industries, and the green path represents the impact of industry D itself.

all industries). Figure 6 shows that the proportion of direct impact from SIIs to their direct downstream industries is approximately 60% or more, the proportion of indirect impact to their direct downstream industries is above 25%, and other indirect impacts are below 2%. Only “mining and quarrying, energy producing products” has roughly equal proportions of direct and indirect impacts on their direct downstream industries. Therefore, while most industries have lower indirect impacts than direct impacts on their direct downstream industries, these indirect impacts still hold a significant share.

Figure 7 shows that the proportion of direct impact from the direct upstream industries for SVIs ranges between 65% and 75%, while the proportion of indirect impact from direct upstream industries is over 30%. This conclusion indicates that the proportion of the decomposed results for systemic vulnerability is relatively stable. Among these factors, the most significant is the direct impact from the direct upstream industries, followed by the indirect impact from the direct upstream industries generated through other industries, and finally, the other indirect impacts. Combining Figs. 6 and 7, it is evident that the production network exhibits risk amplification effects. Industries not only directly generate contagious risks but also transmit risks indirectly through other industries in the production network, and this proportion is non-negligible.

Spillover channel analysis. Next, this section examines the key channels of risk spillover between industries, namely, the

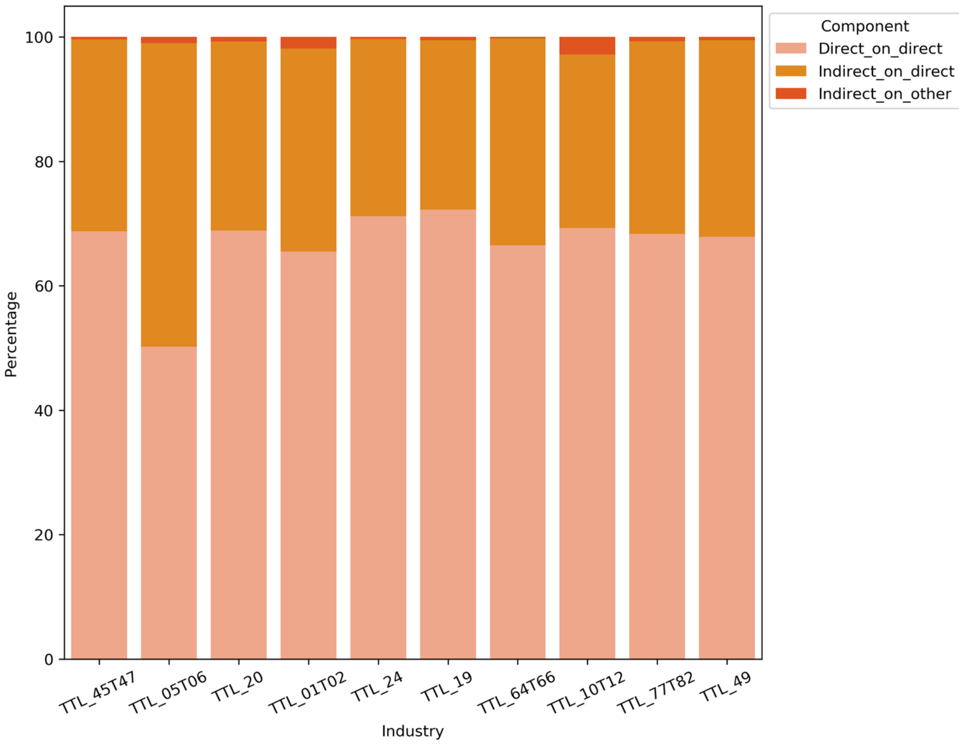

Fig. 6 Systemic importance decomposition. Direct_on_direct represents the direct impact on its direct downstream industries. Indirect_on_direct represents the indirect impact on its direct downstream industries. Indirect_on_other represents other indirect impacts (including impacts on indirect downstream industries and impacts on itself). The proportion of direct impact from SIIs to their direct downstream industries is approximately 60% or more, the proportion of indirect impact to their direct downstream industries is above 25%, and other indirect impacts are below 2%.

