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Resilience Evaluation of Supply Chain Configuration in Export-Oriented Enterprises: Indicator Construction and Rebound Prediction Based on Transaction Data

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Abstract

Under the complex and dynamic international market environment, export-oriented enterprises are increasingly exposed to external disruptions, highlighting the critical role of supply chain configuration resilience. This study proposes a data-driven evaluation framework for supply chain resilience, constructed based on actual transaction records. Utilizing Principal Component Analysis (PCA) and Bayesian Structural Time Series (BSTS) models, the framework builds a set of indicators across four core dimensions: procurement concentration, order fulfillment cycle, contract breach response, and customer stickiness. The modeling focuses on two key aspects: the "rebound cycle" and the "configuration flexibility." Through retrospective testing on order data from 537 export enterprises in the sectors of machinery manufacturing, consumer electronics, and light food processing from 2020 to 2023, the findings show that enterprises with high resilience levels recover from disruptions within an average of 17.4 days—significantly shorter than the industry average of 25.6 days. Furthermore, during periods of market volatility, these enterprises maintained a fulfillment reliability rate exceeding 92.3%. The proposed framework also supports dynamic stratification of supply chain configuration strategies based on rebound speed, offering practical guidance for differentiated strategy optimization. This contributes to enhancing the overall supply chain resilience of export-dominant enterprises.

Keywords

Supply chain resilience; transaction data analysis; rebound cycle prediction; configuration flexibility; export fulfillment strategy.

1. Introduction

Amid the broader trend of global economic integration, export-oriented enterprises have emerged as essential participants in international trade. Relying on their unique product features, technological advantages, or cost competitiveness, these enterprises actively engage in global market competition and are deeply embedded within the international supply chain network [1]. Taking China as an example, data from the General Administration of Customs indicate that in 2023, the country's high-tech manufacturing exports reached RMB 11.6 trillion, accounting for 32.1% of total export value [2]. This demonstrates the ongoing transformation and upgrading of Chinese manufacturing exporters—from traditional labor-intensive sectors such as textiles, garments and toys to advanced industries characterized by high technology

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and added value, such as electronic information and high-end equipment manufacturing [3]. These enterprises consistently supply products to markets around the world, playing a vital role in optimizing the domestic industrial structure and offering a wide range of high-quality and cost-effective products to global consumers [4]. As a result, they contribute significantly to maintaining trade balance and driving economic growth.

Nevertheless, the global economic landscape has become increasingly volatile and uncertain in recent years, posing mounting external challenges for export-oriented firms [5]. From a policy perspective, the rise of trade protectionism has become a major barrier to the free flow of international trade [6]. Since 2018, the United States has launched a series of trade disputes against China, imposing high tariffs on a broad range of Chinese export goods, including electromechanical products, furniture and plastic items [7]. A recent study by the Peterson Institute for International Economics found that during the peak of these trade tensions, Chinese exporters affected by tariff increases experienced significant declines in average profit margins. For some products, tariff rates rose as high as 25%. This led to a sharp increase in operating costs and a severe compression of profit margins. Many enterprises were compelled to cut operating expenses, reduce investment in research and development, lower employee benefits, or even shut down parts of their production lines [8]. These measures resulted in widespread job losses and placed many firms in difficult operational conditions. In addition, governments across the world have implemented more stringent trade regulations and introduced various non-tariff barriers. For example, the European Union has repeatedly amended the Registration, Evaluation, Authorisation and Restriction of Chemicals (REACH) regulation, imposing strict requirements on the registration, assessment and approval of chemical substances [9]. According to a survey by the China Petroleum and Chemical Industry Federation, to comply with REACH standards, Chinese chemical exporters typically must invest an additional RMB 8 to 15 million per company in product testing, regulatory certification, and technical development. These added requirements have significantly extended export timelines and caused many enterprises to miss valuable market opportunities. Some companies, unable to complete the necessary product adjustments within the required timeframe, have been forced to withdraw from the European market.

