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A Risk Identification and Assessment of Cross-border Supply Chain Disruption Based on Bayesian Networks

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Abstract: Cross-border supply chains have become increasingly complex and critical in today's interconnected global economy. However, effective risk management in this context remains a significant challenge. The study analyzes and quantifies the impact of different factors on cross-border supply chains by establishing a Bayesian network model and identifies and evaluates interruption risks based on causal reasoning and diagnostic reasoning techniques. The results show that the combination of Bayesian networks can comprehensively reveal the causal relationships and influences of interruption risks in cross-border supply chains, providing theoretical support for risk control implementation in cross-border supply chain business for banks and other enterprises. This study also proposes control strategies for interruption risks in cross-border supply chains, including strengthening information construction, formulating emergency plans and recovery mechanisms, etc., to reduce the losses caused by interruption risks and ensure the stable operation of the supply chain.

Keywords: Cross-border supply chain, Quantitative finance, Bayesian network, Risk management, Supply chain disruption

1. Introduction

Supply chain disruptions in cross-border supply chains can have significant impacts on production capacity, costs, GDP, employment, inflation, and price fluctuations [1]. They can be caused by natural disasters, political instability, supplier bankruptcies, and trade wars, leading to production disruptions, material shortages, and supply instability [2]. To enhance supply chain efficiency and adaptability, it is important to identify and assess interruption risks in cross-border supply chains. Bayesian network models can effectively analyze and predict interruption risks by examining conditional dependencies between variables. They provide insights into information flows and decision-making processes, enabling cross-border supply chains to better adapt to global changes and enhance resilience. These models facilitate optimized resource allocation, risk management, and decision-making in the global value chain, resulting in reduced costs and improved accuracy. However, there is limited research in this area, with a lack of comprehensive understanding, empirical studies, standardized approaches, and comparative studies. Further research efforts are needed to address these gaps and develop effective strategies for managing cross-border supply chains. This study aims to identify key factors causing interruption risks, determine risk indicators, evaluate overall interruption risks, and analyze risk factors to optimize cross-border supply chains and reduce losses from interruptions.

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2. Cross-Border Supply Chain Risk Management with Bayesian Networks

The use of Bayesian networks helps enhance the understanding of uncertainties and dependencies within the supply chain, facilitating proactive risk mitigation and improving overall supply chain resilience.

2.1. Bayesian Network

Bayes' theorem is a theorem about the conditional probability of random events A and B [3]. Bayesian network, also known as a "causal network" or "knowledge graph", is an effective model for representing and reasoning about uncertain knowledge. It is a directed acyclic graph (DAG), that is used to represent probabilistic dependencies between variables or events. Each node in the graph represents a variable or event, and directed edges represent the dependency relationships between nodes. Each node is associated with a conditional probability table (CPT) that represents the degree of dependency between the variable and its parent nodes [4, 5, 6]. Mathematically, it can be described as $\mathrm{BN} = (\mathrm{DAG}, \mathrm{CPT})$, whe $\mathrm{DAG} = \{|(X_i \in X, X_j \in \mathrm{XParents(i)})|\}$ represents a directed acyclic graph, $\mathrm{XParents(i)}$ represents the set of parent nodes for the $i-th$ node, and $X_j$is a parent node of X_i, $\mathrm{CPT} = \{p(X_i \mid \mathrm{XParents(i)}) \mid X_i \in X\}$ represents the conditional probability table. In essence, a Bayesian network can be understood as a special representation of the joint probability distribution. Given the prior probabilities of the parent nodes and the conditional probabilities of the child nodes, it allows the calculation of each entry in the joint probability distribution. The calculation formula is as follows:

$$P(x_1, \ldots, x_n) = P(x_i \mid \mathrm{parents}(X_i)), \tag{1}$$

where X_i is the $i-th$ random variable, X_i is a specific value of the random variable X, $\mathrm{Parents(Xi)}$ is the set of parent nodes for X_i,and $\mathrm{Parents(Xi)}$ is a specific value of $\mathrm{Parents(Xi)}$.

