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Supply chain network viability: Managing disruption risk via dynamic data and interaction models☆

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A R T I C L E I N F O

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A B S T R A C T

This study addresses the challenge of enhancing viability of an interconnected supply chain network, particularly in the context of low-probability high-impact events that recur unpredictably. We re-examine the viability from the views of agility, resilience, and sustainability, and propose a novel hybrid approach which integrates dynamic network data and multi-echelon interaction. Diverging from traditional static approaches, we introduce a dynamic decision-making framework that strategically maintains long-term survival by coordination between timely response actions and the risk of overreaction. A data-driven hidden Markov model is built to update the risk forecasting via dynamic network data. A Bayesian network game theoretical model is developed to support collaborative risk mitigating via the multi-echelon interaction. The main findings are as follows. In the short term, we encourage enterprises to engage in collaborative risk mitigating to significantly increase the likelihood of reaching a consensus on achieving a more cost-efficient level of risk mitigation, marked by an intriguing interplay between weakened individual fairness and the tendency to mitigate network-wide risk more economically. In the long term, we advocate building a data-driven, structure-dynamic, and interaction-focused risk response timing system to enable the network to adapt to changes swiftly and achieve desired viable levels efficiently.

1. Introduction

The viability of supply chain (SC) is regarded as the SC ability to survive in a changing environment by redesigning structures and re-planning performance [1]. It is vital to examine SC viability from three dimensions: agility, resilience, and sustainability, particularly in the new era in the wake of a global pandemic [2]. The COVID-19 pandemic has taught us a profound lesson. Approximately 94% of Fortune 1000 enterprises have been affected [3]. The outbreak of COVID-19 pandemic is commonly recognized as a black swan event. However, its follow-up weakened and variant versions are much closer to low-probability high-impact (LPHI) recurring events in the post-COVID era [4]. In this context, this study examines the viability of an interconnected supply chain network (SCN) from the three dimensions. The agility view requires timely responses to disruption risk, although the risk that appears to be really threatening should be perceived first due to the low-probability nature of LPHI events [5]. The resilience view requires effective proactive-reactive response actions. Proactive actions are particularly emphasized because of the high-impact nature of LPHI events [6]. Most of all, the sustainability view requires long-term survival, and advocates for appropriate coordination between timely response actions and the risk of overreaction because the event may recur unpredictably. Therefore, exploring the optimal timing for the effective actions integrates the three dimensions and finally enhances the SCN viability. This motivates us to address the SCN disruption-risk-response timing problem (SCNDRRTP).

In the context of an LPHI recurring event, ensuring an accurate risk forecasting plays a crucial role in pursuing agility. The mainstream forecasting method is scenario-based [7,8,9,10]. Its downside is three-fold. The first is mixing up the disruption risk with the event scenario. The scenario-based method neglects building the causal relationship between disruption risk and event scenario. However, the disruption

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risk and the event scenario in the real world are presented in chronological order, that is, the disruption risk is likely to emerge based on an occurred event scenario [11]. The second is the predetermination of the explicit information for the disruption risk and the event scenario. This is also not in line with the real world. Precise probabilistic information particularly at the beginning of an event is difficult to determine because of the ambiguities associated with various event characteristics [12,13,14]. The third is the neglect of the spatiotemporal dynamics. The disruption risk is time-varying because an event keeps developing [15]. The spatial dynamics result from a diversity of enterprises (or other entities) with different managerial behaviors and risk attitudes in an interconnected SCN [16]. Therefore, the necessity of considering the causality, ambiguity, and dynamics simultaneously leads to the difficulty in tackling the SCNDRRTP.

The second difficulty is related to resilience. Good resilience mirrors the phenomenon that the network swiftly returns to an initial or more desirable low-risk level [17]. The combination of proactive actions (e.g., effort for risk mitigation) and reactive actions (e.g., redesign of network structure) can effectively enhance the resilience [10]. Proactive actions such as taking resilience-enhancing efforts are, to some extent, more fruitful in reducing socio-economic impacts [6]. However, resilience-enhancing efforts lessen the disruption risk but increase the cost. Precisely optimizing the resilience-enhancing efforts in an economical and sustainable manner is still challenging [18]. Moreover, resilience enhancement should be considered from not only individual but also network-wide perspectives, because the individual enterprises are involved in an interdependent network structure [19]. There is a ripple effect described as an impact of resilience-enhancing interaction on risk propagation [20,21,22]. Therefore, the resilience enhancement in combination with interaction calls for an ingenious formulation of collaborative risk mitigating.

The sustainability, as a key dimension further extended to survivability, emphasizes the long-term survival to adapt to the changing environment. The lesson taught by the COVID-19 pandemic shows that it might be still challenging to optimize efficiency, timeliness, and economy simultaneously for an interconnected SCN. A reasonable compromise therefore seems inevitable [23]. When the disruption risk appears really threatening, the response efficiency and timeliness will have priority over economy. Conversely, an appropriate response time delay is economically viable during a regular low-risk period. In the real-world anti-pandemic practices, reaching this compromise is usually by experience and mainly depends on experts' knowledge, foresight, and discrimination [24]. Their low interpretability and knowledge limitations contribute to low-quality decision making characterized by unreliability and inaccuracy. Therefore, exploring reliable data-driven risk-response timing to ensure scientifical managing of the disruption risk for an interconnected SCN becomes an urgent necessity.

In view of the above difficulties, this study will address three fundamental research questions (RQs) as follows.

- RQ1. How should the features of disruption risk in an interconnected SCN be reconsidered? Under such a reconsideration, how are the causality, ambiguity, and dynamics simultaneously addressed to support risk forecasting?
- RQ2. How should the effect of resilience enhancement on disruption risk be modelled? In such a model, how are the resilience enhancement in combination with interaction optimized to support collaborative risk mitigating?
- RQ3. How should the data-driven risk-response timing system be built? In such a system, how are risk forecasting and collaborative risk mitigating incorporated together to enhance the SCN viability?

This study proposes a novel hybrid approach that integrates dynamic network data and multi-echelon interaction to find answers to the above RQs. A data-driven hidden Markov model (DDHMM) is built to update the risk forecasting via dynamic network data. The Bayesian network game theoretical approach is utilized to optimize the total cost affected by the multi-echelon resilience-enhancing interaction. The risk perception, like a switch, enables the hybrid approach to determine the optimal timing of the disruption risk response. As a result, this study provides at least three contributions to the extant literature. First, this study is among the very first to employ the above hybrid approach to address the comprehensive issues of risk forecasting (i.e., dynamic network data) and collaborative risk mitigating (i.e., multi-echelon resilience-enhancing interaction) in SCN viability management. Second, this study is also among the very first to simultaneously consider network causality, ambiguity, and dynamics; to be specific, this study focuses on simultaneously enriching the network data and mitigating the mixed uncertainty for SCN viability management. Third, this study investigates how a data-driven risk-response timing system enhances the viability of an interconnected SCN from the positions of agility, resilience, and sustainability. To the best of our knowledge, coordinating the timely response actions with the risk of overreaction in SCN viability management is rarely studied in the extant literature.

We organize the rest of the paper as follows. In Section 2 we review the relevant literature to position our study. In Section 3 we introduce the problems to be addressed. In Section 4 we respectively present the dynamic network data model, the resilience-enhancing interaction model, and the response timing model. In Section 5 we present the results of the numerical study and comparative studies conducted to generate insights from the findings. Finally, in Section 6, we conclude the paper and suggest topics for future research.

2. Literature review

2.1. SCN viability

The SC viability is an intriguing concept focusing on the SC ability to survive or to exist [2,25]. It becomes an increasingly crucial topic in the wake of the COVID-19 pandemic, particularly in the context of LPHI events that recur unpredictably [4] [26]. Because of the conceptual novelty, several different criteria for SC viability are proposed [27]. For example, SC viability encompasses the integration of resilience, adaptability, and sustainability [1], its properties involve agility, resilience, and sustainability [2,28], its adaptation strategies include intertwining, scalability, substitution, and repurposing [29], its evaluation criteria include the sustainability, resiliency, and Industry 4.0 adaptation [30], and it can be integrated with digital, lean, and green metrics [31]. If the conceptualization of SC viability needs to reach a consensus among the researchers, then the methodology of coordination among the multiple criteria seems indisputable. For example, Sawik [32] builds stochastic optimization SC viability models to balance the cost and customer service level; Sawik and Sawik [22] develop stochastic optimization models to coordinate conditional cost-at-risk and conditional service-at-risk. Their common limitation is examining the viability of an SC rather than a more complex SCN. Therefore, Alizadeh et al. [14] develop multi-stage stochastic optimization models to examine the healthcare SCN viability; Liu et al. [6] and Lotfi et al. [33] build robust optimization models to optimize the SCN viability, respectively, under the worst-case condition and under the digital technology consideration. However, their considered network structures are not interconnected. As first pointed out by Ivanov and Dolgui [1], an interconnected SCN is more complex than a traditional SCN. Regarding the actions, most studies agree that both the proactive and reactive actions are needed to enhance the SCN viability [34]. Commonly, the boundary between proactive and reactive actions in traditional disruption management mainly depends on the occurrence of the disruption. Proactive actions focus on the network reinforcement and risk mitigation before the disruption, while reactive actions consist of the repair and redesign of the network in the aftermath of the disruption [19]. However, it is not always acceptable, particularly in view of the high-impact nature of an LPHI recurring event. Mitigating the risk to avoid adding up to a qualitative change (i.e.,

Table 1
Summary of several relevant studies.

Paper	*Topic*	*SCN*	*Digital technology*	*Resilience*	*Viability*	*Uncertainty*		
						Causality	*Ambiguity*	*Dynamics*
Bhuiyan et al. [46]	Reliable SCN design under random disruption	✔		✔			✔	
Alikhani et al. [50]	Retail SCN design with concurrent resilience capabilities	✔		✔			✔	
Li et al. [20]	Ripple effect simulation in the SCN	✔		✔			✔	✔
Phadnis and Joglekar [7]	Configuring SC dyads for regulatory disruptions			✔		✔	✔	
Foroozesh et al. [67]	Green-resilient SCN design under disruption risk	✔		✔			✔	
Guan et al. [58]	Robust SC considering risk aversion	✔		✔			✔	
Manupati et al. [64]	Disrupted SCN recovery by employing blockchain	✔	✔	✔			✔	
Liu et al. [60]	SC viability with risk minimization			✔	✔	✔	✔	✔
Shafiee et al. [11]	Risk causality analysis for perishable product SCN	✔		✔		✔	✔	
Timonina-Farkas et al. [13]	Bilevel stochastic optimization against SCN disruptions	✔		✔			✔	
Aldrighetti et al. [10]	Efficient resilience portfolio design in a multi-echelon SCN	✔		✔			✔	
Alizadeh et al. [14]	Healthcare SCN viability for a pandemic	✔		✔	✔		✔	✔
Canbilen Sütiçen et al. [19]	Reinforcement and repair for network resilience	✔		✔			✔	
Ivanov [34]	SC stress-testing, resilience and viability		✔	✔	✔			
Liu et al. [6]	Robust SC resilience and viability			✔	✔	✔	✔	✔
Sardesai and Klingebiel [63]	SC viability with reconfiguration evaluating		✔	✔	✔		✔	
Zheng et al. [23]	Sourcing decisions with random production disruptions			✔			✔	✔
Lotfi et al. [33]	Robust SCN viability by employing blockchain	✔	✔	✔	✔		✔	
Sawik and Sawik [22]	Risk-averse SC viability under propagated disruptions			✔	✔		✔	✔
This study	**Managing SCN viability via dynamic data and interaction**	✔	✔	✔	✔	✔	✔	✔

leading to the occurrence of the disruption) is more fruitful than encountering a real-life disruption [6]. We therefore use risk-oriented rather than disruption-oriented proactive-reactive actions. To the best of our knowledge, the optimal determination of the risk-oriented proactive-reactive actions from the spatial-temporal perspective has scarcely been studied in the extant literature. In this context, this study examines the viability of an interconnected SCN from the positions of agility, resilience, and sustainability. We investigate how the spatial-temporal, risk-oriented proactive-reactive actions are optimized, by coordinating the conflicting objectives such as timely response actions and the risk of overreaction.