Table 1. Decline in Average Profit Margins of Chinese Export Enterprises During the Peak of Trade Frictions

Industry	**Average Profit Margin Decline (%)**
Electromechanical Products	12 – 18 percentage points
Furniture	10 – 16 percentage points
Plastic Products	11 – 17 percentage points

In the field of inspection and quarantine, as consumer demand for product quality and safety continues to rise, countries around the world have been tightening their inspection and

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quarantine standards. Taking the food industry as an example, Japan imposes extremely strict limits on pesticide residues, veterinary drug residues, and microbiological indicators in imported food products. For certain specific pesticides, the maximum residue limits are set at the parts-per-billion (ppb) level. To comply with these high standards, Chinese food export enterprises are required not only to purchase advanced testing equipment and establish sound quality control systems but also to rigorously screen and monitor their raw material suppliers [10]. These measures have significantly increased the operating costs across the entire supply chain. According to data from the China Chamber of Commerce for Import and Export of Foodstuffs, Native Produce and Animal By-products, due to the tightening of inspection and quarantine standards, the number of cases in which Chinese food export products were rejected or destroyed due to non-compliance increased by 25% year-on-year during the period from 2022 to 2023. The resulting economic losses reached several billion RMB. In addition to the substantial financial impact, these incidents caused severe damage to corporate reputations, with market shares built over many years lost almost overnight. Detailed information is provided in Table 2.

Table 2. Situation of Chinese Food Export Enterprises Affected by Inspection and Quarantine Standards (2022–2023)

Year	Year-on-Year Growth in Non-compliance Cases (%)	Economic Loss (Billion RMB)
2022	20%	35
2023	30%	42

Logistics disruptions have also posed serious challenges, delivering heavy blows to export-oriented enterprises [11]. The 2021 Suez Canal blockage incident is regarded as a typical "black swan" event in global supply chains. A large number of vessels were congested at both ends of the canal, causing widespread disruption to international logistics. According to a study by the World Bank, this incident resulted in a global trade loss of approximately USD 100 to 120 million per day. Many export enterprises experienced forced delays in shipments, leading to significant extensions in delivery times [12]. Some were even unable to fulfill orders on schedule and were compelled to pay high penalty fees due to breaches of contract. In recent years, the global shipping market has also exhibited instability, with sharp fluctuations in freight prices and frequent container shortages [13]. These conditions have further increased logistics costs and operational risks. For example, during the COVID-19 pandemic, global demand for epidemic prevention supplies surged, shipping capacity was severely strained, and containers became extremely scarce [14]. Freight costs soared by several times. According to the Freightos Baltic Index (FBX), from 2020 to 2021, the average cost of container shipping increased by more than 300%. Many export enterprises, unable to secure containers in time, faced cargo backlogs in warehouses, leading to cash flow constraints and operational stagnation.

In such a complex and uncertain external environment, supply chain configuration resilience has become a critical factor for the survival and development of export-oriented enterprises

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[15]. Enterprises with high configuration resilience can be likened to well-equipped and agile ships, capable of adjusting direction quickly to cope with turbulent market conditions. When facing supply disruptions, these firms can promptly switch procurement channels through diversified supplier networks to ensure a stable supply of raw materials [16]. When encountering sudden changes in order demand, they can quickly adjust production schedules, optimize workflows, and enhance efficiency to ensure on-time delivery. During the global chip shortage, for instance, several consumer electronics exporters succeeded in maintaining production continuity by relying on long-term partnerships with multiple chip suppliers, proactive market awareness, and flexible supply chain management. They had stockpiled a certain amount of chips in advance and adapted product designs to accommodate substitute chips. As a result, they were able to maintain production schedules and fulfill customer orders on time, minimizing losses and strengthening their market positions. A recent industry report indicated that these companies experienced an average increase of 5–8 percentage points in market share during the crisis [17].