2.2. Cross-border Supply Chain

A cross-border supply chain involves multiple countries or regions and includes logistics, production, distribution, and service activities. It aims to meet global market demands by coordinating the flow of goods and information across different stakeholders. The objectives of a cross-border supply chain are efficient resource allocation, cost reduction, improved product quality, and responsiveness to market fluctuations. Challenges include legal regulations, cultural disparities, language barriers, and currency exchange rate fluctuations. Effective management strategies are necessary for efficient global operations.

3. Risk identification

3.1. Identification of key risk indicators

Key risk indicators refer to a system of critical indicators used to monitor specific business activities and control environments. Guo analyzed international logistics supply chain risk types from both internal and external perspectives internal risks include political, economic, technological, and natural risks, while external risks include risks related to organizational management, ethics, operational processes, and investment. Guo's research focuses on cross-border supply chain risk disruptions. Therefore, the logistics interruption rate is identified as a key risk indicator. When the interruption rate exceeds a certain threshold, it is necessary to identify the points where risks originate and implement appropriate risk control measures [7].

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3.2. Identification of key risk factors

The key risk factors are certain risk traits or characteristics that are random factors causing specific risks. This study analyzes the quality risks in the cross-border supply chain from the perspective of collaboration among the participating entities and the overall supply chain. It identifies the main causes of supply chain quality risks, which include the composition of the supply chain, coordination among enterprises, operational risks of suppliers, operational risks of core enterprises, operational risks of sales enterprises, operational risks of logistics service providers serving the entire supply chain, and their corresponding sub-indicators. The main influencing factors of the supply chain structure are the length, quantity, supplier selection criteria, and relationship with suppliers. The influencing factors of operational risks in the supply chain include supply risk, demand risk, manufacturing process risk, information risk, use of information technology, equipment adequacy, employee structure and quality, and application of advanced quality management techniques. The risk of cross-border trade logistics interruptions can be categorized into internal risks and external risks. The internal risks mainly consist of strategic risk and supply risk, while the external risks include warehousing risk, packaging and transportation risk, and other five categories [8]. Chan et al. developed a comprehensive supplier selection model that considers risk as a selection criterion. Sub-risk factors include geographic location, political stability, foreign policy, exchange rates, economic conditions, terrorism, and crime rates [9]. Other scholars also employed defined criteria to capture the uncertainty in decision preferences [10]. Lee proposed a supplier selection framework based on four metrics: incentives, opportunities, costs, and risks associated with the prospective suppliers. Sub-risk requirements encompass capabilities, constraints, pricing adjustments, financial parameters, supplier efficiency, credibility, and climate control [11].

3.3. Risk Identification Results

Based on the analysis of Section 3.2 and combined with the characteristics of each link in the cross-border supply chain, the key risk factors for supply chain disruption and index to measure the level of risk, are obtained. The details are shown in Table 1.

Table 1: Risk identification findings

<table>
<tr><th>Risk Name</th><th>Key Risk Factors</th><th>Key Risk Indicators</th></tr>
<tr><td>Packaging warehousing risk</td><td>Packaging standardization risk
Packaging material quality risk
Level risk of storage facilities and equipment
Warehouse management personnel safety awareness risk</td><td rowspan="3">Logistics risk interruption rate</td></tr>
<tr><td>Transportation and distribution risk</td><td>Risk of cargo damage
Risk of shipment and loss of goods
Means of transport connection risk
Reverse logistics risk caused by return, exchange, and rejection</td></tr>
<tr><td>Cross-border customs clearance risk</td><td>Clearance rate risk
Commodity inspection level risk
Customs clearance efficiency risk
The nature of the product affects the risk</td></tr>
</table>

Table 1: (continued).

