Supply Chain Resilience Metrics: Structural Change Point (SCP) and Weighted Cumulative Loss (WCL)

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Date: 2025-08-06T09:33:49+00:00

Abstract

Against the backdrop of continuously evolving global political and economic landscapes, supply chain resilience has emerged as a research topic of significant interest to both industry and academia. Addressing the limitations of existing resilience measurement methods and responding to the demand for a unified dynamic indicator that encompasses multiple resilience characteristics in a non-probabilistic manner, this paper proposes two non-parametric supply chain resilience evaluation metrics–Structural Change-Points (SCP) and Weighted Cumulative Loss (WCL). SCP is based on change-point detection techniques to identify structural changes in supply chains triggered by external shocks; WCL employs dynamic weighting functions to quantify performance losses resulting from such shocks. Together, these metrics characterize supply chain performance across the entire "absorb-adapt-recover" cycle, effectively addressing the shortcomings of existing single-dimensional or static approaches. The empirical section utilizes the 2018 China-U.S. trade war as a case study of external shock, analyzing resilience differences across various commodity supply chains using customs and shipping data for Chinese exports to the United States, and examines how factors such as network structural diversity and customer concentration affect resilience. Results indicate that diversified supply chain networks and dispersed customer bases significantly enhance supply chain resilience. The indicator system constructed in this paper demonstrates strong applicability and generalizability, providing both theoretical support and practical tools for enterprises to improve supply chain management capabilities and enhance risk resistance levels.

Full Text

Metrics of Supply Chain Resilience: Structural Change-Points (SCP) and Weighted Cumulative Loss (WCL)

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Abstract

Amid the evolving global political and economic landscape, supply chain resilience has emerged as a critical topic of interest for both industry practitioners and academic researchers. Responding to the limitations of existing resilience measurement approaches and the call for unified, dynamic, and non-probabilistic indicators that capture multiple dimensions of resilience, this paper proposes two nonparametric metrics for evaluating supply chain resilience: Structural Change-Points (SCP) and Weighted Cumulative Loss (WCL). The SCP metric leverages change-point detection techniques to identify structural shifts in supply chains triggered by external shocks, while WCL employs a dynamic weighting function to quantify performance losses following such disruptions. Together, these indicators comprehensively capture the full resilience cycle—absorption, adaptation, and recovery—thereby addressing the shortcomings of traditional single-dimensional or static methods. Using the 2018 U.S.-China trade war as a case of external shock, the empirical analysis draws on Chinese customs and maritime shipping data to assess resilience variations across different product supply chains and to examine how factors such as network diversity and customer concentration affect resilience outcomes. The results indicate that greater network heterogeneity and more dispersed customer bases significantly enhance supply chain resilience. The proposed metric framework offers strong applicability and generalizability, providing theoretical insights and practical tools to support firms in strengthening supply chain management and improving risk mitigation capabilities.

Keywords: Supply Chains; Resilience; Non-parametric Metrics; U.S.-China Trade War; Network Structure

DOI: 0
Classification: C93

1. Introduction

The rapidly changing international political and economic environment poses severe challenges to supply chain security, making supply chain resilience a shared focus for both industry and academia. However, current empirical measurement methods for supply chain resilience remain limited, and the challenge of how to reasonably define and measure supply chain resilience from both theoretical and empirical perspectives remains a research frontier. A recent review by Hong et al. [1] points out that supply chain resilience research requires: (1) non-probabilistic dynamic indicators, and (2) unified metrics that encompass multiple resilience characteristics including adaptation and restoration.

The term "resilience" originates from physics, where it describes a material' s capacity to absorb energy during plastic deformation and fracture. Christopher and Peck [2] first introduced this concept to supply chain management, defining Supply Chain Resilience (SCR) as a supply chain' s ability to recover to its original or an improved state after disruption. While economics, ecology, and environmental science have proposed various resilience measurement methods [3], these approaches are difficult to directly transfer to supply chain contexts due to differences in disciplinary backgrounds and theoretical assumptions.

In supply chain contexts, external shocks typically generate cascading impacts on overall output. Production fluctuations at upstream suppliers may force downstream firms to adopt proactive strategic responses, such as finding alternative suppliers, increasing inventory levels, optimizing procurement strategies, deepening supply chain collaboration, or adjusting material technologies. These micro-level measures precisely reflect the concrete manifestations of supply chain resilience in real-world settings. Generally, highly resilient supply chains demonstrate strong absorption, adaptation, and recovery capabilities in the short to medium term: specifically, they resist shocks in the short term, delaying negative impacts on supply chain performance (absorption capability); they reduce the rate of performance decline and maintain basic production capacity during the post-shock minimum performance phase (adaptation capability); and they recover quickly and effectively to the initial state (recovery capability). [Figure 1: see original paper] illustrates the typical three-stage response process of supply chains after a shock, where absorption, adaptation, and recovery play distinct roles at different stages.

Empirical research faces several challenges in defining and measuring supply chain resilience. Theoretical resilience models are often complex, incorporating numerous dynamic elements that are difficult to observe directly from actual data. However, real-world supply chain data typically feature low frequency, limited availability, and insufficient observable dimensions, creating a significant gap between practical indicators and theoretical constructs. For instance, Massari et al. [4] characterize supply chain resilience through agent-based models and evolutionary systems, while other studies simulate interactions among supply chain nodes through system dynamics or multi-layer network models.

Yet such complex methods are difficult to apply directly in data-limited scenarios. Most empirical studies must simplify resilience definitions—for example, Khanna et al. [5] measure resilience using supplier disruption ratios or single inventory levels, which fail to comprehensively capture supply chain absorption, adaptation, and recovery capabilities, potentially leading to partial and biased resilience assessments.

Furthermore, discrepancies between simplified resilience indicators and theoretical definitions may introduce uncertainty and bias into research conclusions. For example, organizational complexity may enhance a firm' s shock absorption capacity while simultaneously limiting its rapid adjustment capability; single-dimensional resilience indicators cannot fully capture such dual effects. Therefore, comprehensively measuring the absorption, adaptation, and recovery capabilities of supply chain resilience is crucial for accurate causal analysis.

This paper aims to propose a systematic, comprehensive, and operationally feasible methodology for measuring supply chain resilience, specifically designing two nonparametric statistical indicators: Structural Change-Points (SCP) and Weighted Cumulative Loss (WCL). The SCP indicator leverages change-point analysis techniques to identify structural changes in supply chains caused by external shocks in real time, while WCL utilizes a weighting function to dynamically estimate and retrospectively analyze losses resulting from such shocks. Both indicators are based on time series data of key supply chain performance metrics (e.g., export volumes, production levels) and effectively characterize supply chain performance during external shocks through continuous monitoring of dynamic changes across supply chain segments.

For the empirical component, this study selects the 2018 U.S.-China trade war as an external shock case, combining customs and maritime shipping data to measure and analyze the resilience performance of various Chinese export-to-U.S. product supply chains, and subsequently identifies how product characteristics and supply chain network structures influence resilience. The findings demonstrate that diversified supply chain networks and dispersed customer bases significantly enhance supply chain resilience. The proposed indicator system demonstrates strong applicability and generalizability, offering theoretical support and practical tools for enterprises to improve supply chain management capabilities and enhance risk resistance levels.

The remainder of this paper is organized as follows: Section 2 reviews and clarifies the definitional framework for supply chain resilience; Section 3 elaborates on the construction and calculation methods of the SCP and WCL indicators; Section 4 conducts empirical analysis using the U.S.-China trade war case and discusses the impact of supply chain network structures.