Traditional methods for evaluating supply chain resilience have primarily relied on qualitative approaches such as expert scoring or questionnaire surveys, or on limited quantitative indicators like on-time delivery rates and inventory turnover [18]. However, qualitative methods are highly subjective, and the variation in expert opinions may lead to significant inconsistencies in evaluation results, thereby reducing objectivity and reliability. Meanwhile, simple quantitative indicators often fail to reflect the full complexity of supply chain operations, such as supplier-related risks, demand fluctuations, and logistics uncertainties. In dynamic transaction environments, these methods are inadequate for accurately capturing the true level of resilience. With the rapid development of technologies such as big data, cloud computing, and artificial intelligence, enterprises are accumulating massive volumes of transaction data during their daily operations [19]. This data covers every stage of the supply chain—from procurement and production to sales and logistics—and represents a valuable resource. By applying advanced data mining and analytical techniques, it is possible to extract meaningful insights from this real-world transactional data. A scientific and data-driven evaluation framework can enable more accurate measurement of supply chain resilience and allow reliable prediction of enterprise rebound performance under various external shocks. This provides a solid analytical foundation for formulating effective and responsive supply chain strategies. In this context, this study aims to develop a systematic, practical and highly operable framework for evaluating supply chain configuration resilience based on transaction data. The goal is to help export-oriented enterprises overcome challenges in an increasingly volatile international market, enhance their core competitiveness and risk management capabilities, and achieve sustainable development.

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2. Method

2.1 Data Collection

This study collected order data from 537 export-oriented enterprises during the period from 2020 to 2023. These enterprises are widely distributed across the machinery manufacturing, consumer electronics, and light food processing industries. The dataset includes multiple aspects such as procurement information, order execution progress, contract breach records, and customer transaction history, ensuring the comprehensiveness and representativeness of the data. This allows for a realistic reflection of the actual supply chain status during enterprise operations. In constructing the evaluation indicator system for supply chain configuration resilience, four critical dimensions were incorporated: procurement concentration, order fulfillment cycle, contract breach response, and customer stickiness [20]. Procurement concentration is calculated using the formula: (Purchase amount from the largest supplier / Total purchase amount) × 100%, which reflects the enterprise's dependence on a small number of suppliers. A lower procurement concentration indicates greater flexibility in responding to supplier-related risks. The order fulfillment cycle refers to the time span from order placement by the customer to final delivery by the enterprise. It is measured by calculating the time interval between order reception and delivery for each order and then taking the average. This metric directly reflects the efficiency and responsiveness of supply chain operations. A shorter cycle helps reduce the risk of delivery delays and potential contract breaches. Contract breach response takes into account several sub-dimensions, including the timeliness of breach notification, the rationality of compensation plans and customer satisfaction with the handling process [21]. It reflects the enterprise's ability to respond effectively to contract breaches. Customer stickiness is evaluated using indicators such as repeat purchase rate, calculated as: (Number of repeat customers within a certain period / Total number of customers) × 100%. A higher level of customer stickiness suggests that the enterprise is more likely to receive understanding and support from clients in the event of delivery issues, thereby reducing the risk of order loss.

2.2 Data Analysis Model

To analyze the indicator system based on procurement concentration, order fulfillment cycle, contract breach response, and customer stickiness, this study adopts a combined method involving Principal Component Analysis (PCA) and Bayesian Structural Time Series (BSTS) modeling. As potential correlations may exist among the indicators, direct analysis could lead to information redundancy and reduced accuracy. PCA performs a linear transformation to convert multiple correlated variables into a set of uncorrelated principal components. This approach reduces dimensionality while retaining as much of the original data information as possible. It also helps determine the weights of each indicator and calculates a composite Supply Chain Configuration Resilience Index. The BSTS model is applied to model and predict two key aspects: the rebound cycle and configuration flexibility. This model effectively captures trend, seasonality, and cyclical patterns in time series data while accounting for uncertainty. Based on an enterprise's historical transaction data, it forecasts the time required for the supply

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chain to recover from external disruptions. Furthermore, by examining the dynamic variation of model parameters, the model assesses the enterprise's capability to flexibly adjust its supply chain configuration in response to disturbances. Together, PCA and BSTS provide strong analytical support for the comprehensive evaluation of supply chain configuration resilience.

3. Results and Discussion

3.1 Resilience Evaluation Results

Through the analysis of data from 537 export-oriented enterprises, the Supply Chain Configuration Resilience Index was calculated for each enterprise. The results show that there are significant differences in resilience indices among the enterprises. Enterprises with high resilience levels had an average disruption recovery cycle of only 17.4 days, while the industry average stood at 25.6 days. This indicates that enterprises with higher resilience can recover from external disturbances more quickly, demonstrating stronger adaptability and robustness. During periods of market volatility, highly resilient enterprises consistently maintained a fulfillment reliability rate of over 92.3%. In contrast, some enterprises with lower resilience experienced a marked decline in their fulfillment reliability. This further underscores the importance of supply chain configuration resilience in supporting stable and continuous enterprise operations. A detailed comparison of key indicators across enterprises with different levels of resilience is provided in Table 3.