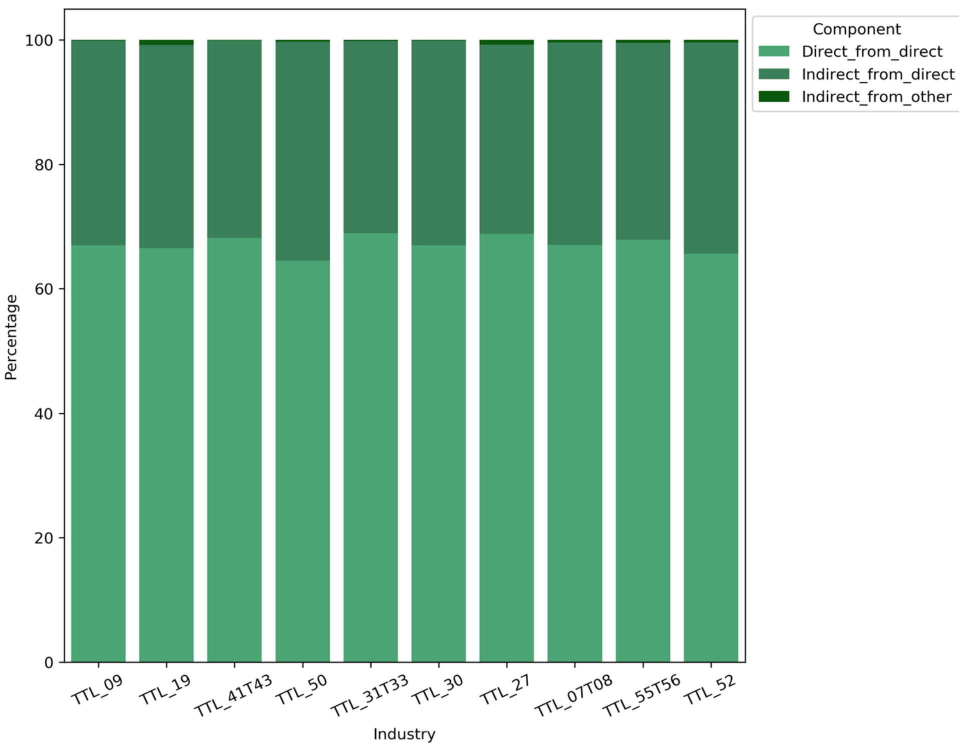

Fig. 7 Systemic vulnerability decomposition. Direct_from_direct represents the direct impact from its direct upstream industries. Indirect_from_direct represents the indirect impact from its direct upstream industries. Indirect_from_other represents other indirect impacts (including impacts from indirect upstream industries and impacts from itself). The proportion of direct impact from the direct upstream industries for SVIs ranges between 65% and 75%, while the proportion of indirect impact from direct upstream industries is over 30%.

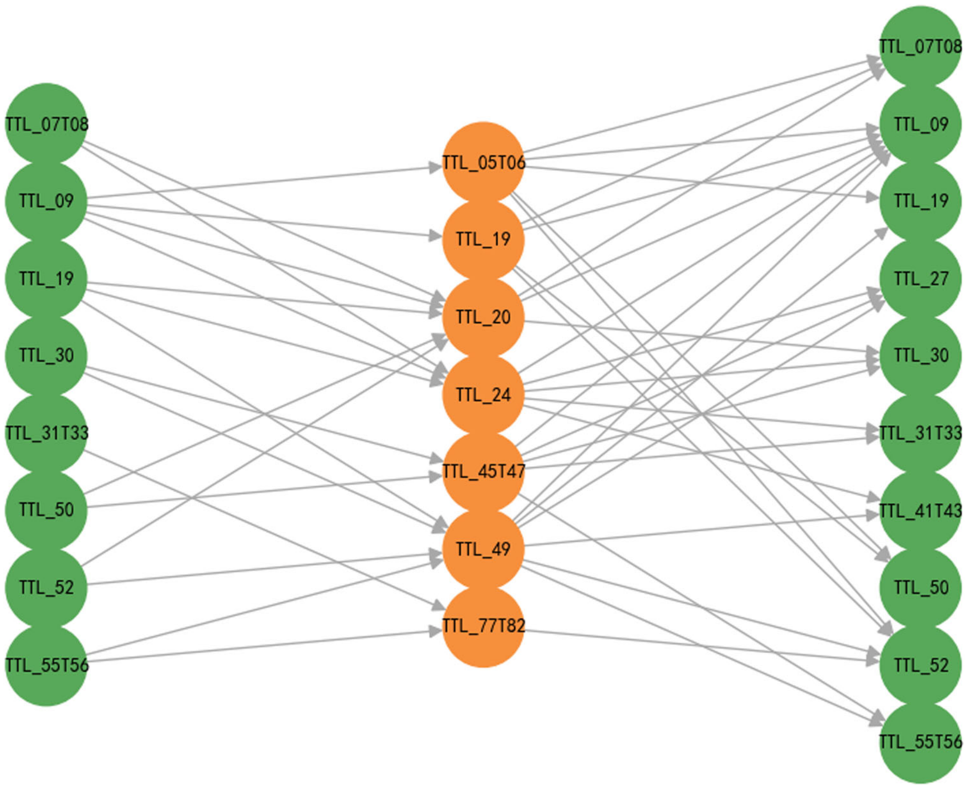

Fig. 8 Risk spillover pathway. Green-coloured industries represent SVIs, while red-coloured industries represent SIIs. The edges indicate the paths of risk spillover. In 2018, a total of 75 complete risk spillover pathways were identified.