2.2. SCN uncertainty

Uncertainty examining is vital for an SC or SCN to manage its viability. The traditional view in the extant literature divides

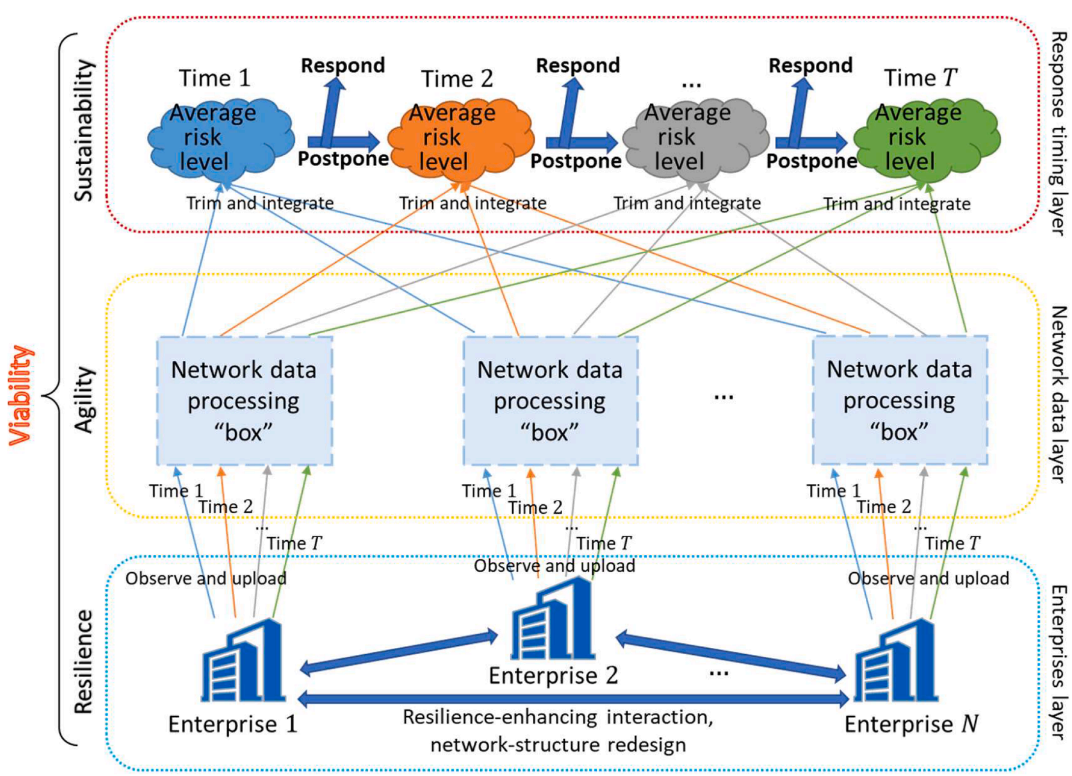

Fig. 1. The three-layer problem framework.

uncertainty into two types: internal uncertainty and external uncertainty [35,36]. The internal uncertainty, produced by operational misconduct on the production and logistics side, mainly focuses on product quality degradation [37,38], supply-demand imbalance [13,39,40], transport time delay [41,42], and so on. The external uncertainty mainly results from natural and man-made disasters [15,43]. More and more researches address internal-external uncertainty which involves operational uncertainty and disruption [44], major disruptions and supply-demand interruptions [23,45], and endogenous and exogenous uncertainty under random disruption [46]. In the context of an LPHI recurring event, the traditional view cannot mirror the difference between the uncertainties caused by a traditional disaster and by an LPHI recurring event. We therefore re-examine the uncertainty and conclude the aforementioned three features (see Section 1): causality, ambiguity, and dynamics. However, a summary (see Table 1) of several viability and resilience studies shows that the extant literature mainly focuses on how the ambiguity is mitigated. The prominent formulation is scenario planning [7,8,10,19,46,47,48,49,50]. This approach seems sound if the scenarios are out of the attitude towards risk. For example, low-probability scenarios of an LPHI recurring event are likely to be amplified by risk-averse enterprises. That is, the attitude towards risk may influence the decision making in scenario-based research. Numerous studies develop robust optimization models [51,52,53,54,55,56] or hybrid robust-stochastic optimization models [57,58] by incorporating attitude towards risk with scenario planning. Robust optimization emphasizes the optimal worst-case situation, and therefore seems more suitable for a traditional disaster than an LPHI recurring event. Moreover, most extant literature assumes that the event scenarios are independent of each other, therefore the causality and dynamics are usually ignored. Only Li et al. [20], Phadnis and Joglekar [7], Ekinci et al. [59], Liu et al. [60], Shafiee et al. [11], Canbilen Sütiçen et al. [19], and Liu et al. [6] investigate the interdependent network structure. In addition, decision-making digitalization has aroused increasing scholarly interest in examining uncertainty by digital technologies such as machine learning [61,62], digital twin [34,63], blockchain [33,64], and big data [65,66]. In this context, this study employs machine learning to simultaneously address the network causality, ambiguity, and dynamics. Specifically, this study focuses on enriching the network data and mitigating mixed uncertainty in an interconnected SCN. To the best of our knowledge, this study is among the very first to address these comprehensive issues.

3. Problem description

We propose a three-layer problem framework (see Fig. 1) including enterprises layer, network data layer, and response timing layer for the SCNDRRTP, based on our surveys of several interconnected SCNs facing product-quality degradation and environmental deterioration. The enterprises layer mainly focuses on network-data observation, resilience-enhancing interaction, and network-structure redesign. The network data layer processes the data observed and uploaded by each enterprise, and mitigates the mixed uncertainty of the disruption risk triggered by an LPHI recurring event. Enlightened by our collaborative study [15], the response timing layer advocates for long-tern survival when coordinating limited supply and recurring demand in practice. In view of the lack of mature guidelines for scientifical managing of the disruption risk triggered by an LPHI recurring event in the post-COVID era, we propose such a three-layer problem framework to simultaneously enhance resilience (in combination with network-structure redesign), agility (by benefiting from uncertainty mitigation), and sustainability (by maintaining long-term survival), and finally enhance the SCN viability.

The network data layer is built as a data platform. We temporarily use a network data processing "box" for each enterprise in Fig. 1 to simplify the figure. The details are presented in Section 4.1. This data platform tries to address the mixed uncertainty from the three key dimensions: causality, ambiguity, and dynamics.

First, regarding the causality, the platform enables each enterprise to learn the disruption risk by its observed network data, because the disruption risk is hidden and hard to be directly observed. For example, during the COVID-19 pandemic, the enterprises in some area could be aware of their employees' biometric data by regular health monitoring from handheld devices, wearables, or biosensors in the workplaces, and then gain the risk information provided by the analytics engine [68,69]. In the post-COVID era, these devices partly become the upfront investment of digitalization. Furthermore, the policy support from the government may make up the follow-up costs of digitization [70]. Therefore, this study assumes that the expenditure for building a data platform is a sunk cost, and we mainly focus on the data processing via this existing platform. In view of the high-impact nature of an LPHI recurring event, this study adopts a novel risk-oriented strategy, similar to Liu et al. [6], to emphasize the risk mitigation "before" rather than "after" a disruption. That is, the enterprise deploys risk-response planning by evaluating "the probability of disruption risk" rather than "the probability of disruption". For example, a risk-averse enterprise may regard the disruption probability of 5% as a high-level risk and therefore respond to this risk. We build a DDHMM in Section 4.1 to demonstrate the causal relationship between disruption risk and observed network data.

Second, the platform addresses two types of ambiguity: the initial ambiguity and the mitigated ambiguity. The platform initializes the ambiguity that the enterprises face at the beginning by assuming that each enterprise has the same initial probability (because of the lack of observed network data). The platform mitigates the ambiguity by processing the enriched network data at latter times via machine learning. Not only the initial probability, but also the other parameters of the DDHMM are periodically trained via machine learning. Machine learning plays a critical role in risk forecasting and monitoring during or after the COVID-19 pandemic [61,62,69,71–73]. However, the traditional disruption-oriented strategies cannot address the challenge very effectively in mitigating the data unbalance when applying machine learning to a low-probability event. In the context of our risk-oriented strategy, "the probability of disruption risk" can be viewed as the transformation from disruption to risk, emphasizing the coordination between high impact and low probability. Thus, machine learning can perform well via this novel transformation.

Third, the dynamics are considered from the spatiotemporal perspective. This is in line with Nikolopoulos et al. [72] and Brusset et al. [74]. For an enterprise, the time-varying data are dynamic depending on the response actions. Stemming from information asymmetry and mistrust, any two enterprises have a network data matrix which is dynamic depending on periodical machine learning. For the entire SCN, network redesign leads to a dynamic network structure [75]. Moreover, the dynamics shown in the pandemic disruption profile [68] unfold the limited changing degree of percentage of incapacitated manpower in the short term. Therefore, we choose the trimming method to remove a specified percentage of the highest and lowest data points from the uploaded network data. This enables the platform to conduct data cleansing to ensure fewer abnormal or extreme values, and to some extent enhance the credibility of the uploaded network data.

The enterprises layer engages in risk mitigating in a general SCN. A general SCN means the SCN is not involved in any extreme scenarios illustrated in Section 4.2. The business connection between a pair of enterprises is represented by a bidirectional arc. If a disruption occurs in one enterprise, the other will be affected by the break of their business connection. We measure all the connections by a time-dependent symmetric adjacency matrix, and there are no ambiguous business connections. Each enterprise in this layer has two tasks: uploading its own observed data to the data platform, and responding to the risk (including swiftly enhancing the resilience and gradually redesigning the network) at appropriate times. The resilience-enhancing strategies are different depending on the threat level of a disruption risk. For example, one enterprise may put forward a fortification plan such as workplace sterilizing, hand washing, social distancing, and mask wearing. All the enterprises will cooperate with their linked neighbors to pursue the global equilibrium (see Section 4.2). If the enterprises take a response action presently (i.e., the risk is highlighted), the network structure will be converted into a more decentralized version in the future; otherwise, it will be converted into a more centralized version.

The response timing layer focuses on the coordination between timely response actions and the risk of overreaction. This is a dynamic decision-making process in which two optional actions including "Response" and "Postponement" are available at each time. The low-probability nature of an LPHI recurring event is a "double-edged sword". Unless the risk appears really threatening, the "neglect of probability" is more likely to occur. Under this premise, taking proactive measures to prevent possible disruption is not economically viable, and therefore the enterprise will choose "Postponement". Even if the disruption risk is perceived by the enterprises, the enterprises with different attitudes towards risk probably do not respond to the disruption risks simultaneously, and therefore cause the free-rider problem [76]. The free-rider problem weakens the positivity of the enterprises, and finally induces all the enterprises to choose "Postponement" for the long term. Based on our surveys, a regulatory agency (abbreviated as regulator) will avoid this free-rider problem. The regulator can be replaced by a policy, a contract, or a built-in function of the data platform. Acting as a referee, the regulator monitors the average risk level of the entire SCN, and takes punitive measures to achieve group risk perception if necessary. For details, please see Section 4.3.

4. Models

We present in this section a dynamic network data model, a resilience-enhancing interaction model, and a response timing model to respectively answer the three RQs.

The nomenclature of this part is represented as follows.

Abbreviations	
NDEP	Network data enrichment period
NDS	Network data series
PEEPPDR	Post-effort expected posterior probability of disruption risk
Sets and indices	
$\mathbf{T}$	Set of times, $\mathbf{T} = \{t \mid t = 1, \cdots, T\}$.
$\mathbf{N}$	Set of enterprises, $\mathbf{N} = \{i \mid i = 1, \cdots, N\}$.
$\mathbf{L}$	Set of disruption-risk states, $\mathbf{L} = \{n \mid n = \theta_1, \cdots, \theta_M\}$.
$\mathbf{M}$	Set of network-data states, $\mathbf{M} = \{m \mid m = 1, \cdots, M\}$.
$\mathbf{S}_t$	Set of NDS states at time t, $\mathbf{S}_t = \{\tau \mid \tau = 1, \cdots, M^t\}$.
$\mathbf{R}_t$	Set of layers of tree structure, $\mathbf{R}_t = \{r \mid r = 1, \cdots, t-1\}$, if $t > 1$; $\mathbf{R}_t = \varnothing$, otherwise.
$\mathbf{N}_{-i}$	Set of enterprises exclusive of i.
$\mathbf{N}_{-ij}$	Set of enterprises exclusive of both i and j.
Parameters	
p_t	Disruption risk at NDEP $[1, t]$.
s_{it}	Network data observed by enterprise i at time t.
$\mathbf{s}_{it}$	NDS observed by enterprise i at NDEP $[1, t]$.
$\mathbf{s}_{it}^{(\tau)}$	τ-th NDS state observed by enterprise i at NDEP $[1, t]$.
l_t	Loss caused by a disruption at NDEP $[1, t]$.
L	Penalty cost.
ϑ	Threshold for penalizing the inactive enterprises, also for indicating the regulator's attitude towards risk.
$\mathbb{E}$	Expectation operator.
$\mathbb{P}$	Probability operator.
e	Efficiency of the effort.
$\mathbf{g}$	General SCN.
g_{ijt}	Business connection between enterprise i and enterprise j at NDEP $[1, t]$. $g_{ijt} = g_{jit} = 1$, if i and j have a connection; $g_{ijt} = g_{jit} = 0$, otherwise.
$\mathbf{G}_t$	Adjacency matrix including all business connections.
$\lambda_{max}(\mathbf{G}_t)$	Largest eigenvalue of the adjacency matrix $\mathbf{G}_t$.
$\gamma_t^{(\tau\upsilon)}$	Conditional probability of that one enterprise observes υ-th NDS state given that another enterprise observes τ-th NDS state at NDEP $[1, t]$.
$\mathbf{\Gamma}_t$	Network data matrix including all conditional probabilities.
$\lambda_{max}(\mathbf{\Gamma}_t)$	Largest eigenvalue of the network data matrix $\mathbf{\Gamma}_t$.