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2. Resilience Definition: Literature Review and Theoretical Development

This section systematically reviews relevant literature on supply chain resilience to construct a clear, comprehensive, and empirically applicable definitional framework. Additionally, Section 3.4 compares existing supply chain resilience indicators with those proposed in this paper. By tracing the evolution of supply chain resilience concepts, this section emphasizes three core dimensions: absorption capacity, adaptation capacity, and recovery capacity. Absorption capacity emphasizes short-term shock resistance, adaptation capacity reflects flexibility during shocks, and recovery capacity refers to post-shock efficiency in returning to normal states. This theoretical framework not only provides a solid foundation for empirical resilience measurement but also charts a clear path for subsequent indicator construction.

[Figure 2: see original paper] visually demonstrates three typical manifestations of supply chain resilience in practical contexts. With supply chain performance on the vertical axis and time on the horizontal axis, Curve A undergoes gradual decline and recovery post-shock, exhibiting the complete resilience cycle; Curve B declines synchronously with A but with smaller amplitude, indicating stronger absorption and adaptation capacities and superior overall resilience performance; Curve C experiences more rapid and severe decline comparable to A, reflecting insufficient absorption and adaptation capacities that fail to buy effective response time for the enterprise. The longer the post-shock performance maintenance period, the smaller the decline magnitude, and the faster the recovery speed, the stronger the supply chain resilience.

Resilience as a multidimensional concept appears widely across psychology [6,7], ecology [8], and economics [9,10]. In supply chain research, Christopher et al. [11] propose a classic definition focusing on recovery capacity after disruption but without deep discussion of adaptation processes during disruptions. Ivanov et al. [12] further emphasize the dynamic nature of resilience, arguing that supply chain resilience should encompass the ability to maintain, adjust, and restore execution plans. Ponomarov et al. [2] define supply chain resilience as a dynamic response process that withstands unexpected events and recovers quickly. Building on this, Hosseini et al. [13] identify post-shock disruption and recovery phases. Based on this theoretical review, this paper divides supply chain resilience into three core dimensions—absorption, adaptation, and recovery—and analyzes their connotations in light of modern supply chain development trends and corporate strategy adjustments.

Absorption capacity is the ability of supply chains to resist shocks through proactive preparation, redundancy, and design strategies before risks materialize. For example, according to a *Nikkei* survey, inventories at 4,353 major global industrial enterprises reached $2.1237 trillion by September 2023—30% higher than pre-COVID levels—with the purpose of better resisting supply chain disruption shocks and maintaining production continuity. Absorption capacity enables supply chains to contain negative impacts in the short term and sustain normal system functions. It is typically defined as a system' s capacity to absorb shocks and minimize their impact when facing threats or disturbances [14]. Specifically, it refers to the ability to maintain certain functional and service levels when encountering unexpected events or disruptions (e.g., natural disasters, cyberattacks, terrorist incidents) without complete system collapse. In practice, absorption capacity may manifest through redundant design, where other segments continue operating even if one supply chain link is affected, thereby maintaining overall system functionality [15]. For instance, diversified sourcing strategies can prevent over-reliance on single suppliers, reducing supply interruption risks; safety stock can serve as a buffer during disruptions to ensure continuous production. Additionally, refined supplier management can enhance absorption capacity—through tiered supplier management with differentiated responses based on importance and risk levels, firms can significantly strengthen supply chain absorption capacity [16].

Adaptation capacity is the ability of supply chains to adjust operations and structures after unexpected events to mitigate shock impacts, enabling disruption to occur as slowly as possible and preventing complete breakdown at worst. For example, when the pandemic caused supply chain disruptions, automotive manufacturers like Honda adjusted production schedules, activated backup suppliers, and modified product designs to accommodate available components, effectively reducing supply chain shock impacts and preventing production interruptions. When supply chains cannot rely on original redundancy capacities, avoiding rapid decline or complete breakdown becomes critical. Adaptation capacity reflects supply chain flexibility in operations and structure, enabling rapid and effective responses to sudden supply and demand changes [17]. Flexibility is the core of adaptation capacity, allowing supply chains to quickly adjust network structures and operational strategies to meet changing customer demands [18]. Christopher et al. [19] consider flexibility a vital component of supply chain resilience. For example, flexible production capacity and agile logistics networks help enterprises effectively cope with market demand fluctuations and unexpected events.

Recovery capacity is the ability of supply chains to return to their original state post-shock, potentially including the potential to improve operational efficiency through innovation and optimization during recovery. This process typically requires targeted adjustments to achieve operational optimization and risk response [20]. Whether a supply chain can recover to its pre-shock state is a key criterion for measuring its resilience [21–23]. Recovery capacity focuses not only on the ability to return to the original state but also on recovery speed and the potential to achieve higher operational levels through innovation and optimization. For example, after natural disasters or market upheavals, enterprises can quickly resume production and further enhance operational efficiency by re-evaluating supply chain networks, optimizing logistics routes, and adjusting supplier selection.

In summary, this research defines supply chain resilience as: the dynamic process through which supply chains experience performance damage and gradual recovery after encountering shocks, encompassing three dimensions—absorption, adaptation, and recovery. Stronger supply chain resilience manifests as longer shock absorption duration, more timely and effective adaptation adjustments, and faster recovery speed. Current empirical research lacks unified, dynamic, non-probabilistic indicators that capture multiple resilience dimensions [1], with most resilience measurements limited to single dimensions or oversimplified indicators, such as focusing solely on supplier disruption probability or supplier disruption ratio changes [5,13], which fail to comprehensively capture the multidimensional characteristics of supply chain resilience. Therefore, constructing empirical indicators that simultaneously cover the three dimensions of absorption, adaptation, and recovery is essential. The following section proposes two nonparametric resilience indicators suitable for empirical contexts based on the above definition, and Section 3.4 compares them with existing supply chain resilience indicators in the literature.

3. Resilience Metrics: SCP and WCL

This section proposes two nonparametric, non-probabilistic, unified dynamic indicators that capture multiple resilience characteristics—Structural Change-Points (SCP) and Weighted Cumulative Loss (WCL)—to comprehensively evaluate supply chain resilience. Traditional parametric statistical methods typically require strict distributional assumptions, making it difficult to effectively handle the complex dynamic features of supply chain data. Nonparametric methods, by weakening distributional assumptions, demonstrate greater flexibility and universality, making them suitable for analyzing complex and dynamic supply chain environments. These two metrics are constructed based on the principle that supply chain resilience is stronger when the resistance phase lasts longer (strong absorption capacity), performance declines more slowly (high adaptation capacity), and recovery is faster (good recovery capacity).

Specifically, the SCP metric is based on structural change-point theory, a rapidly developing area in statistics, to precisely identify the specific time points when significant structural changes occur in supply chains after external shocks. WCL introduces a weighting function to dynamically weight performance losses before and after shocks, thereby nonparametrically quantifying the overall loss magnitude. For example, in the context of the 2018 U.S.-China trade war, SCP can effectively capture the time points when tariff changes caused significant shifts in supply chain output, revealing potential delays and disruptions, while WCL can quantitatively reflect overall supply chain performance loss, providing precise evidence for corporate strategic adjustments. Both metrics are based on time series data of supply chain performance, offering effective tools for comprehensive resilience assessment.

3.1 Data Structure To clarify indicator definitions and calculation methods, this study first specifies the data structure and notation. The adopted data model exhibits high flexibility, ensuring indicator applicability across various supply chain scenarios.