"SVIs→SIIs→SVIs" risk spillover path. Analysing this pathway is fundamental to understanding the genesis of systemic risk.

We take the top ten SVIs each year as the origin of risk contagion. SIIs, which rank in the top ten for the magnitude of spillover they receive from SVIs, are considered the key intermediary sectors that amplify systemic risk in the real sector. The SVIs that rank in the top ten for the degree of risk spillover they receive from the SIIs are regarded as the ultimate industries. This method aims to depict and analyse the essential spillover pathways. The specific steps are as follows.

1. We characterize the pathway from SVIs to SIIs. (1) We designate SVIs as the source of risk spillover. (2) We rank the degree of risk spillover from each SVI to other industries and select the top ten industries with the highest spillover degrees. (3) We verify whether these ten industries are SIIs that serve as the second industry in the risk spillover pathway.

2. We characterize the pathway from SIIs to SVIs. (1) We designate SIIs as the risk amplification industries. (2) We rank the degree of risk spillover from each SII to other industries and select the top ten industries with the highest spillover degrees. (3) We verify whether these ten industries are SVIs that serve as the final industry in the risk spillover pathway.

Figure 8 illustrates the key pathways using the 2018 input-output relationships as an example. In the diagram, green-coloured industries represent SVIs, while red-coloured industries represent SIIs. The edges indicate the paths of risk spillover. In 2018, a total of 75 complete risk spillover pathways were identified. Among them were 17 pathways originating from "mining support service activities", 14 pathways from "coke and refined petroleum products", and 11 pathways from "other transport equipment". These pathways passed through SIIs such as "chemical and chemical products", "basic metals", "wholesale and retail trade; repair of motor vehicles" and "land transport and transport via pipelines" with 15, 15, 10, and 24 pathways, respectively. Hence, it is essential to closely monitor the risks in these industries, achieving precise risk alerts and prevention.

This paper employs an alternative approach to construct risk spillover paths and finds consistent results. We search for the "SVIs→SIIs→SVIs" risk spillover paths among the risk spillover results with output changes exceeding 0.5%. In Supplementary Table S8, a total of 16 paths are identified. Except for the 9th and 10th paths, all other paths coincide with the paths found using the previous method, demonstrating the robustness of the previous approach. Taking paths 1–5 as an example, once "mining and quarrying, nonenergy producing products" experiences a shock, it spills risks over to "basic metals", resulting in a 1.19% decrease in output. Subsequently, "basic metals" poses further risks to various industries, such as "mining support service activities" (1.22%), "electrical equipment" (2.31%), "other transport equipment" (1.58%), "manufacturing nec; repair and installation of machinery and equipment" (0.73%), and "construction" (1.47%).

Next, we select 9 closed-loop paths for analysis (see Supplementary Table S9). Specifically, when the "mining support service activities" industry experiences a shock, it is highly likely to spill risks to multiple SIIs. Subsequently, it affects itself through these SIIs, creating multiple impacts and forming a risk feedback loop. Therefore, special attention should be given to preventing and mitigating risks within this loop. In addition, "coke and refined petroleum products", "water transport", "other transport equipment", "mining and quarrying, nonenergy producing products", and "accommodation and food service activities" are also part of the risk feedback loop, highlighting the need for their careful consideration and management.

Robustness tests. Considering the potential bias in our model's simulation results due to external shock intensity and year-to-year input-output table differences, this paper conducts model-based robustness tests in above two aspects, specifically analysing: (1) baseline results, (2) SIIs and SVIs, and (3) spillover channels.

Firstly, as the external shock parameter significantly influences the results, we conduct robustness tests by varying the external shock parameter ρ to 0.8, 0.85, and 0.95, respectively. We observe a consistent order in the risk spillover degree among industries, indicating that the structural pattern of risk spillover remains unchanged while the magnitudes vary. Results such as the indirect spillover ratio, SVIs and SIIs, and the spillover channel exhibit consistency. Supplementary Table S13 illustrates the maximum spillover degree under four external shocks based on the simulation results from 2018. In terms of the degree of risk spillover, we note that a 5% increase in the external shock level corresponds to an approximately 3% increase in the maximum spillover.