(*continued on next column*)

(*continued*)

Parameters	
$\mathbf{I}_{M^t \cdot N}$	$(M^t \cdot N) \times (M^t \cdot N)$ identity matrix.
$\mathbf{I}_N$	$(N \times N)$ identity matrix.
1_N	N-dimensional vector of ones.
$\otimes$	Kronecker product.
Decision variables	
T	Response time.
$x_{it}(\mathbf{s}_{it}^{(\tau)})$	Effort taken by enterprise i when observing τ-th NDS state at NDEP $[1, t]$.
$\pi_{it}(\mathbf{s}_{it}^{(\tau)})$	PEEPPDR obtained by enterprise i when observing τ-th NDS state at NDEP $[1, t]$.
$\boldsymbol{\Pi}_t^{(\tau)}$	Matrix form of all PEEPPDRs when each enterprise observes τ-th NDS state at NDEP $[1, t]$, i.e., $\boldsymbol{\Pi}_t^{(\tau)} = \left(\pi_{1t}^*(\mathbf{s}_{1t}^{(\tau)}), \cdots, \pi_{Nt}^*(\mathbf{s}_{Nt}^{(\tau)})\right)^T$.
$u_{it}(\mathbf{s}_{it}^{(\tau)})$	Post-effort expected posterior cost function obtained by enterprise i when observing τ-th NDS state at NDEP $[1, t]$.
$U_{it}(\mathbf{s}_{it}^{(\tau)})$	New post-effort expected posterior cost function obtained by enterprise i when observing τ-th NDS state at NDEP $[1, t]$.
$z_{it}(\mathbf{s}_{it}^{(\tau)})$	Action-taking decision for enterprise i when observing τ-th NDS state at NDEP $[1, t]$. It equals 1, if choosing "Response"; It equals 0, otherwise.
$\pi_{it}^{*\varepsilon}$	Post-effort disruption probability of the εth-echelon effort taken by enterprise i at NDEP $[1, t]$.
$\boldsymbol{\Pi}_t^{\varepsilon}$	Matrix form of all optimal post-effort disruption probabilities of the εth-echelon effort at NDEP $[1, t]$, i.e., $\boldsymbol{\Pi}_t^{\varepsilon} = \left(\pi_{1t}^{*\varepsilon}, \cdots, \pi_{Nt}^{*\varepsilon}\right)^T$.
E_t	Top echelon in multi-echelon resilience-enhancing interaction at NDEP $[1, t]$.

4.1. *Dynamic network data model*

To answer RQ1, we propose in this section a dynamic network data model to reveal how each network data processing "box" works in the network data layer. The network data processing involves two aspects: network data enrichment and network data updates.

4.1.1. *Network data enrichment*

Network data enrichment is available when the enterprises choose "Postponement" in the response timing layer. Without loss of generality, we suppose the enterprises always choose "Postponement" at each decision-making time of the time horizon $[1, t]$, then each enterprise can obtain a set of network data. We have the following definitions.

Definition 1. *If the enterprises always choose "Postponement" at each decision-making time of the time horizon* $[1, t]$*, then we call this time horizon an NDEP where the NDS enriched by enterprise i at NDEP* $[1, t]$ *is written by* $\mathbf{s}_{it} = (s_{i1}, s_{i2}, \cdots, s_{it})$.

Fig. 2 shows that the network data are periodically enriched in each network data processing "box". Enlightened by Liu et al. [60] and Liu et al. [6], we decompose the possible values of the distribution risk and the network data, respectively, into M states. Then, enterprise i at NDEP $[1, t]$ obtains the NDS $\mathbf{s}_{it} = (s_{i1}, s_{i2}, \cdots, s_{it})$ where each network-data state belongs to $\{1, 2, \cdots, M\}$. That is, each network data has M states. Therefore, $\mathbf{s}_{it}$ has totally M^t states. $\mathbf{s}_{it}^{(\tau)}$ represents the τ-th state (in a pre-specified order) such that $\tau = 1 + (s_{i1} - 1) \cdot M^0 + \cdots + (s_{it} - 1) \cdot M^{t-1}$. With respect to another arbitrary enterprise j, the NDS $\mathbf{s}_{jt}$ also has totally M^t states, and $\mathbf{s}_{jt}^{(\upsilon)}$ represents the υ-th state such that $\upsilon = 1 + (s_{j1} - 1) \cdot M^0 + \cdots + (s_{jt} - 1) \cdot M^{t-1}$. Obviously, $\mathbf{s}_{it}^{(\tau)} = \mathbf{s}_{jt}^{(\tau)}$. We then have the following definition.

Definition 2. *At NDEP* $[1, t]$*, the network data matrix of any two enterprises, denoted by* $\mathbf{\Gamma}_t = [\gamma_t^{(\tau\upsilon)}]$*, is defined as an* M^t*-order square matrix. Its* (τ, υ)*-entry is a conditional probability and represented as*

$$\gamma_t^{(\tau\upsilon)} = \mathbb{P}\left(\mathbf{s}_{jt}^{(\upsilon)} \middle| \mathbf{s}_{it}^{(\tau)}\right). \tag{1}$$

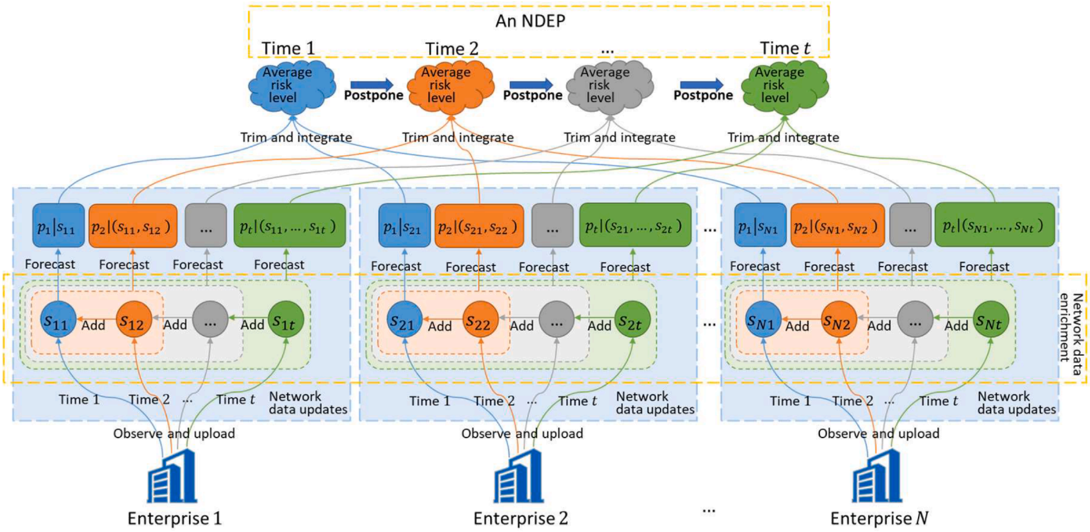

Fig. 2. Dynamic network data at an NDEP.

4.1.2. Network data updates

Given that each enterprise observes the network data to learn the latest state of the disruption risk, we build a DDHMM composed of three key parameters: transition probability $\mathbb{P}(p_t|p_{t-1})$, emission probability $\mathbb{P}(s_{it}|p_t)$, and initial probability $\mathbb{P}(p_t)$. Transition probability can be regarded as an internal factor which reflects the evolution law of the disruption risk. Emission probability can be viewed as an external factor which links the disruption risk and the network data.

These three parameters can be derived from two aspects: the historical statistical data and the present network data [15]. The historical statistical data decide their initial values, and the present network data decide their latest updates trained by machine learning. We employ the Baum-Welch Algorithm to train these three parameters.

We then employ the joint probability of the disruption risk and the NDS (we write "joint probability" for short) to forecast the disruption risk. If $t > 1$, the relationship between the joint probabilities respectively at NDEP $[1, t]$ and NDEP $[1, t-r]$ can be drawn as an $(r+1)$-layer tree structure (see Fig. 3). The joint probability at NDEP $[1, t]$ is the root (Layer 0), and the joint probabilities at NDEP $[1, t-r]$ with a given p_{t-r} are the branches (Layer r). Each node in the tree has a weight, for example, the node in the Layer r has a weight $\omega(s_{i(t-r+1)}, p_{t-r+1}, p_{t-r})$ with a given p_{t-r}. We then have the following proposition (see the Appendix for the proof).

Proposition 1. *The joint probability at NDEP $[1, t]$ is the multi-layer-weighted mean of the joint probabilities at NDEP $[1, t-r]$ with a given p_{t-r}. Its formula is represented as*

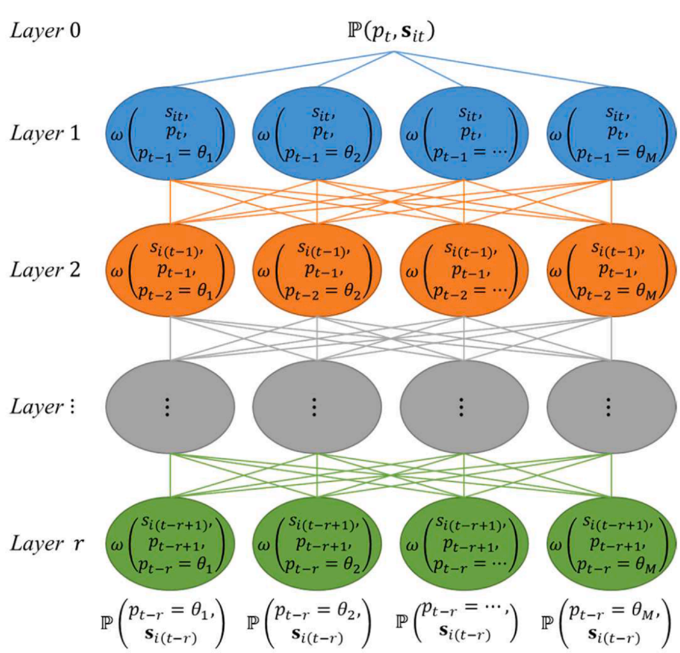

Fig. 3. The $(r+1)$-layer tree structure.

$$\mathbb{P}(p_t, \mathbf{s}_{it}) = \sum_{p_{t-1}} \left(\omega(s_{it}, p_t, p_{t-1}) \cdot \sum_{p_{t-2}} \left(\omega(s_{i(t-1)}, p_{t-1}, p_{t-2}) \cdots \sum_{p_{t-r}} (\omega(s_{i(t-r+1)}, p_{t-r+1}, p_{t-r}) \cdot \mathbb{P}(p_{t-r}, \mathbf{s}_{i(t-r)})) \right) \right) \tag{2}$$

where

$$\omega(s_{i(t-r+1)}, p_{t-r+1}, p_{t-r}) = \mathbb{P}(s_{i(t-r+1)} | p_{t-r+1}) \cdot \mathbb{P}(p_{t-r+1} | p_{t-r}). \tag{3}$$

We infer from this proposition that the larger the gap between the upper bounds of two NDEPs gets, the more layers the tree yields and therefore the more weights the formula integrates. Of course, we do not ignore the initial condition of the recursion:

$$\mathbb{P}(p_t, \mathbf{s}_{it}) = \mathbb{P}(s_{it} | p_t) \cdot \mathbb{P}(p_t), \textit{if } t = 1. \tag{4}$$

Based on the joint probability, the posterior probability of the disruption risk when enterprise i observes τ-th NDS state at NDEP $[1, t]$ is

$$\mathbb{P}\left(p_t | \mathbf{s}_{it}^{(\tau)}\right) = \frac{\mathbb{P}\left(p_t, \mathbf{s}_{it}^{(\tau)}\right)}{\sum_{p_t} \mathbb{P}\left(p_t, \mathbf{s}_{it}^{(\tau)}\right)}. \tag{5}$$

From the perspective of an arbitrary pair of enterprises, the joint probability is the element to build the formula for determining the entries of the network data matrix. We then have the following proposition (see the Appendix for the proof).