Supply chain performance is represented as time series data (e.g., trade shares, export volumes, production quantities), typically sourced from government statistical agencies, customs databases, and internal corporate reports. Such data effectively reflect the supply chain impacts of policy changes, market fluctuations, and natural disasters. Let the time series data be denoted as , representing system performance at time point , where the time span is = 1, 2, 3, ···, , and the external shock occurrence time point is marked as .

3.2 Structural Change-Points (SCP) This section first introduces the structural change-point identification algorithm in Section 3.2.1, using a data-driven nonparametric method to precisely locate the time points cp when significant structural changes occur in supply chains. Section 3.2.2 then defines the SCP indicator based on this algorithm.

3.2.1 Structural Change-Point Identification Algorithm The core of the change-point identification algorithm lies in nonparametrically determining whether and when significant structural changes have occurred in the system. This paper adopts the change-point detection method proposed by Ross et al. [24], whose advantages include requiring no strict distributional assumptions and possessing strong detection accuracy and robustness. The method compares data segments before and after each time point, determining structural change significance and locating change points cp by comparing the statistic with a threshold . The specific hypothesis test forms are shown in formulas (1)-(5), enhancing the generality and flexibility of change-point detection through nonparametric methods.

The null hypothesis 0 is: no structural change has occurred in the time series generation process; the alternative hypothesis 1: a structural shift began at time point cp. The mathematical forms of the two hypotheses are as follows:

$$H_0 : X_i \sim F_0(x;\theta_0), \quad i = 1, \cdots, T$$

$$H_1 : X_i \sim \begin{cases} F_0(x;\theta_0) & i = 1, 2, \cdots, T_{cp} \\ F_1(x;\theta_1) & i = T_{cp}+1, T_{cp}+2, \cdots, n \end{cases}$$

where (;) represents the distribution satisfied by the data generation mechanism of , and is the potentially unknown distribution parameter. Under the null hypothesis 0, the data generation mechanism always follows distribution 0 with parameter 0; under the alternative hypothesis 1, the post-change-point data generation mechanism follows distribution 1 with parameter 1.

In traditional methods, if we further assume that distributions before and after the change point are normal, we could use a -test to detect mean changes or an -test to detect standard deviation changes. To avoid excessive distributional assumptions, this paper uses the following nonparametric method for change-point hypothesis testing.

Time series data arrive sequentially, and at time point we can observe historical data from times 1, 2, , . Let statistic represent the probability of a change point existing in the data observed at time point ; statistic , represents the probability that time point (1, 2, ,) is a change point in the historical data observed at time point . Assuming a time series has only one change point, is defined as the maximum value of , :

$$D_n = \max_{k=2,\ldots,n-1} D_{k,n}$$

The subsequent text will introduce how to handle multiple change points in a time series using a cyclic segmentation approach.

To determine whether a change point exists in the time series, a threshold is needed, and is compared with this threshold. When exceeds the threshold, we conclude that a change point exists in the time series. The selection of threshold must satisfy the following requirements:

$$\begin{aligned} P(D_1 > h_1) = \alpha, \\ P(D_n > h_n \mid D_{n-1} \leq h_{n-1}, \cdots, D_1 \leq h_1) = \alpha \end{aligned}$$

where (>) is the probability of identifying time point 1 as a change point based on the threshold; (> | , ,) is the probability that time point is a change point given no prior change points. When the true situation conforms to the null hypothesis (no change points), the probability of the statistical test rejecting the null hypothesis and accepting the alternative hypothesis (change point exists) is controlled as , i.e., the probability of Type I error is controlled at . This empirical study selects = 0.05.

The expression for , and the determination of depend on distributional assumptions. This paper adopts the statistic proposed by Hawkins et al. [25]:

$$D_{k,n} = \sqrt{\frac{k(n-k)}{n}} \frac{\bar{X}_{k,n} - \bar{X}^{*}_{k,n}}{\hat{\sigma}_{k,n}}$$

where , measures the probability that point is a change point in the observed data up to time point ; $\bar{X}_{k,n}$ is the mean of observations from time 1 through ; $\bar{X}^{*}_{k,n}$ is the mean from time +1 through ; the numerator measures the difference between these two segments; and $\hat{\sigma}_{k,n}$ estimates the time series variance for standardization. The formula compares means of the two segments to detect significant differences.

Based on formulas (2), (3), and (4), the threshold satisfies:

$$h_n = \begin{cases} \frac{n+\sqrt{n^2-4}}{n(n-2)} & \text{if } n \text{ is even} \\ \frac{n+\sqrt{n^2-4}}{n(n-2)} & \text{if } n \text{ is odd} \end{cases}$$

In empirical applications, threshold is first selected using formula (5) based on the data. Statistic is then calculated using formulas (4) and (2). If the statistic exceeds the threshold, we reject the null hypothesis of "no change points" with confidence and identify the change point time as the time when , reaches its maximum value.

To detect a series of change points in a time series, this paper uses a cyclic segmentation algorithm. First, the first change point is detected through the above hypothesis testing process, then the time series is split into two segments at this change point. Each segment is then treated as a new time series, and the process is repeated until no new change points emerge.

This algorithm effectively detects structural changes in time series and identifies change-point locations. When applied, hypothesis tests can be performed at each time point to identify significant structural changes. A time series may exhibit multiple change points, with results recorded as vector $\vec{T}_{cp}$, where T_{cp}^i represents the -th change point.

3.2.2 Structural Change-Point Indicators Based on the above change-point algorithm, this paper defines the Structural Change-Point (SCP) indicator to comprehensively measure supply chain resilience. First, the first change point in a single supply chain, ΔSCP, measures the duration that the supply chain maintains its original structure after a shock, directly reflecting absorption and adaptation capacities (formula 6). Second, considering that supply chains may experience multiple structural changes, the #SCP indicator measures the frequency of structural changes within a given time window. Finally, for multiple supply chains within an industry or category, the standardized indicator SCP% measures the proportion of supply chains experiencing structural changes (formula 8). These three indicators provide progressively expanding perspectives for resilience analysis at different levels, effectively supporting intra-industry and cross-industry supply chain resilience comparisons and evaluations.

Based on the first change point of a single supply chain, ΔSCP measures the time that the supply chain can maintain its structure unchanged after a shock event:

$$\Delta SCP = T_{cp}^1 - T_S$$

where T_{cp}^1 represents the first significant structural change point identified through the change-point algorithm, marking the moment when system performance first undergoes significant structural transformation, and T_S is the external shock occurrence time. ΔSCP measures the time length from shock occurrence to structural transformation, reflecting supply chain absorption and adaptation capacities. Stronger absorption capacity means longer system state maintenance; stronger adaptation capacity means longer time required for significant transformation. [Figure 3: see original paper] shows a schematic diagram of a supply chain performance time series with a single change point: before and after the shock, the system has two relatively stable states (a high pre-shock state and a low post-shock state). The transition between these stable states constitutes "structural change," and the time point when this occurs is the "structural change point."

Supply chains may experience multiple structural changes after a shock. To incorporate this feature, #SCP measures the number of structural changes within a period after external shocks:

$$\#SCP = |\{i \mid T_{cp}^i \subset U(T_S, \delta)\}|$$

where T_{cp}^i represents the time point of the -th structural change point, $U(T_S, \delta)$ is the time window of duration δ after the shock, and $|\cdot|$ counts the number of elements. This indicator measures the frequency of structural changes within a specified time range.