Secondly, we have analysed the risk spillover using input-output tables from 2006 to 2018. In this section, we verify the results for the year 2018 by examining data from years 2016 and 2017. We identify the indirect spillover ratio (see Supplementary Fig. S2) and risk spillover pathways (see Supplementary Fig. S3) for 2016 and 2017, and find that the results are not significantly different from Figs. 2 and 8.

Factors driving risk spillovers

In this section, based on the Cobb-Douglas production function, we choose key factors and apply an empirical model to examine the mechanisms behind the formation of SIIs and SVIs.

Model design. Taking the logarithm of both sides of the Cobb-Douglas production function, we obtain Eq. (18).

$$\mathrm{lny}_j = \mathrm{z}_j + \alpha_j \mathrm{lnl}_j + \sum_i \beta_{ij} \mathrm{lnx}_{\mathrm{ij}} \tag{18}$$

This paper builds an empirical model based on Eq. (18) to further analyse the factors influencing the systemic importance and systemic vulnerability of industries.

$$y\_importance_{i,t} = \alpha_0 + \alpha_1 TFP_{i,t} + \alpha_2 Labor_{i,t} + \alpha_3 Use_{i,t} + \lambda_i + \mu_t + \varepsilon_{i,t} \tag{19}$$

$$y\_vulnerability_{i,t} = \beta_0 + \beta_1 TFP_{i,t} + \beta_2 Labor_{i,t} + \beta_3 Input_{i,t} + \lambda_i + \mu_t + \varepsilon_{i,t} \tag{20}$$

In the model, the subscript i represents the industry, and the subscript t represents the year. The dependent variables, $y\_importance_{i,t}$ and $y\_vulnerability_{i,t}$, represent the systemic importance and systemic vulnerability of industry i in year t, respectively. $Input_{i,t}$ represents the natural logarithm of the total intermediate inputs received by industry i from all its upstream industries in year t, i.e., $Input_{i,t} = \ln\left(\sum_j IO_{ji}\right)$, and it is related to the industry's systemic vulnerability. $Use_{i,t}$ represents the natural logarithm of the total intermediate inputs provided by industry i to all its downstream industries in year t, i.e., $Use_{i,t} = \ln\left(\sum_j IO_{ij}\right)$, and it is related to the industry's systemic importance.

$TFP_{i,t}$ represents the total factor productivity of industry i in year t, calculated using the LP method. This paper employs firm-level measures of total revenue, number of employees, net fixed assets, and cash payments for goods and services received as proxies for output, labor, capital, and intermediate inputs, respectively. The residuals of the estimated equations using the LP method at the firm level are considered the firm-level TFP, and the industry-level TFP is obtained by weighting these residuals by the total revenue of firms. $Labor_{i,t}$ represents the number of employees in industry i in year t, and it is obtained by weighting the firm-level number of employees by the total revenue of firms. λ_i and μ_t represent industry fixed effects and year fixed effects, respectively. $\varepsilon_{i,t}$ is the error term. This paper applies industry-level clustered standard errors.

Baseline results. This paper selects data from A-share listed companies and the OECD China input-output table for the period 2006 to 2018. Due to the particularities of accounting standards in the financial and real estate industries, as well as the social and nonprofit nature of the public administration and defence industries, this paper excludes ST enterprises and the financial, real estate, and public administration and defence industries. The analysis focuses on 41 industries, resulting in 533 observations for these 41 industries over the 13-year period.

The descriptive statistics are presented in Supplementary Table S10. The mean value of industry systemic importance is 6.66%, with a minimum value of 0.117% and a maximum value of 24.428%. On the other hand, the mean value of industry systemic vulnerability is 2.01%, ranging from a minimum of 2.3% to a maximum of 11.892%. This indicates that the variability of the systemic importance indicator is greater than that of the systemic vulnerability indicator. The average value of intermediate input is 12.05, and the average value of intermediate usage is 11.95, suggesting that, on average, industries receive more intermediate inputs than they provide.

The baseline regression results are presented in Table 2. Columns (1) and (2) show the results of the systemic importance regression, while Columns (3) and (4) display the systemic vulnerability regression. Columns (1) and (3) do not include the variables of total factor productivity (TFP) and labor input, while Columns (2) and (4) incorporate these variables.

The coefficient for intermediate usage in Column (2) is 2.973, which is significant at the 99% confidence level. This conclusion indicates that if an industry increases its supply of intermediate input to its downstream sectors by one unit, its systemically important role would increase by 2.973%. The coefficient for intermediate input received from upstream industries in Column (4) is 3.371, which is significant at the 99% confidence level. This finding suggests that if an industry receives an increase of one unit in intermediate input from its upstream sectors, its systemic vulnerability would increase by 3.371%. Thus, it is evident that the input-output relationship plays a significant role in determining both the systemic importance and systemic vulnerability of an industry. The more intermediate input is provided to downstream industries, the greater the industry's systemic importance; similarly, the more intermediate input is received from upstream industries, the greater the industry's systemic vulnerability.