Proposition 2. *In the network data matrix of an arbitrary enterprise pair (i,j), each entry is determined by the Bayesian formula built as $\mathbb{P}(\mathbf{s}_{jt}|\mathbf{s}_{it}) = \mathbb{P}(\mathbf{s}_{it}, \mathbf{s}_{jt}) / \sum_{\mathbf{s}_{jt}} \mathbb{P}(\mathbf{s}_{it}, \mathbf{s}_{jt})$. Taking $\mathbb{P}(p_t)$ as the weight, the joint probability $\mathbb{P}(\mathbf{s}_{it}, \mathbf{s}_{jt})$ is presented as the weighted mean of the product of the two likelihood functions $\mathbb{P}(\mathbf{s}_{it}|p_t)$ and $\mathbb{P}(\mathbf{s}_{jt}|p_t)$,* i.e.,

$$\mathbb{P}(\mathbf{s}_{it}, \mathbf{s}_{jt}) = \sum_{p_t} (\mathbb{P}(p_t) \cdot \mathbb{P}(\mathbf{s}_{it}|p_t) \cdot \mathbb{P}(\mathbf{s}_{jt}|p_t)) \tag{6}$$

where

$$\mathbb{P}(\mathbf{s}_{it}|p_t) = \frac{\mathbb{P}(p_t, \mathbf{s}_{it})}{\sum_{\mathbf{s}_{it}} \mathbb{P}(p_t, \mathbf{s}_{it})} \tag{7}$$

and

$$\mathbb{P}(\mathbf{s}_{jt}|p_t) = \frac{\mathbb{P}(p_t, \mathbf{s}_{jt})}{\sum_{\mathbf{s}_{jt}} \mathbb{P}(p_t, \mathbf{s}_{jt})}. \tag{8}$$

Remark 1. *The role of dynamic network data in this model is mainly twofold. First, dynamic network data use machine learning to periodically train the DDHMM parameters, including an internal factor and an external factor. Second, dynamic network data contribute to building the joint probability, and therefore mitigate both the individual-enterprise and the network-wide uncertainties.*

4.2. Resilience-enhancing interaction model

To answer RQ2, we propose in this section a resilience-enhancing interaction model to match the situation when each enterprise no longer chooses "Postponement" but starts to respond to the disruption risk.

From the perspective of an enterprise, the knowledge sources of the disruption risk are twofold. First is the observation of the NDS state. The enterprise will gain a posterior probability of the disruption risk. Second is the resilience-enhancing effort. The enterprise will gain a reduced post-effort probability. Therefore, enterprise i at NDEP $[1, t]$ will obtain a PEEPPDR:

$$\pi_{it}\left(\mathbf{s}_{it}^{(\tau)}\right) = \mathbb{E}\left(p_t | \mathbf{s}_{it}^{(\tau)}\right) - e \cdot \sqrt{x_{it}\left(\mathbf{s}_{it}^{(\tau)}\right)} \tag{9}$$

To ensure that Eq. (9) makes sense, $x_{it}\left(\mathbf{s}_{it}^{(\tau)}\right)$ is chosen in the range $\left[0, \frac{\left(\mathbb{E}\left(p_t|\mathbf{s}_{it}^{(\tau)}\right)\right)^2}{e^2}\right]$.

Then, enterprise i at NDEP $[1, t]$ will obtain a post-effort expected posterior cost function:

$$u_{it}\left(\mathbf{s}_{it}^{(\tau)}\right) = x_{it}\left(\mathbf{s}_{it}^{(\tau)}\right) + l_t \cdot \pi_{it}\left(\mathbf{s}_{it}^{(\tau)}\right) + l_t \cdot \left(1 - \pi_{it}\left(\mathbf{s}_{it}^{(\tau)}\right)\right) \cdot \sum_{j \in \mathbf{N}_{-i}} \left(\mathbb{E}\left(\pi_{jt} | \mathbf{s}_{it}^{(\tau)}\right) \cdot g_{ijt} \cdot \prod_{k \in \mathbf{N}_{-ij}} \left(1 - \mathbb{E}\left(\pi_{kt} | \mathbf{s}_{it}^{(\tau)}\right)\right) \right) \tag{10}$$

As an objective function of the resilience-enhancing interaction model, this cost function considers not only the endogenous disruption risk mitigated by the enterprise itself, but also the exogenous disruption risk mitigated by the peers.

Enlightened by Chen et al. [76], we further assume that no two or more disruptions would occur simultaneously due to the low-probability nature of an LPHI recurring event, i.e., $\mathbb{E}\left(\pi_{jt}|\mathbf{s}_{it}^{(\tau)}\right) \cdot \mathbb{E}\left(\pi_{kt}|\mathbf{s}_{it}^{(\tau)}\right) = 0$. Then, Eq. (10) is converted into a simplified version:

$$u_{it}\left(\mathbf{s}_{it}^{(\tau)}\right) = x_{it}\left(\mathbf{s}_{it}^{(\tau)}\right) + l_t \cdot \pi_{it}\left(\mathbf{s}_{it}^{(\tau)}\right) + l_t \cdot \left(1 - \pi_{it}\left(\mathbf{s}_{it}^{(\tau)}\right)\right) \cdot \sum_{j \in \mathbf{N}_{-i}} \left(\mathbb{E}\left(\pi_{jt} | \mathbf{s}_{it}^{(\tau)}\right) \cdot g_{ijt} \cdot \left(1 - \sum_{k \in \mathbf{N}_{-ij}} \mathbb{E}\left(\pi_{kt} | \mathbf{s}_{it}^{(\tau)}\right)\right) \right). \tag{11}$$

Inserting Eq. (9) into Eq. (11), the final version of the post-effort expected posterior cost function is given by

$$u_{it}\left(\mathbf{s}_{it}^{(\tau)}\right) = \frac{\pi_{it}^2\left(\mathbf{s}_{it}^{(\tau)}\right)}{e^2} + \left(l_t - \frac{2 \cdot \mathbb{E}\left(p_t|\mathbf{s}_{it}^{(\tau)}\right)}{e^2}\right) \cdot \pi_{it}\left(\mathbf{s}_{it}^{(\tau)}\right) + \frac{\left(\mathbb{E}\left(p_t|\mathbf{s}_{it}^{(\tau)}\right)\right)^2}{e^2} + l_t \cdot \left(1 - \pi_{it}\left(\mathbf{s}_{it}^{(\tau)}\right)\right) \cdot \sum_{j \in \mathbf{N}_{-i}} \left(\mathbb{E}\left(\pi_{jt} | \mathbf{s}_{it}^{(\tau)}\right) \cdot g_{ijt} \cdot \left(1 - \sum_{k \in \mathbf{N}_{-ij}} \mathbb{E}\left(\pi_{kt} | \mathbf{s}_{it}^{(\tau)}\right)\right) \right). \tag{12}$$

Seeking to ensure a well-defined post-effort expected posterior loss function, we suppose that the unit disruption loss and the effort efficiency will be properly given such that $\frac{l_t \cdot e^2}{2} < min\left(\mathbb{E}\left(p_t|\mathbf{s}_{it}^{(\tau)}\right), \frac{1}{\lambda_{max}(\mathbf{G}_t)}, \frac{1}{\lambda_{max}(\mathbf{\Gamma}_t) \cdot \lambda_{max}(\mathbf{G}_t)}\right)$. We then have the following proposition (see the Appendix for the proof).

Proposition 3. *Consider a well-defined post-effort expected posterior loss function for each enterprise in a general SCN* $\mathbf{g}$. *There exists a Bayesian-Nash equilibrium among all enterprises. The optimal PEEPPDR when any enterprise observes any NDS state at NDEP $[1, t]$ is determined by*

$$\begin{pmatrix} \boldsymbol{\Pi}_t^{(1)} \\ \vdots \\ \boldsymbol{\Pi}_t^{(M^t)} \end{pmatrix} = \left(\mathbf{I}_{M^t\cdot N} - \frac{l_t\cdot e^2}{2}\cdot\boldsymbol{\Gamma}_t \otimes \mathbf{G}_t\right)^{-1}\cdot \begin{pmatrix} \left(\mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(1)}\right) - \frac{l_t\cdot e^2}{2}\right)\cdot 1_N \\ \vdots \\ \left(\mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(M^t)}\right) - \frac{l_t\cdot e^2}{2}\right)\cdot 1_N \end{pmatrix}. \tag{13}$$

This proposition provides the optimal consequence of PEEPPDR for each enterprise when starting to respond to the disruption risk. The combined use of network data matrix and adjacency matrix in Eq. (13) implies that the optimal PEEPPDR incorporates dynamic network data and resilience-enhancing interaction. We can further obtain the optimal effort by inserting the optimal PEEPPDR in Eq. (9). We have the following proposition (see the Appendix for the proof).

Proposition 4. *In a general SCN* $\mathbf{g}$*, the optimal PEEPPDR for enterprise i when observing* τ*-th NDS state at NDEP* $[1, t]$ *is*

$$\pi_{it}^*\left(\boldsymbol{s}_{it}^{(\tau)}\right) = \mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(\tau)}\right) - \frac{l_t\cdot e^2}{2}\cdot\left(1 - \Omega_{it}^{(\tau)}\right), \tag{14}$$

and the optimal resilience-enhancing effort is

$$x_{it}^*\left(\boldsymbol{s}_{it}^{(\tau)}\right) = \frac{l_t^2\cdot e^2}{4}\cdot\left(1 - \Omega_{it}^{(\tau)}\right)^2 \tag{15}$$

where

$$\Omega_{it}^{(\tau)} = \sum_{j\neq i} g_{ijt}\cdot\sum_{\upsilon\in\mathbf{S}_t}\left(\gamma_t^{(\tau\upsilon)}\cdot\pi_{jt}^*\left(\boldsymbol{s}_{jt}^{(\upsilon)}\right)\right). \tag{16}$$

Recalling that $\gamma_t^{(\tau\upsilon)}$ is the entry of the network data matrix, so we have $\sum_{\upsilon\in\mathbf{S}_t}\gamma_t^{(\tau\upsilon)} = 1$. Then, $\Omega_{it}^{(\tau)}$ can be explained as the sum of weighted mean of the optimal PEEPPDR of all the linked neighbors of enterprise *i*. Because of the low-probability occurrence of disruptions, we assume that $0 < \Omega_{it}^{(\tau)} \leq 1$. This proposition therefore implies that, if the unit disruption loss l_t and the effort efficiency *e* are given, the optimal effort taken by one enterprise on resilience enhancing mainly depends on the optimal PEEPPDR of all its linked neighbors. This proposition can be further extended to the following three corollaries (see the Appendix for the proof of each corollary).

Corollary 1. *Consider the first extreme scenario: The SCN has a completely-non-connected structure,* i.e., $g_{ijt} = 0$ *for any enterprise pair* (i, j)*. The optimal PEEPPDR for enterprise i when observing* τ*-th NDS state at NDEP* $[1, t]$ *is* $\mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(\tau)}\right) - \frac{l_t\cdot e^2}{2}$*, and the optimal resilience-enhancing effort is* $\frac{l_t^2\cdot e^2}{4}$*. Then, in a general SCN,* $\pi_{it}^*\left(\boldsymbol{s}_{it}^{(\tau)}\right) > \mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(\tau)}\right) - \frac{l_t\cdot e^2}{2}$ *and* $x_{it}^*\left(\boldsymbol{s}_{it}^{(\tau)}\right) < \frac{l_t^2\cdot e^2}{4}$.

This corollary indicates that the optimal resilience-enhancing effort has nothing to do with the dynamic network data if without resilience-enhancing interaction. Furthermore, it also indicates that each enterprise in a general SCN will take a smaller resilience-enhancing effort, but mitigate less risk than in a completely-non-connected SCN. Obviously, the more an enterprise acts as a hub, the smaller resilience-enhancing effort it will take and therefore the less risk it will mitigate.

Corollary 2. *Consider the second extreme scenario: The maximum allowable disruption risk is the disruption occurring in one among an enterprise and its linked neighbors after resilience enhancing,* i.e., $1 - \Omega_{it}^{(\tau)} = \pi_{it}^*\left(\boldsymbol{s}_{it}^{(\tau)}\right)$*. Then, in a general SCN,* $\pi_{it}^*\left(\boldsymbol{s}_{it}^{(\tau)}\right) < \frac{\mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(\tau)}\right)}{1+\frac{l_t\cdot e^2}{2}}$ *and* $x_{it}^*\left(\boldsymbol{s}_{it}^{(\tau)}\right) > \frac{l_t^2\cdot e^2}{4}\cdot\left(\frac{\mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(\tau)}\right)}{1+\frac{l_t\cdot e^2}{2}}\right)^2$.