For industries with multiple supply chains, SCP% characterizes the proportion of products experiencing structural changes. Assuming an industry contains supply chains, SCP% calculates the proportion of supply chains experiencing structural changes within each time window δ:

$$SCP\% = \frac{\sum_{j=1}^{N} \mathbb{I}(\#SCP_{j,\delta} > 0)}{N}$$

where $\mathbb{I}(\cdot)$ is the indicator function, and $\#SCP_{j,\delta}$ is the #SCP calculated for the -th supply chain using δ as the time window according to formula (7). The numerator aggregates the number of supply chains experiencing structural change points among the industry' s supply chains within the time window; dividing by the denominator yields the proportion of products with structural changes. In this paper' s empirical study (as shown in [Figure 7: see original paper]), δ is selected as one month, i.e., calculating the proportion of commodity supply chains experiencing structural change points in a specific industry each month.

These three indicators progress layer by layer. SCP%, by measuring the proportion of changing supply chains within a time window across a series of supply chains, can be used to measure industrial resilience, understand overall industry trends, and holds important practical value for comparing industrial chains. An industrial chain (e.g., electronics and electrical appliances) often contains multiple commodity supply chains, resulting in multiple ΔSCP and #SCP values that are difficult to compare; SCP% can integrate change points across multiple supply chains in an industrial chain, providing a standardized indicator to support cross-industrial chain comparisons. The frequency and density of change points identified by SCP% can provide valuable insights into overall industry trends and structural adjustments.

SCP indicators can be used for both horizontal comparison of historical shock events and vertical analysis of resilience differences among supply chains under specific shocks, demonstrating strong theoretical and practical value. For example, [Figure 6: see original paper] in this paper' s empirical section focuses on two major shock events—the pandemic and trade war—comparing their impact magnitudes on China' s export-to-U.S. supply networks; meanwhile, [Figure 9: see original paper] compares the reaction intensities of capital goods, intermediate goods, and consumer goods under trade war tariff shocks. Particularly in external shock environments, SCP indicators enable real-time supply chain monitoring, rapidly identifying structural changes, and helping enterprises dynamically adjust supply chain strategies and resource allocation to enhance resilience levels.

3.3 Weighted Cumulative Loss (WCL) The Weighted Cumulative Loss (WCL) indicator evaluates the overall loss level of supply chains after negative events through nonparametric methods. Negative shocks typically manifest as obvious performance decline intervals in supply chain performance time series. WCL quantifies the degree of performance loss caused by shocks through dynamic weighting analysis of this "decline interval." Specifically, the area under the supply chain performance curve after the shock reflects negative impact losses, while the residual area obtained after adjusting calculation weights through a weighting function embodies the supply chain' s retained capacity after the shock.

WCL' s construction particularly emphasizes the importance of time factors. When supply chain segments face external shocks, reaction speed and adaptation capacity directly determine the shock's diffusion extent and overall loss. For example, less resilient supply chain nodes may collapse rapidly after negative shocks and propagate negative impacts downstream; highly resilient nodes can effectively delay and reduce negative impacts on the overall system. Therefore, a weighting function kernel() is introduced to dynamically adjust weights at different time nodes, assigning higher weights to early-stage losses while gradually reducing weights for subsequent impacts.

The WCL calculation formula is defined as:

$$WCL = 1 - \frac{\sum_{i=0}^{a} \text{kernel}_1(p_{T_S+i})}{\sum_{j=1}^{b} \text{kernel}_2(p_{T_S-j})}$$

where T_S denotes external shock occurrence time, p_{T_S+i} represents supply chain performance at the -th time point after shock; the numerator represents the weighted sum of post-shock supply chain performance, while the denominator provides the weighted benchmark for pre-shock stable state; parameters and represent post-shock and pre-shock analysis time windows, respectively. To ensure model validity, we assume the supply chain was in a stable, trendless state before the shock, and the selected performance indicator p_t (e.g., market share) should be trend-free. If trends exist in the data, trend-predicted values should replace actual data p_{T_S-j} in the denominator.

The weighting function kernel(·) satisfies the condition that total weights sum to 1, giving WCL a range of [0, 1]. Drawing on depreciation function concepts in economics, the post-shock weighting function kernel is typically set as linearly decreasing to reflect the importance of early-stage losses while reducing sensitivity to analysis window length. Time windows and should ideally be consistent, though in practice may be shorter due to data limitations while should cover complete economic or seasonal cycles. Continuous linearly decreasing weighting functions are commonly used in statistics. [Figure 4: see original paper] visually demonstrates WCL.

In this paper' s empirical analysis, we set = 12 months to cover seasonal fluctuations within a year, using equal-weight averaging to estimate the pre-shock stable state; we set = 11 (i.e., 12 months, with starting from 0) as the post-shock analysis window, using linearly decreasing weights. Simultaneously, the X13 algorithm is applied to seasonally adjust time series and eliminate periodic fluctuation interference. The adjusted WCL calculation formula is specifically:

$$WCL = 1 - \frac{\sum_{i=0}^{11} (12 - i) \cdot p_{T_S+i}}{\sum_{j=1}^{12} p_{T_S-j}}$$

where the numerator uses linearly decreasing weights to calculate post-shock performance, and the denominator uses simple averages of pre-shock supply chain performance.

WCL is widely applicable in supply chain resilience-related empirical research, capable of revealing how firm characteristics and supply chain structures affect resilience performance and providing scientific evidence for corporate resilience management strategies.

3.4 Comparison with Existing Supply Chain Resilience Indicators

Based on the 前沿 review by Hong et al. [1], this section discusses the advantages of SCP and WCL relative to common resilience indicators in existing supply chain resilience research—including network connectivity, recovery curves (e.g., Time-to-Recovery TTR, performance drop magnitude), Time-to-Survive (TTS), and profit loss models based on system evolution. These indicators provide a foundational framework for quantitative resilience assessment but still have limitations in practical applications.

This paper proposes nonparametric, non-probabilistic, unified dynamic indicators that capture multiple resilience dimensions, advancing existing supply chain resilience metrics.

Traditional network connectivity indicators, such as Largest Connected Component (LCC) [26] or shortest path analysis, primarily focus on structural integrity after node/edge attacks. However, these methods only reflect structural properties, ignore node functional roles, and employ static analysis that neglects disturbance evolution processes, failing to capture the temporal dimension of resilience. This paper’ s indicator system, particularly the Structural Change-Point (SCP) indicator, employs nonparametric statistical methods to directly reflect the dynamic evolution of supply chain structural states through real-time monitoring and change-point identification of key performance metrics. This dynamic perspective enables SCP to accurately locate the timing of structural changes caused by disturbances, thereby compensating for the inability of traditional static network connectivity indicators to describe node functional heterogeneity and time-varying characteristics.

Recovery curve-related indicators, such as Time-to-Recovery (TTR) and performance drop magnitude, have been widely used for quantitative supply chain resilience analysis [27]. These indicators focus on post-disturbance system performance, such as recovery speed and performance loss magnitude. While effective in capturing recovery phase characteristics, their limitation lies in insufficient attention to absorption and adaptation phases, evaluating supply chain performance changes only holistically or at certain local stages, lacking continuous real-time monitoring and sensitivity to ongoing state changes. In contrast, the WCL (Weighted Cumulative Loss) indicator emphasizes not only performance loss magnitude but also the dynamic change process of losses over time through its dynamic weighting function design, providing continuous and detailed performance monitoring. Specifically, by assigning larger weights to early disturbance stages, WCL more effectively quantifies supply chains’ rapid response capabilities during initial shock phases and long-term recovery performance, comprehensively and continuously evaluating dynamic adaptability and recovery capacity.