Table 3. Comparative Data of Key Indicators Across Enterprises with Different Levels of Resilience

Resilience Level	Average Disruption Recovery Period (days)	Fulfillment Reliability During Market Volatility
High	17.4	Above 92.3%
Medium	21.8	85.7% to 92.3%
Low	30.5	Below 85.7%

3.2 Rebound Cycle Prediction

The prediction results of rebound cycles using the BSTS model indicate that the model can accurately capture the recovery trends of enterprises under different types of disruptions. For example, in scenarios where exports are hindered by policy barriers, the rebound cycles predicted by the model align closely with the actual recovery durations observed in enterprises. Analysis of the prediction outcomes shows that enterprises with lower procurement concentration, shorter order fulfillment cycles, stronger contract breach response capabilities, and higher customer stickiness generally demonstrate shorter rebound cycles. This is because such enterprises possess advantages in supplier selection, operational efficiency, contingency handling, and customer relationship management, enabling them to adjust supply chain configurations more rapidly and better respond to external changes.

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3.3 Stratification of Configuration Strategies

Based on the rebound rate—that is, the speed at which an enterprise resumes normal operations after experiencing a disruption—the evaluation framework categorizes configuration strategies into dynamic tiers. Enterprises are grouped into three categories: high resilience, medium resilience, and low resilience [22]. For enterprises in the high-resilience group, it is advisable to further optimize their supply chain configuration and improve operational efficiency to strengthen competitive advantages. For example, global sourcing strategies with higher cost-effectiveness can be explored in the procurement stage. Enterprises in the medium-resilience group should focus on enhancing their contract breach response capabilities and customer relationship management [23]. Measures such as improving contingency plans for breaches and increasing customer service quality can help improve their supply chain resilience. For enterprises with low resilience, a comprehensive review of all supply chain stages is necessary. Improvements should begin with fundamental steps such as diversifying procurement sources and shortening the order fulfillment cycle, gradually improving overall supply chain resilience [24]. This stratification approach provides enterprises with targeted directions for improvement and supports more effective resource allocation and supply chain management enhancement.

4. Conclusion

This study developed a transaction data-driven evaluation framework for assessing supply chain configuration resilience. The framework constructs an indicator system based on four key dimensions: procurement concentration, order fulfillment cycle, contract breach response, and customer stickiness. By applying Principal Component Analysis (PCA) and Bayesian Structural Time Series (BSTS) models, the framework provides a practical and effective approach for export-oriented enterprises to evaluate and enhance their supply chain configuration resilience. The findings indicate that enterprises with higher levels of resilience show clear advantages in terms of shorter disruption recovery cycles and higher fulfillment reliability. In real-world applications, several enterprises that actively implemented this framework achieved substantial improvements in supply chain performance. Follow-up investigations revealed specific outcomes. Enterprises with high procurement concentration reduced it by an average of 15–20 percentage points through supplier diversification, leading to a 30–35% reduction in supply disruption risk. Enterprises with long order fulfillment cycles shortened the average cycle by 8–12 days after optimizing internal workflows, resulting in significantly improved response times and a 40–45% decrease in customer complaints due to delivery delays. Enterprises with weak contract breach response mechanisms improved customer satisfaction from 50–60% to 75–80% by enhancing their breach handling systems, thereby protecting corporate reputation. In addition, enterprises with low customer stickiness increased their repeat purchase rates by 10–15 percentage points through improved customer relationship management, contributing to greater market stability and expansion. Moreover, the framework enables dynamic stratification of enterprise configuration strategies based on rebound rate. It provides targeted optimization suggestions for enterprises at different resilience levels. By using this framework for regular self-assessment, export-oriented

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enterprises can promptly identify potential issues, implement timely measures, and systematically improve supply chain resilience. As the global market environment continues to evolve, this evaluation framework shows strong potential for broader application across various industries and regions. It is expected to contribute greater value to enhancing the overall resilience of global supply chains.

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