The scenario in this corollary can be regarded as the bottom line on the optimal PEEPPDR and the optimal effort. Incorporating Corollaries 1 and 2, we have $\pi_{it}^*\left(\boldsymbol{s}_{it}^{(\tau)}\right) \in \left(\mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(\tau)}\right) - \frac{l_t\cdot e^2}{2}, \frac{\mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(\tau)}\right)}{1+\frac{l_t\cdot e^2}{2}}\right)$ and $x_{it}^*\left(\boldsymbol{s}_{it}^{(\tau)}\right) \in \left(\frac{l_t^2\cdot e^2}{4}\cdot\left(\frac{\mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(\tau)}\right)}{1+\frac{l_t\cdot e^2}{2}}\right)^2, \frac{l_t^2\cdot e^2}{4}\right)$.

Corollary 3. *Consider the third extreme scenario: The SCN has no information asymmetry and mistrust among the enterprises. The optimal PEEPPDR for enterprise i when observing* τ*-th NDS state at NDEP* $[1, t]$ *is*

$$\pi_{it}^*\left(\boldsymbol{s}_{it}^{(\tau)}\right) = \mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(\tau)}\right) - \frac{l_t\cdot e^2}{2}\cdot\left(1 - \Theta_{it}^{(\tau)}\right), \tag{17}$$

and the optimal resilience-enhancing effort is

$$x_{it}^*\left(\boldsymbol{s}_{it}^{(\tau)}\right) = \frac{l_t^2\cdot e^2}{4}\cdot\left(1 - \Theta_{it}^{(\tau)}\right)^2 \tag{18}$$

where

$$\Theta_{it}^{(\tau)} = \sum_{j\neq i} g_{ijt}\cdot\pi_{jt}^*\left(\boldsymbol{s}_{jt}^{(\upsilon)}\right) \tag{19}$$

This corollary shows that the difference between $\Omega_{it}^{(\tau)}$ and $\Theta_{it}^{(\tau)}$ mainly lies in whether employing the network data matrix or not.

Remark 2. *The role of resilience-enhancing interaction in this model is mainly threefold. First, resilience-enhancing interaction enables the role of dynamic network data on determining the optimal resilience-enhancing effort, particularly in the context of information asymmetry and mistrust among the enterprises. Second, resilience-enhancing interaction triggers that each enterprise takes a smaller and therefore more economical resilience-enhancing effort, even if the investment of effort has a bottom line. Third, the hub enterprises are motivated to take smaller and therefore more economical resilience-enhancing efforts than others. This may weaken the fairness among the all enterprises.*

4.3. Response timing model

To answer RQ3, we propose in this section a response timing model to maintain long-term survival and finally enhance the SCN viability by coordinating timely response actions with the risk of overreaction. Recall that the enterprises are usually "sleeping", because the "neglect of probability" occurs. Then, the cost function in Eq. (10) is converted into $u_{it}\left(\boldsymbol{s}_{it}^{(\tau)}\right) = x_{it}\left(\boldsymbol{s}_{it}^{(\tau)}\right)$. This implies that taking resilience-enhancing efforts is not economically viable. The enterprises will be awakened when the disruption risk rises beyond their attitudes towards risk. Based on our surveys, the regulator carries a much heavier burden of social responsibility and is much more risk-averse than any enterprise. In other words, the regulator will be awakened earlier than any enterprise when the disruption risk rises. Therefore, the regulator can timely impel the enterprises to take synchronous resilience-enhancing efforts, by imposing a penalty cost *L* on the cost function of each enterprise. By using the action-taking decision variable $z_{it}\left(\boldsymbol{s}_{it}^{(\tau)}\right)$, enterprise *i* at NDEP $[1, t]$ will obtain a new post-effort expected posterior cost function:

$$U_{it}\left(\boldsymbol{s}_{it}^{(\tau)}\right) = \left(1 - z_{it}\left(\boldsymbol{s}_{it}^{(\tau)}\right)\right)\cdot L + z_{it}\left(\boldsymbol{s}_{it}^{(\tau)}\right)\cdot u_{it}\left(\boldsymbol{s}_{it}^{(\tau)}\right) \tag{20}$$

The penalty cost equals a very big number such that $L \gg u_{it}\left(\boldsymbol{s}_{it}^{(\tau)}\right)$, if the average disruption risk level of the entire SCN is larger than the penalty threshold ϑ; $L = 0$, otherwise. Therefore, the timing of taking synchronous efforts is realized for economic reasons.

However, if the average optimal PEEPPDR of the entire SCN is much

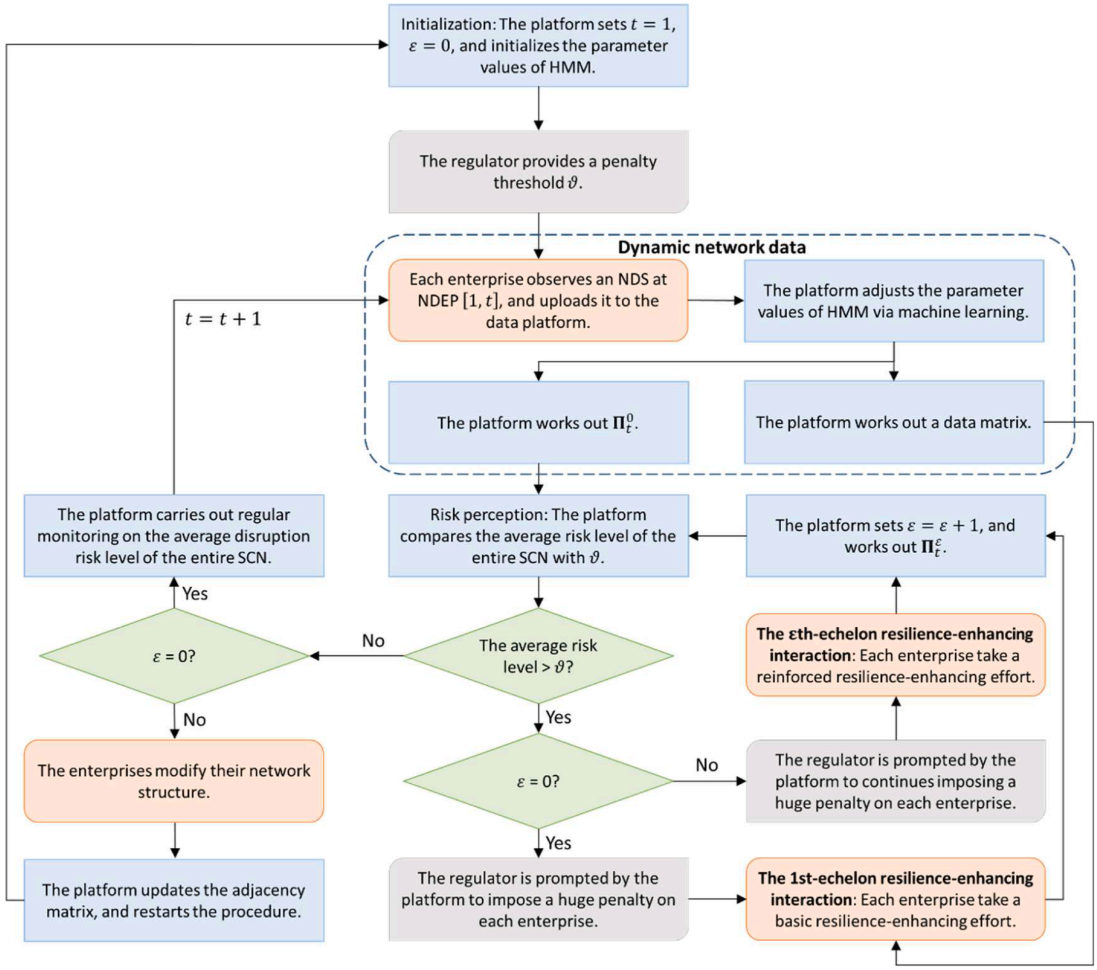

Fig. 4. The overall decision-making procedure.

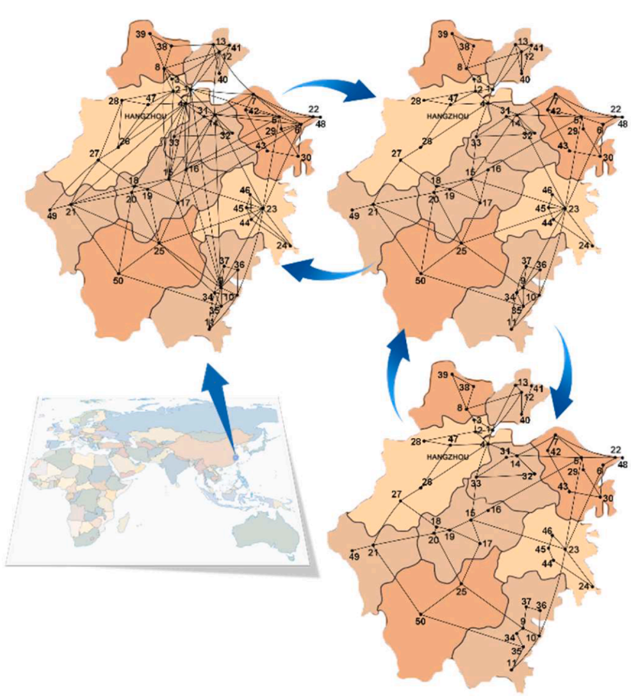

Fig. 5. The dynamic business connections.

larger than the penalty threshold, the equilibrium proposed in Proposition 3 is short-sighted and not stable. We therefore have the following proposition (see the Appendix for the proof).

Proposition 5. *Consider the situation where the average optimal PEEPPDR of the entire SCN is much larger than the penalty threshold. The enterprises then will take reinforced resilience-enhancing efforts to obtain a lower optimal post-effort disruption probability than before and reach a new equilibrium (they will repeat this process if necessary) until the average optimal post-effort disruption probability of the entire SCN is no longer beyond the penalty threshold. Let $\pi_{it}^{*1} = \pi_{it}^{*}\left(\boldsymbol{s}_{it}^{(\tau)}\right)$, then the optimal post-effort disruption probability of the εth-echelon effort at NDEP $[1, t]$ is determined by*

$$\boldsymbol{\Pi}_t^\varepsilon = \left(\mathbf{I}_N - \frac{l_t \cdot e^2}{2} \cdot \mathbf{G}_t\right)^{-1} \cdot \left(\boldsymbol{\Pi}_t^{\varepsilon-1} - \frac{l_t \cdot e^2}{2} \cdot \mathbf{1}_N\right), \ \varepsilon = 2, 3, \cdots, \mathrm{E}_t, \tag{21}$$

where E_t satisfies both $\frac{\sum_{i=1}^{N} \pi_{it}^{*\mathrm{E}_t - 1}}{N} > \vartheta$ and $\frac{\sum_{i=1}^{N} \pi_{it}^{*\mathrm{E}_t}}{N} \leq \vartheta$.

Diverging from the resilience-enhancing model that demonstrates how to take a basic resilience-enhancing effort (e.g., workplace sterilizing and hand washing) when facing a moderate risk, this model underscores the importance of taking reinforced resilience-enhancing efforts (e.g., social distancing and mask wearing) to maintain the long-term survival and finally enhance the SCN viability when facing a serious risk. This is a multi-echelon resilience-enhancing strategy. We have the following corollary (see the Appendix for the proof).

Corollary 4.

Table 2
The initial value of transition probability.