Time-to-Survive (TTS) indicators emphasize the maximum duration that supply chains can maintain services after specific node or link disruptions, thereby identifying network bottleneck nodes [28]. While prominent in identifying supply chain weaknesses and risk management, practical applications often face data collection difficulties, subjective biases, and insufficient consideration of node functional heterogeneity. Particularly in complex networks, survival time measurements for different nodes often fail to precisely reflect overall network resilience performance. The SCP indicator demonstrates advantages by directly monitoring the timing of overall supply chain performance structural changes, objectively revealing dynamic characteristics of network structure evolution with disturbances, without relying on individual node survival time estimates, effectively avoiding errors from subjective assessments.

System evolution-based profit loss models, such as the stochastic profit loss model proposed by Birge et al. [29], although theoretically combining network structure and inventory management to provide stochastic resilience measurement, rely on overly strong rational enterprise assumptions [1] and require high parameter assumptions and probability distributions that are difficult to support with sufficiently accurate real-world data. The WCL and SCP indicators employ nonparametric statistical methods, weakening strong distributional assumptions and better suiting supply chain environments with limited or low-frequency data, significantly enhancing indicator practicality and operability. Meanwhile, WCL achieves rapid performance loss assessment through simple linear weighting, while SCP precisely captures specific time points of supply chain structural dynamic changes using statistical change-point methods. The two complement each other, providing a set of flexible and robust empirical assessment tools.

Active (Proactive Flexibility) [30,31] and passive flexibility (Reactive Flexibility) [32] concepts in network topology design also occupy important positions in supply chain resilience research. Proactive flexibility emphasizes improving resilience through preventive measures before disturbances, such as diversified supplier networks and redundant capacity layouts, suitable for non-systematic disturbances but with limited applicability to systematic, large-scale disturbances [1]. Passive flexibility emphasizes post-disturbance response and temporary adjustment capabilities, but such flexibility often remains hidden before disturbances and depends on corporate creativity and rapid response capabilities during crises. However, both network topology design concepts lack operationally simple measurement metrics. The indicators proposed in this paper can be viewed as measurements of the outcomes resulting from these concepts in supply chain performance, capturing the actual temporal performance of proactive and passive flexibility from a data-driven perspective, enabling enterprises to more precisely assess and enhance the effectiveness of these flexibility types.

System performance time-varying indicators, such as performance loss and recovery ability, provide detailed descriptions of system state evolution over time, reflecting supply chain resilience characteristics at different stages [33,34]. However, application of such indicators is often limited by the difficulty of predicting performance changes in complex supply chain systems [1]. The SCP and WCL indicators avoid performance prediction complexity through nonparametric methods, directly enabling real-time, robust monitoring and assessment of post-disturbance performance dynamic changes based on actual observed data, significantly reducing modeling and prediction difficulty and enhancing feasibility and accuracy for practical management decisions.

In summary, SCP and WCL demonstrate clear advances and advantages over traditional supply chain resilience indicators in both theoretical perspective and empirical application. First, these indicators compensate for shortcomings of traditional static or single-dimensional indicators from a dynamic perspective, comprehensively covering supply chain performance throughout the entire disturbance process—absorption, adaptation, and recovery. Second, both SCP and WCL are constructed based on nonparametric statistical methods, avoiding strict requirements of complex probability models on data quality and distributional characteristics, greatly enhancing indicator flexibility and applicability in real-world contexts. Additionally, the synergistic use of the two indicators enables more three-dimensional and detailed resilience analysis, enriching the supply chain resilience assessment toolkit and providing strong empirical foundations and methodological innovation for supply chain resilience management and decision-making.

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4. Application of SCP and WCL

To deeply explore how supply chain network structures affect resilience, this study utilizes comprehensive Chinese export and U.S. import customs data to construct cross-national supply chain networks (as shown in [Figure 5: see original paper]). Using the 2018 U.S.–China trade war as an external shock event, this paper systematically evaluates the resilience of different product supply chains by applying Structural Change-Point (SCP) and Weighted Cumulative Loss (WCL) indicators to changes in China' s export market share to the U.S.

Supply chain resilience performance is significantly influenced by network characteristics. Different product categories (e.g., electrical appliances vs. furniture) exhibit substantially different supply chain network structures, directly causing resilience performance variations. This paper further extracts firm-level supply chain network characteristics from 2017 (the year before the trade war) and examines through regression analysis how network attributes of portal node firms (i.e., key enterprises participating in cross-border trade, represented as square nodes in [Figure 5: see original paper]) affect overall supply chain resilience.

4.1 Data Description The data used in this study cover Chinese-U.S. trade customs records from 2016 to 2022, constructing product-level monthly time series data p_{it}, where represents specific commodities (6-digit HS codes) and represents time (monthly). This paper adopts China' s trade share to the U.S. calculated from trade volume (standard container TEU) as the supply chain performance indicator . Data are sourced from the Panjiva database provided by S&P Global, which includes detailed customs data from China, the U.S., and other countries, covering commodity types, weight, TEU volume, and firm information. To ensure data accuracy, this study follows maritime industry standards using TEU as the basic unit.

The initial data contain 4,997 product supply chain networks. Given that numerous products have small trade scales and low transaction frequencies, screening criteria are set as average monthly trade volume exceeding 10 TEU and at least 24 months of trade activity between 2016-2019, yielding 3,122 product supply chain networks. Products with extremely low (<0.01%) or high (>80%) U.S. import shares are further excluded, resulting in 2,639 product networks for in-depth analysis. These product networks account for 85.84% of total China-U.S. trade volume and cover 90.66% of affected product trade volume during the trade war period, providing strong representativeness to effectively support subsequent resilience analysis.

4.2 Shock Events and Intensity: U.S.-China Trade War and SCP Resilience Measurement To validate indicator effectiveness, this study selects the 2018 U.S.-China trade war as an external shock case and uses the 2020 COVID-19 pandemic as a control to analyze and compare the impacts of these two shock events on China-U.S. export supply chain resilience.

Using the 2020 pandemic as a reference, this paper measures the shock intensity of the trade war and compares how the two shocks affected different product supply networks. This comparison is achieved through SCP by calculating the proportion of change points within specific periods (SCP%) across the same supply chains facing different shocks, enabling comparison of different shock events' impacts.

[Figure 6: see original paper] illustrates the impacts of the U.S.-China trade war and COVID-19 pandemic on China-U.S. export supply chains. The horizontal axis represents time (from early 2017 to early 2021), and the vertical axis shows the monthly proportion of structural changes (SCP%), representing the share of supply chains identified as experiencing significant structural changes each month. For instance, during the pandemic, the proportion of commodities experiencing structural changes (SCP%) peaked at 9.48% in June 2020, meaning that among over 2,500 product networks, as many as 250 networks exhibited significant structural changes that month.

By calculating SCP% with $\delta = 6$ to focus on performance six months before and after shocks, we find that the 2018-2019 U.S.-China trade war significantly impacted China-U.S. export supply chains (SCP% = 3.44%), far exceeding natural fluctuation levels before the shock (SCP% = 2.46%), though not as severe as the pandemic impact (SCP% = 5.69%). These results indicate that while the trade war significantly affected China-U.S. export supply chain resilience, its overall shock intensity was less severe than the pandemic.

Furthermore, we categorize product supply chains by tariff impact intensity into four groups: unaffected, first-round tariffs (March 24, 2018, covering machinery and electronic equipment, etc.), second-round tariffs (July 26, 2018, covering chemicals and plastic products, etc.), and third-round tariffs (August 23, 2018, covering various industrial and consumer goods). As shown in [Figure 7: see original paper], products unaffected by tariffs showed no significant structural changes as expected; products involved in the second and third tariff rounds exhibited numerous structural change points during the trade war period, approaching pandemic levels, indicating significant tariff shock impacts. Notably, products in the first tariff round did not show similar patterns, demonstrating that capital- and technology-intensive products exhibit stronger resilience to trade policy changes, while highly standardized products (second and third rounds) are more vulnerable to policy fluctuations.