Cross-border environmental risk	Risk of linguistic and cultural differences Currency exchange rate fluctuation risk Industry policies, laws, and regulations risk Degree of political stability risk

4. Construction of cross-border supply chain disruption risk assessment model

4.1. Feasibility of Bayesian Networks for cross-border supply chain risk assessment

Bayesian networks are feasible for evaluating the risk of cross-border supply chain disruption. A Bayesian network is a probabilistic inference network defined as $B = \langle G, \theta \rangle$. It consists of two parts: the Bayesian network structure G and network parameters θ. The Bayesian network structure G is composed of a set of nodes and directed edges, where directed edges represent causal relationships between variables, and arrows pointing to child nodes indicate the direction of influence. Another part of the Bayesian network is the conditional probability table (CPT), which reflects the correlation between variables.

Bayesian networks are effective for evaluating cross-border supply chain disruption risk by representing causal information and predicting the magnitude of risks. They can calculate and infer the relationship between risk factors using conditional probability tables [12]. With Bayesian networks, accurate risk assessment and management can be achieved.

4.2. Construction of the Risk Assessment Model

4.2.1. Basic Assumptions of the Model

The model assumes that external environmental factors, such as changes in market demand, major natural disasters, international laws, regulations, and policy changes, are disregarded. The factors influencing cross-border supply chains primarily stem from two aspects: the operations of individual enterprises and collaboration with other members of the supply chain. Therefore, this paper analyzes the key drivers of cross-border supply chain disruption risks from these two perspectives.

The research focuses on supply chains with enterprise cross-border trade as the core. When studying the impact of various participants in the supply chain on operational risks, each node is regarded as independent. This implies that the effect of each node on the operational risks of the supply chain is not influenced by other nodes.

4.2.2. Determination of Bayesian network structure

In the developed cross-border supply chain disruption risk assessment model, the structure of the cross-border supply chain has a significant impact on the collaborative risks within the supply chain. This is because the supply chain structure determines the ease of communication and collaboration among companies involved in the cross-border supply chain, as well as the relationships between the members of the supply chain. Similarly, the operational risks of individual companies affect the operation of the cross-border supply chain. However, the operational risks of the supply chain may not necessarily impact the operational risks of individual companies. Therefore, the operational risks of individual companies serve as the parent node of the supply chain’s operational risks and are the underlying causes of the supply chain’s operational risks.

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Based on the aforementioned approach, an assessment of the interdependencies among various indicators is conducted to determine the Bayesian network topology structure for assessing the interruption risk in cross-border supply chains, as illustrated in Figure 1.

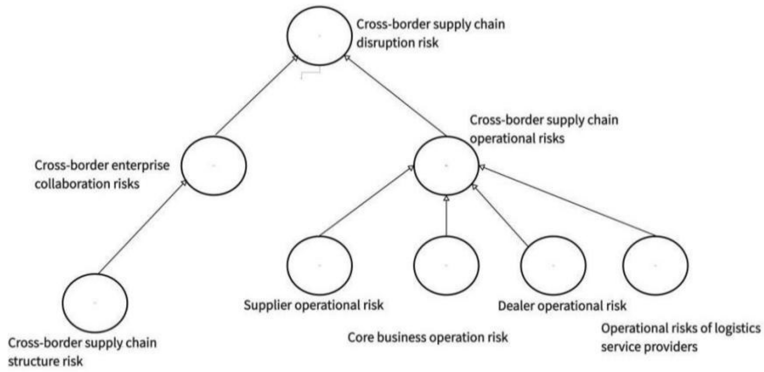

Figure 1: Bayesian network topology of transboundary supply chain disruption risk.

4.2.3. Determination of Parameter θ

θ represents a set of parameters used for quantifying the network. For each variable X, there exists a parameter $\theta\_(X/Pa(X_i))$ that specifies the conditional probability of an event occurring given a particular configuration.