Next state / Present state	Very Low	Low	Slightly Low	Medium	Slightly High	High	Very High
Very Low	0.26	0.33	0.19	0.11	0.06	0.03	0.02
Low	0.11	0.21	0.27	0.18	0.12	0.07	0.04
Slightly Low	0.05	0.12	0.23	0.26	0.18	0.1	0.06
Medium	0.04	0.07	0.11	0.21	0.28	0.19	0.1
Slightly High	0.03	0.05	0.08	0.12	0.22	0.31	0.19
High	0.03	0.05	0.07	0.1	0.15	0.28	0.32
Very High	0.02	0.04	0.07	0.09	0.13	0.2	0.45

(1) Any resilience-enhancing effort (including basic resilience-enhancing effort and reinforced resilience-enhancing effort) in a general SCN (with resilience-enhancing interaction) is smaller and therefore more economical than that in a completely-non-connected SCN (without resilience-enhancing interaction).
(2) The total resilience-enhancing efforts in a general SCN (with resilience-enhancing interaction) are only ***probabilistically*** *smaller and therefore* ***probabilistically*** *more economical than those in a completely-non-connected SCN (without resilience-enhancing interaction).*

Remark 3. *The multi-echelon resilience-enhancing strategy can scientifically manage a serious risk to maintain the long-term survival and enhance the SCN viability. From the perspective of network-wide risk mitigation, while the multi-echelon resilience-enhancing interaction does not guarantee absolute economy, it significantly increases the likelihood of reaching a consensus on the more economical level of risk mitigation. However, we cannot ignore that multi-echelon resilience-enhancing interaction may still weaken the fairness among the individual enterprises. The hub enterprises may take much smaller and therefore much more economical total resilience-enhancing efforts than others.*

Finally, we incorporate the dynamic network data model and the resilience-enhancing interaction model to the response timing model to address the SCNDRRTP. Let $\pi_{it}^{*0} = \mathbb{E}\left(p_t|\mathbf{s}_{it}^{(\tau)}\right)$. The main task is to determine the optimal resilience-enhancing echelon E_t at an optimal response time T. Fig. 4 shows the details of the overall decision-making procedure.

5. Numerical study

5.1. Data gathering

We present a numerical example in this section to illustrate how our models work in practice. This example mainly involves a cold-chain SCN built for imported frozen product in Eastern China. In the past decade, the demand of high-quality frozen products in Eastern China had a dramatical boost, and therefore more and more cold-chain enterprises ran their businesses associated with imported meat products, seafoods, and fruits. The regular endogenous risk monitoring has been carried out via the Food Safety Information Traceability Enterprise Platform to protect the cold-chain enterprises from the operational misconduct within the SCN. As a regular endogenous risk management tool, the platform cannot address the challenge resulting from the LPHI recurring events which threaten the viability of the SCN in the post-COVID era.

Based on our surveys of the cold-chain SCN, some related data are predetermined to support our numerical study. First is the geographic data of the fifty enterprises (nodes) and their business connections (arcs) (see Fig. 5). Three versions of the SCN structure are concluded by our on-the-spot investigation. Second is the evaluation of both the unit disruption loss and the effort efficiency. Because the annual operating income of a mid-scale cold-chain enterprise is approximately $30,000,000$ (*yuan*) and the profit rate is approximately 10%, we regard the unit disruption loss as the missing profit due to a one-week shutdown, i.e., $3 \cdot 10^7 \cdot (1/52) \cdot 10\% = 57,692$ (*yuan*). We estimate the risk-mitigation effort efficiency as 0.05%, in comparison with the 0.10% $\sim$ 0.15% in some industries that gain high return on investment in risk mitigation [76]. Third is the approximations of the initial values of DDHMM parameters: transition probability (see Table 2), emission probability (see Table 3), and initial probability. Their initial values are roughly decided by historical statistical data, and will be further adjusted by machine learning. For example, in view of the fact that the cold-chain SCN experiences a disruption every twenty-six weeks on average, we estimate that the initial values of initial probability of Very Low (~0.005), Low (0.005~0.015), Slightly Low (0.015~0.025), Medium (0.025~0.035), Slightly High (0.035~0.045), High (0.045~0.055), and Very High (0.055~) respectively are 0.12, 0.15, 0.17, 0.19, 0.14, 0.12, and 0.11.

5.2. Results interpretation

We train the DDHMM by employing the Baum-Welch Algorithm, where the maximum number of iterations is 10, convergence threshold is 0.1, and the trimming rate is 0.1. An example of network data observation is shown in Table B1 (see the Appendix for the table). We run the program coded by MATLAB language. We consider different scenarios: The regulator's attitude towards risk shifts from adventurous to conservative. Our models visualize the spatiotemporal dynamics of the disruption risk from different angles of view when the penalty threshold is given (see Fig. 6).

The risk mitigation is highly risk-attitude-driven, and the average risk level of the entire SCN is highly risk-attitude-dependent. Both the average risk level of the entire SCN and the fluctuation of different spatiotemporal cells decrease when the penalty threshold decreases. This reveals that the collaborative risk mitigating enables enterprises to share resilience-enhancing efforts with peers by their interactions, and efficiently let the average risk of the entire SCN achieve any desirable level.

5.3. Further discussions

5.3.1. Comparative study

We compare four different models: (a) Interaction, machine learning

Table 3
The initial value of emission probability.

Employees' positive rate / Disruption probability	Very Low	Low	Slightly Low	Medium	Slightly High	High	Very High
Very Low	0.39	0.25	0.16	0.1	0.06	0.03	0.01
Low	0.18	0.36	0.17	0.12	0.09	0.05	0.03
Slightly Low	0.1	0.17	0.35	0.18	0.11	0.06	0.03
Medium	0.05	0.09	0.16	0.35	0.17	0.11	0.07
Slightly High	0.03	0.06	0.09	0.18	0.34	0.19	0.11
High	0.03	0.04	0.07	0.12	0.19	0.34	0.21
Very High	0.03	0.05	0.08	0.1	0.14	0.21	0.39

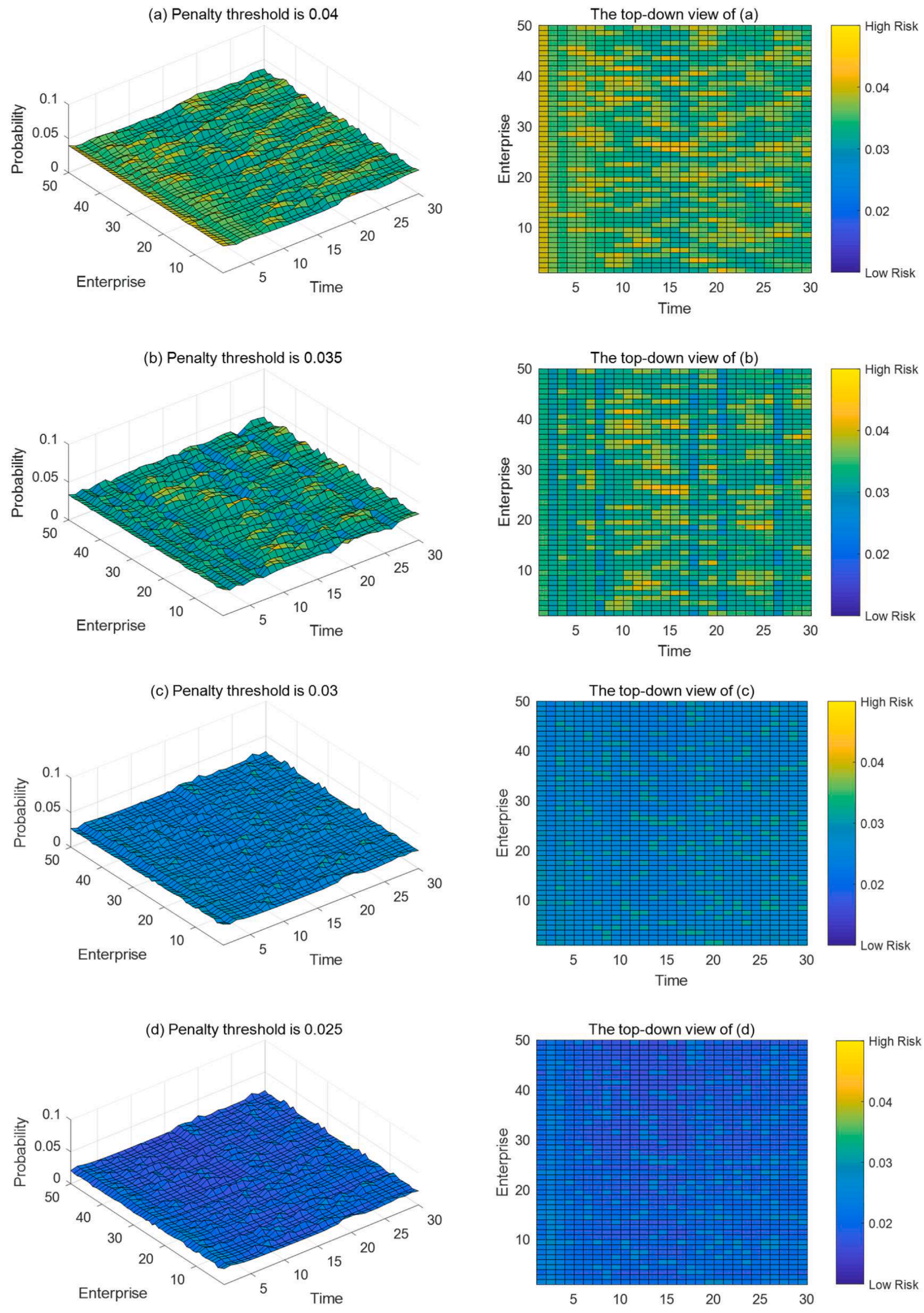

Fig. 6. The spatiotemporal dynamics of the disruption risk.

(i.e., our model); (b) No interaction, machine learning; (c) Interaction, no machine learning; and (d) No interaction, no machine learning. We investigate how the enterprises in different models engage in mitigating the average risk level of the entire SCN when facing a known penalty threshold (ranging from 0.03 to 0.01), in view of the fact that each enterprise will take timely actions at any time when penalty threshold is below 0.03. The conclusions are as follows.

On the one hand, the multi-echelon resilience-enhancing interaction increases the likelihood of reaching a consensus on the more economical level of risk mitigation. In Figs. 7 and 8, the curves in the left sub-figures appear higher than those in the right sub-figures. Furthermore, in Fig. 7, the gaps of two neighboring curves in the left sub-figures appear more

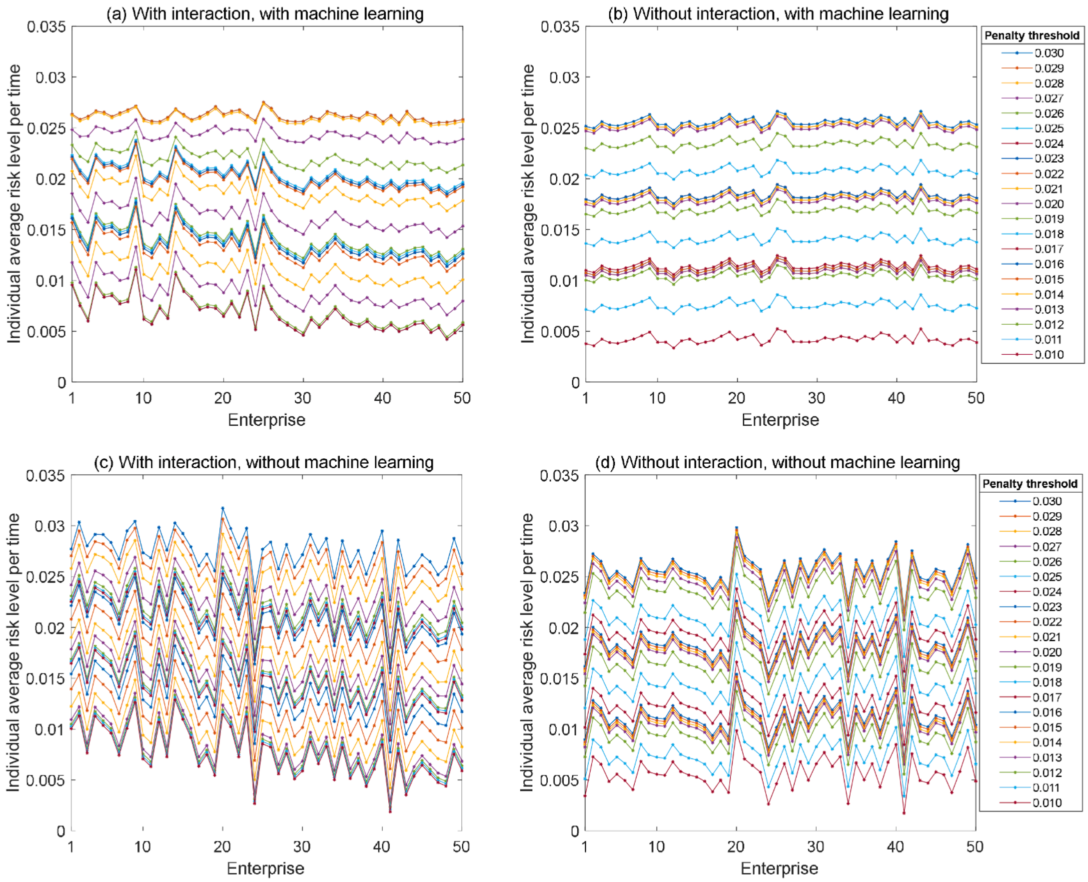

Fig. 7. The individual average risk level per time with a changing enterprise.

homogeneous. Similarly, in Fig. 8, the curves in the left sub-figures fluctuate more slightly. On the other hand, the multi-echelon resilience-enhancing interaction may weaken the fairness among enterprises. The curves in the left sub-figures of Fig. 7 fluctuate more seriously, and the curves in the left sub-figures of Fig. 8 become more dispersed. They both indicate that some hub enterprises mitigate fewer risks than others.