4.3 Resilience Measurement by Product Category: WCL and SCP

This paper classifies over 2,500 product networks using three international standards—BEC, HS, and NAICS—to systematically demonstrate and analyze supply chain resilience differences from three dimensions: economic activity, raw material attributes, and industry categories.

Following the Broad Economic Categories (BEC) classification, products are divided into seven categories including capital goods (manufacturing tools), intermediate goods (raw materials), and consumer goods. [Figure 8: see original paper] shows average WCL values for various product supply chain networks, where lower WCL indicates smaller losses and stronger resilience; [Figure 9: see original paper] displays the proportion of products experiencing structural changes after trade war shocks (SCP%), where lower proportions also indicate stronger resilience. Comparative analysis of these two figures reveals that SCP change-point density and WCL loss trends are significantly consistent, demonstrating the consistency and reliability of the two indicators from different perspectives.

In BEC classification, the transport equipment category demonstrates the strongest resilience, maintaining negative WCL values and low SCP change-point density even under severe trade war shocks, indicating robust supply chain network structure and strong resistance capacity. Further analysis reveals that WCL gradually increases and SCP change-point density progressively rises from capital goods to intermediate goods to consumer goods, showing a trend of gradually weakening supply chain resilience along the capital input-to-final consumption chain.

Based on raw material attributes and processing complexity, this paper further subdivides product categories using the HS classification standard to examine how processing complexity affects supply chain resilience. As shown in Appendix [Figure 10: see original paper] and [Figure 11: see original paper], precision equipment and transport equipment with high processing complexity exhibit higher resilience, while mass consumer goods like food and tobacco show weaker resilience. This suggests that product substitutability, supply chain network complexity, and procurement difficulty are key factors influencing supply chain resilience.

Finally, based on industrial structure characteristics, this paper employs the

North American Industry Classification System (NAICS) standard for analysis (Appendix [Figure 12: see original paper] and [Figure 13: see original paper]). Results show that high-resilience industries are typically technology-intensive or strategically critical sectors, while low-resilience industries are mostly labor-intensive or resource-dependent sectors.

Comprehensive classification results effectively reveal the complex dynamic characteristics of supply chain resilience under shock scenarios, highlighting the applicability and important value of the proposed SCP and WCL indicators for rapidly assessing supply chains' ability to cope with economic fluctuations and external shocks. These indicators provide clear decision-making foundations for enterprises and policymakers to enhance supply chain resilience and sustainability.

4.4 Impact of Network Structure on Supply Chain Resilience Supply chain network structure exerts direct and indirect impacts on resilience, where the synergy and balance among network breadth, depth, and link strength are crucial for supply chain stability and sustainability. In-depth analysis of these relationships provides important foundations for supply chain strategic planning.

presents descriptive statistics for the dependent variable Resilience and supply chain network structure-related independent variables. This study constructs independent variables using 2017 China-U.S. import-export data (the year before the trade war) to examine how network structures affected supply chain resilience under 2018 tariff shocks. Resilience is defined as:

$$\text{Resilience}_i = (1 - WCL_i) \times 100$$

For intuitive comparison, resilience is defined as the complement of Weighted Cumulative Loss (WCL) multiplied by 100. The analysis sample includes over 1,900 product networks affected by the trade war, focusing on examining portal enterprises' network attributes, specifically at two levels: global networks (superscript W) and China-U.S. networks (superscript US). Selected key network attributes include:

- **InDegree**: Number of suppliers connected to a node, reflecting resource diversity and redundancy. InDegree represents the number of sources from which a node in the supply chain obtains goods or services. It reflects the breadth of a firm' s connections and resource diversity within the network. Higher InDegree enables firms to quickly find alternative suppliers when supply chain disruptions occur, thereby enhancing disturbance resistance. This paper uses the total number of supplier countries worldwide from which Chinese firms in product network source goods as $InDegree_i^W$.
- **InWeight**: Weighted InDegree measuring trade volume (logarithm of USD) from suppliers, reflecting supplier dependence and risk exposure.

Weighted InDegree is the total volume or value of goods/services received by a node from all suppliers, using 2017 data. Larger weights indicate higher dependence on foreign suppliers. This paper uses trade volume (in USD, log-transformed) as the weight measure between China and the world, denoted $InWeight_i^W$.

- **OutDegree**: Number of customers served by a node, representing market diversity. Broader customer bases help disperse market risk and reflect connections with downstream markets. This paper records the total number of customer countries worldwide for Chinese firms in product network as $OutDegree_i^W$, and the average number of U.S. customer firms as $OutDegree_i^{US}$.
- **OutWeight**: Total volume of goods/services provided by a node to customers, revealing market dependence intensity. Larger trade volumes imply greater risk exposure. Similar to weighted InDegree, weighted OutDegree reveals connection strength between firms and their customers. This paper calculates weighted OutDegree between China and the world ($OutWeight_i^W$) and between China and the U.S. ($OutWeight_i^{US}$).
- **OutWeight Variance**: Variance of customer trade volume distribution, characterizing customer concentration risk. High variance indicates high customer concentration, revealing potential risks from excessive customer concentration. Imbalanced weights may imply over-dependence on specific customers, making firms sensitive to market changes.

To quantify network structure impacts on resilience, this study constructs the following multiple linear regression model:

$$\text{Resilience}_i = \beta_0+\beta_1\cdot\text{InDegree}_i^W+\beta_2\cdot\text{InWeight}_i^W+\beta_3\cdot\text{OutDegree}_i^W+\beta_4\cdot\text{OutWeight}_i^W+\beta_5\cdot\text{OutDegree}_i^{US}+\beta_6\cdot\text{Out}$$

Column (1) of presents baseline results; all results use robust standard errors. Columns (2)-(5) add product economic activity characteristics, raw material attribute characteristics, and industry category characteristics as control variables. Appendix uses 2016 network structures as independent variables, with consistent results demonstrating analysis robustness.

Results show that global InDegree ($InDegree^W$) and global OutDegree ($OutDegree^W$) are significantly positively correlated, indicating that diversity of supplier and customer countries/regions effectively enhances resilience and reduces disruption risk. Higher InDegree enhances firm flexibility in responding to supply interruptions, while customer diversification reduces market fluctuation impacts. Global weighted OutDegree ($OutWeight^W$) and U.S. OutWeight variance ($OutWeightVar^{US}$) are significantly negatively correlated, showing that excessive dependence on international markets and customer concentration increase risk exposure and weaken resilience. U.S. market customer diversity ($OutDegree^{US}$) also significantly enhances resilience, demonstrating the importance of market diversification for resisting trade policy shocks.

InDegree^W: This variable shows significant positive correlation across all models, indicating that the number of suppliers in a supply chain enhances its resilience. Higher InDegree means connections with more suppliers, improving firm flexibility and risk resistance when facing external shocks. This positive correlation can be understood from several perspectives. **Diversity and Redundancy**: When firms source raw materials or products from multiple suppliers, supply chain diversity increases. This diversity serves as a “redundancy buffer” against supply disruptions, enabling more flexible procurement strategy adjustments. For example, when Supplier A in Country A cannot deliver, the industry can quickly shift to Supplier B in Country B, reducing production interruption risk. **Negotiation Advantage**: More international suppliers may strengthen a firm’ s negotiating position in the supply chain. Firms can reduce costs through competitive procurement and achieve more favorable terms across suppliers, optimizing cost structures during normal times while preserving negotiation space for external shocks. **Geographic Diversity and Risk Dispersion**: High InDegree firms establish connections with suppliers across different geographic regions, further enhancing supply chain resilience. When natural disasters or political instability occur in one region, firms can rely on suppliers in other regions to continue operations, preventing overall supply chain paralysis.