In other words, $\theta\_(X/Pa(X_i))$: $P[X/Pa(\hat{X_i})]$,where $i = 1,2, \dots ,8$. Here, $Pa(X_i)$ represents the set of parent variables for variable Xi in graph G. The probability distribution of variables without parent nodes is represented by marginal probabilities. There are two primary methods for determining the parameters θ: the expert method and the data method. The expert method involves obtaining the probability distribution of each variable based on expert experience, while the data method involves analyzing and learning the probability distribution of variables from data. By incorporating the variables and the probability distributions of each node, represented by conditional probability tables (CPTs), into the base Figure 1, the Bayesian network topology structure for supply chain quality risk can be obtained, the details are shown in Figure 2.

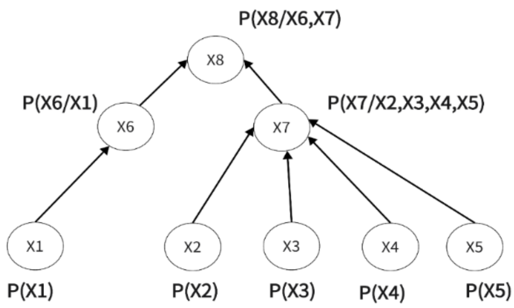

Figure 2: Bayesian network topology of transboundary supply chain disruption risk after adding variables.

4.2.4. Model for Solving the Objective Function

To determine the comprehensive cross-border supply chain disruption risk and the relative importance of each supply chain disruption factor to the comprehensive risk, the objective function is to determine the marginal probabilities of each node, except for the root node. That is, $P(Xi)$, where $i = 1,2, \dots ,8$.

Different algorithms are used for determining the probability distributions under specified conditions and belief updating.

① Algorithm without belief updating

The joint probability of each node is calculated as:

$$\mathrm{P}[\mathrm{Pa}(\mathrm{X_i}) \times \mathrm{X_i}] = \mathrm{Pa}(\mathrm{X_i}) \times \mathrm{P}[\mathrm{X_i}/\mathrm{Pa}(\mathrm{X_i})] \ \ \mathrm{i} = 1,2,\ldots,8. \tag{2}$$

The calculation of the marginal probabilities at any non-evidence node X in different states.

$$\mathrm{P}(\mathrm{X_i}) = \textstyle\sum_{\mathrm{Pa}(\mathrm{X_i})} \ \mathrm{P}[\mathrm{X_i} \times \mathrm{Pa}(\mathrm{X_i})], \mathrm{i} = 1,2\ldots,8. \tag{3}$$

According to the Bayesian network topology structure of supply chain quality risk, it can be known

$$\mathrm{Pa}(\mathrm{X_8}) = \{\mathrm{X_6}, \mathrm{X_7}\}, \tag{4}$$

$$\mathrm{Pa}(\mathrm{X_7}) = \{\mathrm{X_2}, \mathrm{X_3}, \mathrm{X_4}, \mathrm{X_5}\}. \tag{5}$$

② Belief updating algorithm with exclusivity

The posterior probability distribution of an exclusive node X, given evidence E, is referred to as the belief degree $\mathrm{Bel(X)}$ of that node. Based on the characteristics of Bayesian network inference, the belief degree of an exclusive node can be decomposed into two parameters: the diagnostic parameter $\alpha(\mathrm{X})$ and the causal parameter $\pi(\mathrm{X})$, thus $\mathrm{Bel(X)} = \alpha(\mathrm{X})\pi(\mathrm{X})$ (where a is a normalization constant). The diagnostic parameter $\alpha(\mathrm{X})$ is calculated based on the information propagated from the $\mathrm{j-th}$ child node of exclusive node X, while $\mathrm{n(X)}$ is calculated based on the messages transmitted between child nodes' exclusivities and parent node exclusivity

$$\lambda(\mathrm{X}) = \textstyle\prod \lambda_{\mathrm{j}}(\mathrm{X}). \tag{6}$$

The information transmitted to the $\mathrm{j-th}$ child node of node X is referred to as the propagation of information from the j-th child node of node X.

$$\pi(X) = \textstyle\sum_{U_1,U_2,\cdots,U_i} P(X/U_1, U_2, \cdots, U_n) \prod \pi_x(U_i). \tag{7}$$

Information is passed to the parent of exclusivity X for a node.