Next, this paper focuses on SIIs and utilizes direct and indirect impacts on direct downstream industries, as well as other indirect effects, as the dependent variables to analyse the influence of intermediate usage. The results of the decomposition of SIIs are presented in Panel A of Supplementary Table S11. It can be observed that intermediate usage has a significant impact on all three subindicators of systemic importance.

Subsequently, this paper shifts its focus to SVIs, utilizing direct and indirect impacts from direct upstream industries, along with other indirect effects, as the dependent variables for regression analysis. The results of the decomposition of SVIs are presented in Panel B of Supplementary Table S11. It can be observed that intermediate input has a significant impact on all three subindicators of systemic vulnerability. Comparing these results to the first column, the coefficients in Columns (2) to (4) are relatively smaller. This is due to the decomposition of both systemic importance and systemic vulnerability into three parts while maintaining the significance of the explanatory variables. These conclusions further validate the importance of input-output relationships in risk spillover.

Table 2 Baseline regression results.

Variables	(1) y_importance	(2) y_importance	(3) y_vulnerability	(4) y_vulnerability
Use	2.933***	2.973***		
	(3.395)	(3.542)		
Input			3.380***	3.371***
			(6.440)	(6.492)
TFP		−0.073		−0.038
		(−1.143)		(−0.677)
Labor		0.185		−0.034
		(1.646)		(−0.423)
Constant	−27.669**	−28.987***	−33.133***	−32.540***
	(−2.681)	(−2.869)	(−5.238)	(−5.229)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	533	533	533	533
Adjusted R^2	0.982	0.982	0.894	0.894

*, **, *** indicate that the estimates are significant at the 10%, 5% and 1% levels, respectively; t statistics for regression coefficients are in parentheses.

Analysis of network centrality. To analyse the mechanism of how the production network structure drives industry's systemic importance and systemic vulnerability, this paper incorporates network centrality in the baseline regression to explore the role of the centrality characteristics of the production network.

$$y\_importance_{i,t} = \alpha_0 + \alpha_1 TFP_{i,t} + \alpha_2 Labor_{i,t} + \alpha_3 Use_{i,t} + \alpha_4 Centrality_{i,t} + \lambda_i + \mu_t + \varepsilon_{i,t} \quad (21)$$

$$y\_vulnerability_{i,t} = \beta_0 + \beta_1 TFP_{i,t} + \beta_2 Labor_{i,t} + \beta_3 Input_{i,t} + \beta_4 Centrality_{i,t} + \lambda_i + \mu_t + \varepsilon_{i,t} \quad (22)$$

where $Centrality_{i,t}$ represents the centrality of industry i in year t in the network, including degree centrality, betweenness centrality, eigenvector centrality, and closeness centrality. The calculation formulas are as follows:

$$C_d(i) = \frac{d(i)}{N-1} \quad (23)$$

where $C_d(i)$ represents the degree centrality of node i, $d(i)$ signifies the degree or number of connections of node i, and N stands for the total number of nodes in the network to which node i belongs. In the context of the production network, degree centrality refers to the number of other industries directly connected to an industry in the network. The higher the number of connected industries, the higher the degree centrality.

$$C_b(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \quad (24)$$

where $C_b(i)$ represents the betweenness centrality of node i, σ_{st} stands for the number of shortest paths from node s to node t, and $\sigma_{st}(i)$ represents the number of shortest paths that pass through node i. In the context of the production network, betweenness centrality measures the proportion of shortest paths that pass through a specific industry, indicating its role as a bridge in the network. The higher the number of shortest paths passing through an industry, the higher its betweenness centrality.

$$C_e(i) = \frac{1}{\lambda} \sum_{u \in N(i)} C_e(u) \quad (25)$$

where $C_e(i)$ represents the eigenvector centrality of node i, λ denotes the largest eigenvalue, and $N(i)$ indicates the set of nodes directly connected to node i. In the context of the production network, eigenvector centrality measures the collective centrality of industries connected to a particular industry, reflecting the centrality of its cooperative partners. The higher the centrality of an industry's cooperative partners, the higher its eigenvector centrality.

$$C_c(i) = \frac{n-1}{\sum_{u \neq i} d(u,i)} \quad (26)$$

where $C_c(i)$ represents the closeness centrality of node i, n signifies the number of nodes connected to node i in the network, and $d(u,i)$ stands for the shortest path length from node u to node i. In the context of the production network, closeness centrality refers to the reciprocal of the average shortest distance from a specific industry to all other industries. It reflects the degree of closeness between an industry and other industries in the network. If an industry has short distances to other industries, its closeness centrality is higher.