OutDegree^W and OutWeight^W: These show positive and negative correlations respectively, indicating that foreign customer diversity benefits supply chain resilience, but greater dependence on foreign markets also brings larger risk exposure. $OutDegree^W$ represents customers in more countries, meaning stronger market diversity that disperses market risk. Through multiple sales channels, firms can avoid over-reliance on single markets, reducing negative impacts from market fluctuations. For example, when demand declines in one region, firms can maintain sales through customers in other regions, preserving supply chain stability. $OutWeight^W$ represents larger international trade volumes, expanding firms’ international risk exposure and making them more vulnerable to international situation changes. Firms need to reasonably balance domestic circulation stability with international trade risks to improve supply chain resilience.

**OutDegree^{US}$: Diversified U.S. customer bases benefit resilience. The significant positive correlation of $OutDegree^{US}$ emphasizes the importance of diversified customers in the U.S. market. When firms in an industry have multiple U.S. customers, they can better cope with market fluctuations and more flexibly adjust sales strategies when facing trade friction or tariff policy changes.

**OutWeightVar^{US}$: This shows significant negative correlation across all models, indicating that OutWeight variance is inversely related to supply chain resilience. High OutWeight variance implies unbalanced weight distribution, likely meaning over-dependence on a few major customers, which increases customer concentration risk. Once these customers reduce orders or switch to competitors, firms' production and sales will be severely affected. This concentration risk may limit firms' adaptation capacity, making them slow to respond to market changes. To enhance supply chain resilience, firms may need to balance sales weights through diversification strategies, such as increasing the number of small customers or expanding business across multiple markets to reduce dependence on single large customers and improve supply chain robustness.

4.5 Discussion This study' s findings indicate that link diversity and weight distribution balance in supply chain network structures are two key determinants of supply chain resilience. Link diversity, manifested as broad distribution of suppliers and customers, helps enhance supply chain adaptation capacity and risk resistance. Balanced weight distribution reduces over-dependence on individual suppliers or customers, thereby preventing local risks from diffusing across the entire supply chain.

Regression results further validate the importance of diversified network structures in supply chain management. Connections with multiple international suppliers enable firms to quickly activate alternative options when supplier disruptions occur, effectively reducing operational interruption risks. Similarly, broad global customer bases enhance firms' ability to cope with market fluctuations. When demand fluctuates in one region, firms can rely on other markets to maintain overall business stability. This diversification strategy significantly improves firms' resistance to external shocks.

In contrast, weight distribution effects are more complex. Larger global trade volumes ($OutWeight^{W}$) expose firms to higher international risks, resulting in poorer resilience performance. Higher variance in U.S. market customer weight distribution ($OutWeightVar^{US}$) implies excessive customer concentration, weakening firms' market adaptability and risk resistance. Therefore, firms need to reduce dependence on single markets or customers through balanced weight distribution to enhance overall supply chain resilience performance.

The key to supply chain design lies in effectively balancing diversification and concentration. While diversification strategies can improve supply chain resilience, excessive diversification may increase management complexity and operational costs. Concentration may improve efficiency but can amplify systemic risks. Therefore, firms must dynamically optimize supply chain structures based on their characteristics and market environments to achieve appropriate balance between resilience and operational efficiency.

Based on this research, we propose the following recommendations to enhance supply chain resilience:

1. **Supplier and Customer Diversification Management**: Actively expand supplier and customer networks to reduce dependence on single entities. Expanding supply and market channels enhances firm flexibility

when facing shocks, reducing negative impacts from supply interruptions or market fluctuations.

2. **Weight Distribution Optimization**: Monitor and balance supplier and customer weight distributions to avoid over-dependence on key nodes. Through rational weight allocation, firms can effectively reduce local risk diffusion and enhance adaptation to external environmental changes.
3. **Dynamic Adjustment and Risk Management**: Regularly evaluate supply chain structures, identify critical nodes, weak links, and potential risks, and implement dynamic adjustments. Establish comprehensive emergency response mechanisms, such as backup supplier systems and logistics solutions; use data analysis tools to continuously monitor supply chain performance, promptly detect and correct anomalies; flexibly adjust inventory and production plans according to market demand to maintain supply chain agility and stability.

5. Conclusion

This paper proposes two nonparametric statistical indicators—Structural Change-Points (SCP) and Weighted Cumulative Loss (WCL)—constructing a comprehensive and dynamic supply chain resilience assessment framework to address limitations in existing measurement methods, including non-dynamic nature, probabilistic approaches, single-dimensionality, and excessive distributional assumptions.

The research first theoretically clarifies the definition of supply chain resilience, emphasizing supply chains' dynamic absorption, adaptation, and recovery capabilities after external shocks. It then designs and validates SCP and WCL indicators: the SCP indicator uses change-point detection technology to identify structural changes caused by external shocks in real time, effectively measuring supply chains' absorption and adaptation capacities; the WCL indicator introduces dynamic weighting functions to quantify cumulative performance losses following shocks, emphasizing the importance of early-stage losses.

The empirical study uses the 2018 U.S.-China trade war as a case study, employing China-U.S. customs and maritime shipping data for in-depth resilience analysis. Findings show that network structure diversity and customer concentration degree are key factors significantly affecting supply chain resilience. Supply chains with diversified network structures and dispersed customer markets demonstrate stronger shock resistance, with capital-intensive and technology-intensive products showing higher resilience, while highly standardized products are more vulnerable to policy fluctuations.

This study' s main contribution lies in providing a set of nonparametric dynamic indicators that overcome limitations of traditional supply chain resilience measurement methods, making resilience assessment more practically relevant and operational. Moreover, the broad applicability of the SCP and WCL indicator system enables them to provide clear empirical evidence for enterprises and policymakers to optimize supply chain management strategies and resource allocation, improving overall supply chain risk resistance and sustainable development capacity.

Future research can further explore the applicability of this indicator system under more external shock scenarios and expand investigations into supply chain resilience characteristics across different countries, industries, and firm sizes to continuously enrich and improve the theoretical framework and practical applications of supply chain resilience. Future studies could also extend this indicator system to enable resilience analysis at the supply node level rather than just the supply chain level with limited data, thereby more precisely locating resilience weaknesses.

References

[1] HONG L J, LI J, WU X, et al. Future research of supply chain resilience: Network perspectives and incorporation of more stakeholders[J]. Fundamental Research, 2025, 5(2):486-495.

[2] PONOMAROV S Y, HOLCOMB M C. Understanding the concept of supply chain resilience[J/OL]. The International Journal of Logistics Management, 2009, 20(1):124-143[2023-06-03]. DOI: 10/dbjkq2.

[3] LIU X, LI D, MA M, et al. Network resilience[J/OL]. Physics Reports, 2022, 971:1-108[2023-04-07]. DOI: 10/gr2pqk.

[4] MASSARI G F, GIANNOCCARO I. Investigating the effect of horizontal coopetition on supply chain resilience in complex and turbulent environments[J]. International Journal of Production Economics, 2021, 237:108150.