Conversely, the comparison between the upper sub-figures and the lower sub-figures implies that the machine learning can re-strengthen the weakened fairness, but will re-weaken the strengthened economy. Therefore, it is not wise to use multi-echelon resilience-enhancing interaction or machine learning separately. Our model integrates multi-echelon resilience-enhancing interaction and machine learning, and has a more balanced result than the other three models.

5.3.2. Managerial insights

This study advocates for risk-oriented proactive-reactive actions. In the short term, proactive actions, such as multi-echelon resilience-enhancing interaction, encourage enterprises within the SCN to engage in collaborative risk mitigating. These collaborations can significantly increase the likelihood of reaching a consensus on the more cost-efficient level of risk mitigation. We highlight the critical role of machine learning (representing the dynamic network data) in multi-echelon resilience-enhancing interaction, following a process marked by an intriguing interplay between weakened individual fairness and the tendency to mitigate network-wide risks more economically. This phenomenon also guides us to turn our eyes to the hub enterprises if the risk mitigation is not fair enough.

From the perspective of long-term survival, a data-driven risk-response timing system design can coordinate timely response actions with the risk of overreaction. In this context, the role of dynamic network data mainly lies in mitigating both the individual-enterprise and the network-wide uncertainties. Uncertainty mitigation provides accurate time windows to facilitate the reactive actions such as network-structure redesign. Therefore, dynamic network data contribute to supporting the proactive-reactive actions to enhance the SCN viability both in the short term and in the long term.

Thus, the SCN enterprises have an imperative to build a data-driven, structure-dynamic, interaction-focused risk-response timing system. Because the crucial role of dynamic network data, an incremental upgrade of the system is necessary to enhance the data availability and reliability. We advocate for an AI-enabled risk monitoring and warning system. In this system, the automatic monitoring of network data can be enabled by digital technologies (e.g., Blockchain and Internet of Things), and the regulator can be replaced by a built-in algorithm. It is inevitable that the enterprise mainly decides how to engage in resilience-enhancing effort and evaluate its attitude towards risk. Therefore, the system should finally evolve into a human-AI synergistic viability management system.

6. Conclusions

This study can be viewed as data-driven SCN viability management research on coordination of multiple stakeholders within a dynamic programming optimization framework based on real-time network data enriching and updating in the Bayesian setting. A salient innovation of this study is that it leverages real-time observed data to mitigate the mixed uncertainty of disruption risk by employing the DDHMM approach, and then adopts Bayesian network game theoretical approach to enhance the resilience and viability of the entire SCN from the long-term perspective. The hybrid approach strengthens the practical value of this study by achieving the goal of real-time risk governance.

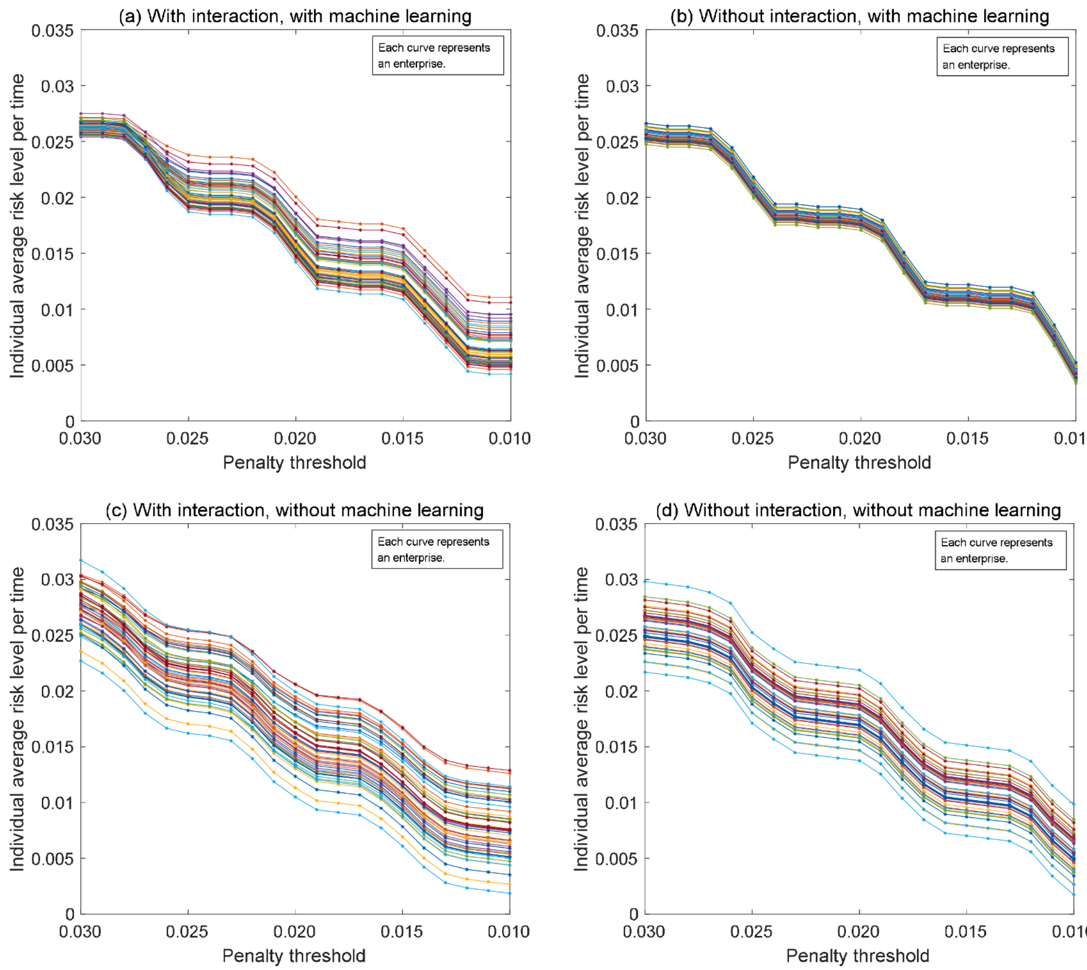

Fig. 8. The individual average risk level per time with a changing penalty threshold.

Furthermore, taking advantage of the Bayesian way, we develop a dynamic (rather than a static) "whether to respond now or later" decision-making model that ensures fostering a resilient and viable risk response plan.

The main findings of this study are as follows. In the short term, this study encourages enterprises within the network to engage in collaborative risk mitigating that can significantly increase the likelihood of reaching a consensus on the more cost-efficient level of risk mitigation, following a process marked by an intriguing interplay between weakened individual fairness and the tendency to mitigate network-wide risks more economically. In the long term, this study advocates building a data-driven, structure-dynamic, and interaction-focused risk-response timing system that enables the interconnected network to enhance the viability by adapting to changes swiftly and achieving desired viable levels efficiently. This study also underscores the importance of dynamic network data, emphasizing an incremental upgrade of the system to enhance the data availability and reliability.

In view of the limitations of this study, we suggest some worthy topics for future research. For instance, instead of only focusing on the seller's sides of the SC, the "last mile" of the SC, i.e., the customer, should be involved in SCN viability management. It is worth investigating how a more comprehensive disruption risk response timing plan is optimized in a more complex SCN. Another topic is to reconsider the tradeoff between real-life complexity and model simplification. Modifying the adjacency matrix and cost function may be meaningful for theoretical advancement and practical applications.

CRediT authorship contribution statement

Sha-lei Zhan: Writing – original draft, Software, Methodology, Conceptualization. **Joshua Ignatius:** Writing – review & editing, Validation, Formal analysis. **Chi To Ng:** Visualization, Supervision. **Daqiang Chen:** Investigation, Data curation.

Declaration of competing interest

none.

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Appendix A. Proofs

Proof of proposition 1

Using mathematical induction, we prove Proposition 1 as follows.

When $r=1$, by following the forward algorithm we have $\mathbb{P}(p_t,\mathbf{s}_{it})=\sum_{p_{t-1}}(\omega(s_{it},p_t,p_{t-1})\cdot\mathbb{P}(p_{t-1},\mathbf{s}_{i(t-1)}))$, therefore Eq. (2) holds;

Suppose that Eq. (2) holds when $r=u$ $(1\le u\le t-2)$, i.e., $\mathbb{P}(p_t,\mathbf{s}_{it})=\sum_{p_{t-1}}\Big(\omega(s_{it},p_t,p_{t-1})\cdot\sum_{p_{t-2}}\Big(\omega(s_{i(t-1)},p_{t-1},p_{t-2})\cdots\sum_{p_{t-u}}(\omega(s_{i(t-u+1)},p_{t-u+1},p_{t-u})\cdot\mathbb{P}(p_{t-u},\mathbf{s}_{i(t-u)}))\Big)\Big)$. Because $\mathbb{P}(p_{t-u},\mathbf{s}_{i(t-u)})=\sum_{p_{t-u-1}}(\omega(s_{i(t-u)},p_{t-u},p_{t-u-1})\cdot\mathbb{P}(p_{t-u-1},\mathbf{s}_{i(t-u-1)}))$ by following the forward algorithm, we have $\mathbb{P}(p_t,\mathbf{s}_{it})=\sum_{p_{t-1}}\Big(\omega(s_{it},p_t,p_{t-1})\cdot\sum_{p_{t-2}}\Big(\omega(s_{i(t-1)},p_{t-1},p_{t-2})\cdots\sum_{p_{t-u-1}}(\omega(s_{i(t-u)},p_{t-u},p_{t-u-1})\cdot\mathbb{P}(p_{t-u-1},\mathbf{s}_{i(t-u-1)}))\Big)\Big)$, i.e., Eq. (2) holds when $r=u+1$.

Proof of proposition 2

First, we have $\mathbb{P}(\mathbf{s}_{it},\mathbf{s}_{jt})=\sum_{p_t}\mathbb{P}(p_t,\mathbf{s}_{it},\mathbf{s}_{jt})=\sum_{p_t}(\mathbb{P}(\mathbf{s}_{jt}|\mathbf{s}_{it},p_t)\cdot\mathbb{P}(\mathbf{s}_{it}|p_t)\cdot\mathbb{P}(p_t))$. Then, because $\mathbf{s}_{jt}$ and $\mathbf{s}_{it}$ are conditionally independent given p_t, we have $\mathbb{P}(\mathbf{s}_{jt}|\mathbf{s}_{it},p_t)=\mathbb{P}(\mathbf{s}_{jt}|p_t)$. Finally, we have $\mathbb{P}(\mathbf{s}_{it},\mathbf{s}_{jt})=\sum_{p_t}(\mathbb{P}(\mathbf{s}_{jt}|p_t)\cdot\mathbb{P}(\mathbf{s}_{it}|p_t)\cdot\mathbb{P}(p_t))$. Therefore, Eq. (6) holds.