Since the directed weighted network in this paper is approximately fully connected, it is not feasible to directly measure its network centrality. Therefore, this study employs a threshold method. Considering both network density and average degree before and after setting the threshold, we choose 0.005 as the threshold of edge weight, retaining only edges with weights greater than 0.005 in the production network, and then calculates the above four network centrality indicators. The specific reasons for the threshold selection are shown in the Supplementary Discussion 2.

Panel A of Table 3 presents the regression results of systemic importance with network centrality. The coefficients of degree centrality and betweenness centrality are significant at the 99% confidence level, and they are positive. This indicates that industries with higher betweenness centrality and degree centrality have stronger systemic importance. In other words, if an industry is connected to many industries in the network or occupies a key position in interindustry relationships, it is more likely to cause risk spillover to other industries and thus has stronger systemic importance.

The coefficients of eigenvector centrality and closeness centrality are negative and not significant, which might be due to the construction of the indicators. Eigenvector centrality measures the systemic importance of an industry's partners. When an industry has higher eigenvector centrality, it means that its partners have stronger systemic importance, and therefore, the systemic importance of this industry may be relatively weaker. Closeness centrality represents the reciprocal of the average

Table 3 Regression results of systemic importance and vulnerability with network centrality.

	(1)	(2)	(3)	(4)
Panel A: The Impact of Network Centrality on Systemic Importance				
Variables	**y_importance**	**y_importance**	**y_importance**	**y_importance**
Use	2.810***	3.056***	2.196***	3.050***
	(3.457)	(3.846)	(2.795)	(3.843)
C_b	22.845***			
	(2.761)			
C_e		−4.999		
		(−1.270)		
C_d			4.922***	
			(3.550)	
C_c				−3.993
				(−1.369)
TFP	−0.059	−0.076	−0.029	−0.073
	(−1.018)	(−1.170)	(−0.508)	(−1.137)
Labor	0.181	0.177	0.147	0.173
	(1.672)	(1.598)	(1.428)	(1.594)
Constant	−27.422***	−29.173***	−23.343**	−27.679***
	(−2.801)	(−3.001)	(−2.525)	(−2.769)
Observations	533	533	533	533
Adjusted R^2	0.982	0.982	0.984	0.982
Panel B: The Impact of Network Centrality on Systemic Vulnerability				
Variables	**y_vulnerability**	**y_vulnerability**	**y_vulnerability**	**y_vulnerability**
Input	3.210***	2.463***	2.971***	2.670***
	(6.345)	(6.703)	(6.224)	(6.511)
C_b	13.723*			
	(1.755)			
C_e		19.394***		
		(6.057)		
C_d			2.137**	
			(2.215)	
C_c				14.284***
				(5.601)
TFP	−0.028	−0.012	−0.013	−0.026
	(−0.476)	(−0.276)	(−0.241)	(−0.523)
Labor	−0.039	−0.021	−0.056	−0.004
	(−0.479)	(−0.314)	(−0.712)	(−0.064)
Constant	−30.839***	−24.697***	−29.311***	−32.040***
	(−5.035)	(−5.470)	(−4.968)	(−6.322)
Observations	533	533	533	533
Adjusted R^2	0.897	0.922	0.899	0.917
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes

*, **, *** indicate that the estimates are significant at the 10%, 5% and 1% levels, respectively; t statistics for regression coefficients are in parentheses.

distance from an industry to all other industries, and the averaging process might lead to an inaccurate measurement of an industry's position in the network, which might not align with the measurement of systemic importance in this paper. Additionally, since the metric here refers to in-closeness centrality, which represents the average reciprocal of the shortest paths from other nodes to a given node, this measures the influence of other industries on that specific industry. However, it does not capture the systemic importance of that industry. In addition, we calculate out-closeness centrality, which represents the average reciprocal of the shortest paths from a given node to other nodes, and confirm its positive effect on systemic importance (see Supplementary Table S12).

Panel B of Table 3 presents the regression results of systemic vulnerability. The coefficients of betweenness centrality, eigenvector centrality, degree centrality, and closeness centrality are all significantly positive, indicating that higher betweenness centrality, eigenvector centrality, degree centrality, and closeness centrality are associated with greater systemic vulnerability. In other words, when a particular industry has more connections with other industries in the network, when it occupies a critical position in interindustry relationships, when its partners have higher centrality, or when it is closer to other industries, it is more likely to be sensitive to shocks from other industries and more susceptible to risk spillovers.