5. Conclusion

The research utilizes key risk indicators and key risk factor analysis, to identify the crucial factors and indicators of cross-border supply chain disruption risks. The application of Bayesian network models demonstrates that in risk management, changes in certain risk indicators have an impact on the variations of other indicators. Enterprises can establish the value ranges of each node's indicators based on past experience, which helps identify the primary factors leading to the occurrence of risks. Furthermore, by modeling and analyzing data from different stages of the supply chain, potential risk sources can be revealed, and their impacts on the entire supply chain can be determined, facilitating risk control and optimization. These serve as the foundation for managers to monitor and manage risks, as well as the basis for establishing a Bayesian network to address supply chain quality risks. The application of this model assists enterprises in effectively monitoring and managing risks in cross-border supply chain disruption risk management.

This study has a limitation in not fully considering the consequences of risks, which are crucial for decision-making and comprehensive risk assessment. Future research should incorporate risk consequences into the Bayesian network model to analyze supply chain quality risks comprehensively and formulate appropriate response strategies. Moreover, it is valuable to explore the integration of other models or algorithms with the Bayesian network to enhance prediction and decision-making accuracy.

References

[1] *Finck, D. and Tillmann, P. (2022). The Macroeconomic Effects of Global Supply Chain Disruptions, BOFIT Discussion Papers, 2022(14), pp. 1–48.*
[2] *Xu, X. and Zhou, S. (2023). Cross-Border E-Commerce Supply Chain Decision-Making Considering Out-of-Stock Aversion Risk and Waste Aversion Risk, IEEE Access, Access, IEEE, 11, pp. 45632–45644. doi:10.1109/ACCESS.2023.3274697.*
[3] *Johnson, A. A. (2022). Bayes rules! : an introduction to applied Bayesian modeling (M. Q. Ott & M. Dogucu (Eds.)). CRC Press.*
[4] *Jensen, F.V. (1996). An Introduction to Bayesian Networks, 1st ed., Springer.*
[5] *Svetlozar, T., Hsu, J., Biliana, S. and Fabossi, F. (2008). Bayesian methods in finance, The Frank J. Fabozzi Series, Wiley Finance, available at: www.academia.edu/39825064/Bayesian_Methods_in_Finance*
[6] *Dalla Pellegrina, L.D. and Masciandaro, D. (2009). The risk-based approach in the new European anti-money laundering legislation: a law and economics view, Review of Law and Economics, Vol. 5 No. 2, p. 6, doi: 10.2202/1555-5879.1422.*
[7] *Guo, H. (2013). Research on International Logistics Supply Chain Risk Assessment. Labor Protection World (Theoretical Version), (12): 121-122.*
[8] *Zheng, X., Li, D., & Wang, Y. (2016). Risk assessment of logistics in China's export cross-border e-commerce. Business Economic Research, 23, 68-69.*
[9] *Chan, H. K., & Chan, F. T. (2010). A review of coordination studies in the context of supply chain.*
[10] *Choi, T.-M., Wen, X., Sun, X., & Chung, S.-H. (2019). The mean-variance approach for global supply chain risk analysis with air logistics in the blockchain technology era. Transportation Research Part E: Logistics and Transportation Review, 127, 178-191.*
[11] *Sahabuddin, M., Alam, M. S., Khokhar, M., Hossain, M. A., Alam, M. F., & Khan, W. (2023). Circular value creation: business models and supply chain strategies. Environmental Science and Pollution Research, 30(47), 103898–103909. https://doi-org.ez.xjtlu.edu.cn/10.1007/s11356-023-29718-9*
[12] *Li D L, Xu W, Wu D, et al. (2019). On learning method of Bayesian network structure. Journal of Naval University of Engineering, 31(6): 61-64.*