Proof of proposition 3

We obtain the first-order conditions $\frac{\partial u_{it}(s_{it}^{(\tau)})}{\partial\pi_{it}}=\frac{2\pi_{it}^*(s_{it}^{(\tau)})}{e^2}+\left(l_t-\frac{2\cdot\mathbb{E}(p_t|s_{it}^{(\tau)})}{e^2}\right)-l_t\cdot\sum_{j\in\mathbf{N}_{-i}}\mathbb{E}\left(\pi_{jt}^*|s_{it}^{(\tau)}\right)\cdot g_{ijt}\cdot\left(1-\sum_{k\in\mathbf{N}_{-ij}}\mathbb{E}(\pi_{kt}^*|s_{it}^{(\tau)})\right)=\frac{2\pi_{it}^*(s_{it}^{(\tau)})}{e^2}+\left(l_t-\frac{2\cdot\mathbb{E}(p_t|s_{it}^{(\tau)})}{e^2}\right)-l_t\cdot\sum_{j\in\mathbf{N}_{-i}}g_{ijt}\cdot\mathbb{E}\left(\pi_{jt}^*|s_{it}^{(\tau)}\right)+l_t\cdot\sum_{j\in\mathbf{N}_{-i}}g_{ijt}\cdot\mathbb{E}\left(\pi_{jt}^*|s_{it}^{(\tau)}\right)\cdot\sum_{k\in\mathbf{N}_{-ij}}\mathbb{E}(\pi_{kt}^*|s_{it}^{(\tau)})=\frac{2\pi_{it}^*(s_{it}^{(\tau)})}{e^2}+\left(l_t-\frac{2\cdot\mathbb{E}(p_t|s_{it}^{(\tau)})}{e^2}\right)-l_t\cdot\sum_j g_{ijt}\cdot\mathbb{E}\left(\pi_{jt}^*|s_{it}^{(\tau)}\right)=0,\ \forall i.$

Then, the optimal PEEPPDR for enterprise i when observing NDS $s_{it}^{(\tau)}$ at NDEP $[1,t]$ is $\pi_{it}^*(s_{it}^{(\tau)})=\mathbb{E}(p_t|s_{it}^{(\tau)})-\frac{l_t\cdot e^2}{2}+\frac{l_t\cdot e^2}{2}\cdot\sum_j\left(g_{ijt}\cdot\mathbb{E}\left(\pi_{jt}^*|s_{it}^{(\tau)}\right)\right)=\mathbb{E}(p_t|s_{it}^{(\tau)})-\frac{l_t\cdot e^2}{2}+\frac{l_t\cdot e^2}{2}\cdot\sum_j\sum_v\left(g_{ijt}\cdot\mathbb{P}\left(s_{jt}^{(v)}|s_{it}^{(\tau)}\right)\cdot\pi_{jt}^*\left(s_{jt}^{(v)}\right)\right)$.

Therefore, we have

$$\pi_{it}^*(s_{it}^{(\tau)})=\mathbb{E}(p_t|s_{it}^{(\tau)})-\frac{l_t\cdot e^2}{2}+\frac{l_t\cdot e^2}{2}\cdot\sum_j\sum_v\left(g_{ijt}\cdot\gamma_t^{(\tau v)}\cdot\pi_{jt}^*\left(s_{jt}^{(v)}\right)\right). \tag{A.1}$$

We re-write the above equation in matrix form as

$$\begin{pmatrix}\boldsymbol{\Pi}_t^{(1)}\\ \vdots\\ \boldsymbol{\Pi}_t^{(M^t)}\end{pmatrix}=\begin{pmatrix}\left(\mathbb{E}(p_t|s_{it}^{(1)})-\frac{l_t\cdot e^2}{2}\right)\cdot 1_N\\ \vdots\\ \left(\mathbb{E}\left(p_t|s_{it}^{(M^t)}\right)-\frac{l_t\cdot e^2}{2}\right)\cdot 1_N\end{pmatrix}+\frac{l_t\cdot e^2}{2}\cdot\boldsymbol{\Gamma}_t\otimes\mathbf{G}_t\cdot\begin{pmatrix}\boldsymbol{\Pi}_t^{(1)}\\ \vdots\\ \boldsymbol{\Pi}_t^{(M^t)}\end{pmatrix}. \tag{A.2}$$

We have supposed that $\frac{l_t\cdot e^2}{2}<min\left(\mathbb{E}(p_t|s_{it}^{(\tau)}),\frac{1}{\lambda_{max}(\mathbf{G}_t)},\ \frac{1}{\lambda_{max}(\boldsymbol{\Gamma}_t)\cdot\lambda_{max}(\mathbf{G}_t)}\right)$, thus $\mathbf{I}_{M^t\cdot N}-\frac{l_t\cdot e^2}{2}\cdot\boldsymbol{\Gamma}_t\otimes\mathbf{G}_t$ is invertible. Finally, we obtain Eq. (13). Therefore, this proposition holds.

Proof of proposition 4

Following Eq. (A.1), we obtain Eq. (14). By inserting the optimal PEEPPDR in Eq. (9), we further obtain Eq. (15). Therefore, this proposition holds.

Proof of corollary 1

In view of $g_{ijt}=0$ in the first extreme scenario, we therefore obtain $\Omega_{it}^{(\tau)}=0$, then further obtain $\pi_{it}^*(s_{it}^{(\tau)})=\mathbb{E}(p_t|s_{it}^{(\tau)})-\frac{l_t\cdot e^2}{2}$ and $x_{it}^*(s_{it}^{(\tau)})=\frac{l_t^2\cdot e^2}{4}$. In view of not all the $g_{ijt}=0$ in a general SCN $\mathbf{g}$, we therefore obtain $\Omega_{it}^{(\tau)}>0$, then further obtain $\pi_{it}^*(s_{it}^{(\tau)})>\mathbb{E}(p_t|s_{it}^{(\tau)})-\frac{l_t\cdot e^2}{2}$ and $x_{it}^*(s_{it}^{(\tau)})<\frac{l_t^2\cdot e^2}{4}$. Therefore, this corollary holds.

Proof of Corollary 2

In view of $1-\Omega_{it}^{(\tau)}=\pi_{it}^*(s_{it}^{(\tau)})$ in the second extreme scenario, we therefore obtain $\pi_{it}^*(s_{it}^{(\tau)})=\mathbb{E}(p_t|s_{it}^{(\tau)})-\frac{l_t\cdot e^2}{2}\cdot\pi_{it}^*(s_{it}^{(\tau)})$, then further obtain $\pi_{it}^*(s_{it}^{(\tau)})=\frac{\mathbb{E}(p_t|s_{it}^{(\tau)})}{1+\frac{l_t\cdot e^2}{2}}$ and $x_{it}^*(s_{it}^{(\tau)})=\frac{l_t^2\cdot e^2}{4}\cdot\left(\frac{\mathbb{E}(p_t|s_{it}^{(\tau)})}{1+\frac{l_t\cdot e^2}{2}}\right)^2$. In view of $1-\Omega_{it}^{(\tau)}>\pi_{it}^*(s_{it}^{(\tau)})$ in a general SCN $\mathbf{g}$, we therefore obtain $\pi_{it}^*(s_{it}^{(\tau)})<\frac{\mathbb{E}(p_t|s_{it}^{(\tau)})}{1+\frac{l_t\cdot e^2}{2}}$ and $x_{it}^*(s_{it}^{(\tau)})>\frac{l_t^2\cdot e^2}{4}\cdot\left(\frac{\mathbb{E}(p_t|s_{it}^{(\tau)})}{1+\frac{l_t\cdot e^2}{2}}\right)^2$. Therefore, this corollary holds.

Proof of Corollary 3

In view of no information asymmetry and mistrust in the third extreme scenario, we obtain the optimal PEEPPDR for enterprise i when observing NDS $\boldsymbol{s}_{it}^{(\tau)}$ at NDEP $[1, t]$ is $\pi_{it}^{*}\left(\boldsymbol{s}_{it}^{(\tau)}\right) = \mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(\tau)}\right) - \frac{l_t \cdot e^2}{2} + \frac{l_t \cdot e^2}{2} \cdot \sum_{j \neq i}\left(g_{ijt} \cdot \mathbb{E}\left(\pi_{jt}^{*}|\boldsymbol{s}_{it}^{(\tau)}\right)\right) = \mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(\tau)}\right) - \frac{l_t \cdot e^2}{2} + \frac{l_t \cdot e^2}{2} \cdot \sum_{j \neq i} g_{ijt} \cdot \pi_{jt}^{*}\left(\boldsymbol{s}_{jt}^{(v)}\right)$. Hence, the optimal PEEPPDR can be presented by Eq. (17). By inserting the optimal PEEPPDR in Eq. (9), we further obtain Eq. (18). Therefore, this corollary holds.

Proof of Proposition 5

We borrow Eq. (17) to formulate the relationship between two optimal post-effort disruption probabilities resulting from neighboring two responses. We therefore write

$$\pi_{it}^{*\varepsilon} = \pi_{it}^{*\varepsilon-1} - \frac{l_t \cdot e^2}{2} \cdot \left(1 - \sum_{j \neq i} g_{ijt} \cdot \pi_{jt}^{*\varepsilon}\right) \tag{A.3}$$

We further re-write the above equation in matrix form as

$$\boldsymbol{\Pi}_t^{\varepsilon} = \left(\boldsymbol{\Pi}_t^{\varepsilon-1} - \frac{l_t \cdot e^2}{2} \cdot 1_N\right) + \frac{l_t \cdot e^2}{2} \cdot \mathbf{G}_t \cdot \boldsymbol{\Pi}_t^{\varepsilon}. \tag{A.4}$$

Because $\frac{l_t \cdot e^2}{2} < min\left(\mathbb{E}\left(p_t|\boldsymbol{s}_{it}^{(\tau)}\right),\ \frac{1}{\lambda_{max}(\mathbf{G}_t)}, \frac{1}{\lambda_{max}(\boldsymbol{\Gamma}_t) \cdot \lambda_{max}(\mathbf{G}_t)}\right)$, thus $\mathbf{I}_N - \frac{l_t \cdot e^2}{2} \cdot \mathbf{G}_t$ is invertible. Finally, we obtain Eq. (21). Therefore, this proposition holds.

Proof of Corollary 4

(1) Regarding any resilience-enhancing effort, we first consider a basic resilience-enhancing effort. Following Proposition 4 and Corollary 1, we obtain the effort in a general SCN as $\frac{l_t^2 \cdot e^2}{4} \cdot \left(1 - \Omega_{it}^{(\tau)}\right)^2$ which is smaller than $\frac{l_t^2 \cdot e^2}{4}$ in a completely-non-connected SCN. We then consider any reinforced resilience-enhancing effort. Following Eq. (A.3), we obtain the effort as $\frac{l_t^2 \cdot e^2}{4} \cdot \left(1 - \sum_{j \neq i} g_{ijt} \cdot \pi_{jt}^{*\varepsilon}\right)^2$ which is smaller than $\frac{l_t^2 \cdot e^2}{4}$ in a completely-non-connected SCN. Therefore, we conclude that any effort in a general SCN is smaller and more economical than that in a completely-non-connected SCN.

(2) Regarding total resilience-enhancing efforts, we only need to consider the top echelon, because only the top echelon may have the possible effort waste. In view of the uncertainty of the desirable entire risk level (i.e., the penalty threshold), without loss of generality, we suppose that the penalty threshold follows a uniform distribution in the top echelon. Due to the property of uniform distribution, we obtain the expected effort waste of the top echelon in a general SCN as $\frac{l_t^2 \cdot e^2}{8} \cdot \left(1 - \sum_{j \neq i} g_{ijt} \cdot \pi_{jt}^{*\varepsilon}\right)^2$ which is smaller than $\frac{l_t^2 \cdot e^2}{8}$ in a completely-non-connected SCN. Therefore, the total efforts in a general SCN are probabilistically smaller and probabilistically more economical than that in a completely-non-connected SCN.

In summary, this corollary holds.

Appendix B. Tables

Table B1
An example of network data observation (50 enterprises × 30 times).

5	3	6	2	7	2	2	5	2	2	7	5	3	2	7	7	6	1	4	4	3	2	6	1	1	2	3	5	3	2
5	7	5	5	2	5	7	4	1	3	7	6	2	2	7	3	1	7	7	6	5	6	2	6	3	3	2	3	6	2
4	2	5	5	2	6	6	4	2	2	6	3	2	7	1	4	4	4	3	5	6	1	5	3	6	3	6	6	6	7
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2	3	6	5	3	6	4	1	6	2	6	3	4	4	4	7	2	5	3	7	4	3	3	4	2	4	5	3	4	1

(*continued on next page*)

Table B1 (*continued*)

4	6	3	7	4	7	6	2	5	7	4	4	4	5	4	4	7	5	1	5	6	7	2	4	2	4	3	2	1	1
5	6	6	7	6	4	3	2	2	7	4	3	2	2	3	3	2	2	4	5	6	6	2	2	1	2	5	4	6	1
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5	2	4	3	2	6	5	6	4	5	6	7	2	5	7	6	4	2	1	1	3	2	7	5	6	4	1	4	2	5
7	3	5	5	3	6	1	2	7	3	3	5	6	4	5	1	3	4	6	5	7	1	6	6	1	7	2	3	1	2
5	2	5	3	2	3	1	3	6	2	5	1	2	5	2	5	4	6	2	6	6	5	7	3	6	4	2	2	2	5
7	2	3	5	7	7	4	6	5	2	3	1	1	3	7	2	3	4	6	1	2	3	6	6	7	4	3	6	3	3
7	3	6	6	4	3	5	2	2	5	4	6	3	5	4	6	4	3	6	3	2	5	3	6	6	6	7	2	6	5
7	7	3	1	7	7	2	3	1	5	7	3	3	6	7	7	3	3	2	4	2	1	3	6	2	2	5	4	1	3

Data availability

Data will be made available on request.

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