To further investigate this, we split the degree centrality into in-degree centrality and out-degree centrality and include them in the baseline model for empirical analysis. Table 4 presents the regression results. We find that industries with higher out-degree centrality are more likely to cause risk spillovers to other industries, indicating stronger systemic importance. On the other hand, industries with higher in-degree centrality are more susceptible to risk spillovers from other industries, indicating higher systemic vulnerability.

Table 4 Regression results of in-degree centrality and out-degree centrality.

Variables	(1) y_importance	(2) y_importance	(3) y_vulnerability	(4) y_vulnerability
Use	1.897***	1.935***		
	(2.986)	(3.061)		
Input			2.483***	2.481***
			(6.332)	(6.371)
C_{d_out}	8.510***	8.390***		
	(6.174)	(6.235)		
C_{d_in}			8.596***	8.556***
			(6.140)	(6.079)
TFP		−0.013		−0.010
		(−0.247)		(−0.226)
Labor		0.088		−0.018
		(0.988)		(−0.280)
Constant	−18.385**	−19.328**	−25.556***	−25.325***
	(−2.464)	(−2.559)	(−5.403)	(−5.433)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	533	533	533	533
Adjusted R^2	0.987	0.987	0.922	0.922

*, **, *** indicate that the estimates are significant at the 10%, 5% and 1% levels, respectively; t statistics for regression coefficients are in parentheses.

Robustness tests. To alleviate endogenous problems including measurement errors and reverse causality, we conduct empirical-based robustness tests.

Firstly, we reduce the measurement error problem from two aspects. On one hand, we employ measures of systemic importance and systemic vulnerability at different shock levels as dependent variables, as shown in Supplementary Tables S14 and S15. The results align with those of our main analysis, revealing no significant differences. Additionally, we find that the stronger the external shock, the greater the impact of intermediate input and intermediate use on systemic importance and systemic vulnerability.

On the other hand, we compute the centrality indicators using thresholds of 0.01, 0.015, and 0.02 for robustness tests. The regression results are presented in Supplementary Tables S16–S18. The conclusions are basically consistent with this paper. An exception is observed in the case of betweenness centrality, which shows non-significance in influencing systemic importance and vulnerability. This may be attributed to the high dependence of betweenness centrality on the path, and as the threshold increases, the number of deleted paths rises, making it challenging to accurately depict the role of betweenness centrality. Additionally, degree centrality is not significant in impacting systemic vulnerability, potentially due to the increasing network density, where the remaining industries are those with high centrality, affecting the vulnerability estimate.

Secondly, we attenuate the reverse causality problem by delaying the core independent variable by one stage. The regression results are presented in Supplementary Table S19. The results in Table S19 show no significant differences compared to the baseline results, confirming the robustness of the findings in this study.

Economic implications

Based on the above analysis, this paper summarizes three important economic implications shown as follows.

First, the input-output network exhibits risk amplification effects, government should pay close attention to this network to prevent systemic risk in the real sector. When an industry experiences a 10% shock, its risk spillover effect on all downstream industries could reach up to about 20%. The proportion of indirect spillover to all spillover effects ranges from 30% to 50% in most scenarios, indicating that indirect spillover is also the main driver of systemic risk. Based on these findings, we conclude that production networks can amplify risk. Therefore, how to prevent risk spillover in the production network is an important issue that needs to be studied.

Second, we should focus on several key nodes and key paths to prevent risk spillovers in the production network. With the highly increasing economic interdependence and deepening of social specialization, the production network can also enhance the production efficiency in the modern economy, thus we cannot prevent risk spillovers or systemic risk by reducing the linkages among industries. In this vein, we should focus on critical nodes and pathways in the production network, especially within closed-loop structures. In this paper, we identify SIIs and SVIs by risk spillover magnitude and direction, and we also find out the risk spillover paths of “SVIs→SIIs→SVIs”. Therefore, we just need to pay attention to these key industries and critical pathways, especially the closed-loop structures in industries such as “mining support service activities”, “coke and refined petroleum products”, “water transport”, etc. Governments can manage systemic risk effectively by regulating SIIs and SVIs and promptly cut off the linkages among these key nodes.

Finally, governments can further develop a risk warning system for the real economy sector by investigating the driving factors of key industries. In the final part, this study explores the factors of critical nodes, revealing that input-output relationships and network centrality contribute to the formation of SIIs and SVIs. For example, if an industry provides more intermediate inputs to other industries or occupies a central position in the production network, it is more likely to become an SII. Take another instance, if an industry receives more intermediate inputs from other industries or holds a central position in the production network, it is more likely to become an SVI. Subsequently, we can use these key factors to construct a risk warning system for the real economy. This system should enable proactive risk monitoring and predict uncertainties in the future, and take effective measures to control risks for key industries and pathways, ensuring the maximization of social welfare and economic stability.

Based on the above implications, we suggest that regulatory authorities should pay attention to the risk amplification function of the production network. Focus on high-network centrality industries and close input-output linkage in the production network, and prevent and resolve the systemic risks of the real sector caused by the risk spillover from the production network. Specifically, the government should implement targeted risk monitoring and management for SVIs and SVIs, and the "SVIs → SIIs → SVIs" risk spillover path must be promptly severed. Finally, it is necessary to implement forward-looking risk monitoring for SVIs and SIIs based on their key drivers.

Conclusions

In modern economic systems, highly interconnected production networks can lead to the transmission and escalation of supply-side shocks throughout the industry chain, even causing macroeconomic fluctuations. Therefore, focusing on the supply-side shocks and studying the risk spillover mechanism of the industrial chain have theoretical significance. This paper constructs a production network risk contagion model and empirically analyses the process of supply-side shocks propagating through the network over multiple rounds using industry data from China. The conclusions of this paper are as follows.

The generation of systemic risk in the real sector originates from two main aspects. First, it arises from the initial shock to specific industries, and second, it results from the interindustry risk contagion effect. When an industry experiences a shock, its maximum spillover effect on a single downstream industry is 6%, meaning that it can reduce the output of a single downstream industry by 6%. However, its risk spillover effect on all downstream industries could reach up to 20%, indicating that the production network plays a significant role in amplifying risks, and the interindustry risk spillover transmitted through other industries in the production network constitutes 30%-50% of the overall network spillover level. This conclusion emphasizes the pivotal role of interindustry risk contagion in driving the rise of systemic risk in the real sector.

During the spillover process, upstream industries in the industry chain play a crucial role as SIIs. These industries are highly likely to transmit risks to other industries in the production network, highlighting their fundamental driving function in the industrial chain production process. If these industries are weak in the industrial chain, there is a high risk of damage across the production network when they are exposed to external shocks.

Based on the spillover round and whether the industry receiving risk spillovers is directly related to the industry propagating them, this paper further decomposes SIIs (SVIs) into three parts: direct impact on direct downstream industries (affected by direct upstream industries), indirect impact on direct downstream industries (affected by risk originating from the direct upstream industry and spread via other industries), and other indirect impacts. The findings reveal that while the direct spillover effect on direct downstream industries is the most substantial within the systemic importance indicator, a significant portion of industries still propagate more than 20% of their spillover effects indirectly on direct downstream industries through their connections with other industries. This finding is similarly valid for the systemic vulnerability indicator. Hence, the investigation of systemic risk requires a focus on the risk contagion and amplification mechanisms within the production network.

In terms of the spillover paths, "mining support service activities", "coke and refined petroleum products", and "other transport equipment", which are three SVIs, are the main sources of risk under supply-side shocks. Risk can propagate through multiple spillover paths to "chemical and chemical products", "basic metals", and "land transport and transport via pipelines", which are three SIIs, leading to an increase in systemic risk in the enterprise sector. Notably, "mining support service activities", "coke and refined petroleum products", "water transport", "other transport equipment", "mining and quarrying, nonenergy producing products", and "accommodation and food service activities" are prone to forming risk feedback loops, resulting in risk accumulation and amplification.

Finally, the pivotal driving factors for systemic importance and systemic vulnerability include input-output relationships and network centrality. When industries have stronger interindustry input-output connections or when the network centrality of industries affected by shocks is higher, the spillover and spread of risks are more likely to occur.

Although this paper simulates the process of risk spillover in the industrial chain, it may have the following limitations. First, when the upstream industry is shocked, the downstream industry may also mitigate the impact by switching suppliers or using other methods. Second, the upstream industry may assume the priority of reducing the intermediate input to customers that are not too important; that is, risk spillover is not well-proportioned. Third, all industries are homogeneous nodes in the production network modelled here, which may cause some errors in the identification of spillover degree. These deficiencies are future research directions.

Data availability

All data generated or analysed during this study are included in this published article and its supplementary information files.

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Notes

1 The entire simulation results for 2006–2018 are available on request.
2 In the 2018 production network, which is a nearly fully connected network with 1891 directed edges, only "fishing and aquaculture" serves as an indirect upstream industry for "mining support service activities", while the remaining industries have direct upstream and downstream relationships with each other. Therefore, in Supplementary Tables S6 and S7, the "Indirect_on_other" effect for "fishing and aquaculture" includes the impact on indirect downstream industries as well as on itself, while others only include the impact on itself. The "Indirect_from_other" effect for the "mining support service activities" industry includes the impact from indirect upstream industries as well as from itself, while others only include the impact from itself.

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