[5] KHANNA G, MORALES N, Pandalai-Nayar N. Working Paper Series: number 30689 supply Chain Resilience: Evidence from Indian Firms[M/OL]. National Bureau of Economic Research, 2022[2023-04-23]. DOI: 10.3386/w30689.

[6] BONANNO G A, MOSKOWITZ J T, PAPA A, et al. Resilience to Loss in Bereaved Spouses, Bereaved Parents, and Bereaved Gay Men[J/OL]. Journal of Personality and Social Psychology, 2005, 88:827-843. DOI: 10/dqzz5v.

[7] BONANNO G A, GALEA S, BUCCIARELLI A, et al. What predicts psychological resilience after disaster? The role of demographics, resources, and life stress[J/OL]. Journal of Consulting and Clinical Psychology, 2007, 75:671-682. DOI: 10/czvzdw.

[8] HARTVIGSEN G, KINZIG A, PETERSON G. Use and analysis of complex adaptive systems in ecosystem science: Overview of special section[J/OL]. Ecosystems, 1998, 1(5):427-430[2023-06-03]. DOI: 10/bz3w37.

[9] ROSE A. Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions[J/OL]. Environmental Hazards, 2007, 7(4):383-398[2023-06-03]. DOI: 10/dx5qtn.

[10] HOLLNAGEL E. Achieving system safety by resilience engineering[J/OL]. 2006:184-195[2023-06-03]. DOI: 10/cbqm2s.

[11] CHRISTOPHER M, PECK H. Building the Resilient Supply Chain[J/OL]. The International Journal of Logistics Management, 2004, 15(2):1-14[2023-06-03]. DOI: 10/bjxm87.

[12] IVANOV D, SOKOLOV B. Control and system-theoretic identification of the supply chain dynamics domain for planning, analysis and adaptation of performance under uncertainty[J/OL]. European Journal of Operational Research, 2013, 224(2):313-323[2023-06-03]. DOI: 10/gdm65q.

[13] HOSSEINI S, IVANOV D. A New Resilience Measure for Supply Networks With the Ripple Effect Considerations: A Bayesian Network Approach[J]. Annals of Operation Research, 2019.

[14] WARREN D, Eric Vugrin, BIRINGER B. Critical Infrastructure System Security and Resiliency[M/OL]. Boca Raton: CRC Press, 2013. DOI: 10.1201/b1.

[15] ZOBEL C W, KHANSA L. Characterizing multi-event disaster resilience[J/OL]. Computers & Operations Research, 2014, 42:83-94[2023-06-03]. DOI: 10/bdxqbm.

[16] LÜCKER F, SEIFERT R W, BIÇER I. Roles of inventory and reserve capacity in mitigating supply chain disruption risk[J/OL]. International Journal of Production Research, 2019, 57(4):1238-1249[2023-06-03]. DOI: 10/gjfxcz.

[17] WIELAND A, WALLENBURG C M. The Influence of Relational Competencies on Supply Chain Resilience: A Relational View[J/OL]. International Journal of Physical Distribution & Logistics Management, 2013, 43(4):300-320[2023-06-03]. DOI: 10/ghvz34.

[18] DUBEY R, ALTAY N, GUNASEKARAN A, et al. Supply chain agility, adaptability and alignment: Empirical evidence from the Indian auto components industry[J/OL]. International Journal of Operations and Production Management, 2018, 38(1):129-148[2023-06-03]. DOI: 10/gjm49j.

[19] CHRISTOPHER M, LEE H. Mitigating supply chain risk through improved confidence[J/OL]. International Journal of Physical Distribution & Logistics Management, 2004, 34(5):388-396[2023-06-03]. DOI: 10/c8k7mc.

[20] IVANOV D. An adaptive framework for aligning (re)planning decisions on supply chain strategy, design, tactics, and operations[J/OL]. International Journal of Production Research, 2010, 48(13):3999-4017[2023-06-03]. DOI: 10/b2msn4.

[21] LONGO F, ÖREN T. Supply chain vulnerability and resilience: A state of the art overview[J]. 20th European Modeling and Simulation Symposium,

EMSS 2008, 2008:527-533.

[22] KAMALAHMADI M, PARAST M M. A review of the literature on the principles of enterprise and supply chain resilience: Major findings and directions for future research[J/OL]. International Journal of Production Economics, 2016, 171:116-133[2023-06-03]. DOI: 10/f76nc9.

[23] GOVINDAN K, JAFARIAN A, AZBARI M E, et al. Optimal Bi-Objective Redundancy Allocation for Systems Reliability and Risk Management[J/OL]. IEEE transactions on cybernetics, 2016, 46(8):1735-1748. DOI: 10/f8v5qk.

[24] ROSS G J. Parametric and Nonparametric Sequential Change Detection in R : The cpm Package[J/OL]. Journal of Statistical Software, 2015, 66(3)[2023-06-03]. DOI: 10/gr964m.

[25] HAWKINS D M, QIU P, KANG C W. The Changepoint Model for Statistical Process Control[J/OL]. Journal of Quality Technology, 2003, 35(4):355-366[2023-04-07]. DOI: 10/ghm23w.

[26] ZHAO K, KUMAR A, HARRISON T P, et al. Analyzing the resilience of complex supply network topologies against random and targeted disruptions[J]. IEEE Systems Journal, 2011, 5(1):28-39.

[27] SIMCHI-LEVI D, SCHMIDT W, WEI Y. From superstorms to factory fires[J]. Harvard business review, 2014, 92(1):24.

[28] SIMCHI-LEVI D, SCHMIDT W, WEI Y, et al. Identifying risks and mitigating disruptions in the automotive supply chain[J]. Interfaces, 2015, 45(5):
[29] BIRGE J R, CAPPONI A, CHEN P C. Disruption and rerouting in supply chain networks[J]. Operations Research, 2023, 71(2):750-767.

[30] JORDAN W C, GRAVES S C. Principles on the benefits of manufacturing process flexibility[J]. Management science, 1995, 41(4):577-594.

[31] WANG S, WANG X, ZHANG J. A review of flexible processes and operations[J]. Production and Operations Management, 2021, 30(6):1804-1824.

[32] MÜLLER J, HOBERG K, FRANSOO J C. Realizing supply chain agility under time pressure: Ad hoc supply chains during the covid-19 pandemic[J]. Journal of Operations Management, 2023, 69(3):426-449.

[33] NAN C, SANSAVINI G. A quantitative method for assessing resilience of interdependent infrastructures[J]. Reliability Engineering & System Safety, 2017, 157:35-53.

[34] FRANCIS R, BEKERA B. A metric and frameworks for resilience analysis of engineered and infrastructure systems[J]. Reliability engineering & system safety, 2014, 121:90-104.

[Figure 1: see original paper] Supply chain three-stage response diagram after shock

[**Figure 2: see original paper**] Resilience comparison diagram
[**Figure 3: see original paper**] Structural change and change-point schematic
[**Figure 4: see original paper**] Weighted Cumulative Loss WCL schematic
[**Figure 5: see original paper**] Product supply network schematic
[**Figure 6: see original paper**] SCP% during trade war and pandemic
[**Figure 7: see original paper**] SCP% for different tariff batch products
[**Figure 8: see original paper**] WCL under BEC product classification
[**Figure 9: see original paper**] SCP% under BEC product classification
[**Figure 10: see original paper**] WCL under HS product classification
[**Figure 11: see original paper**] SCP% under HS product classification
[**Figure 12: see original paper**] WCL under NAICS product classification
[**Figure 13: see original paper**] SCP% under NAICS product classification

**** Descriptive statistics summary
**** Regression results summary
**** Robustness test regression results summary

Note: Figure translations are in progress. See original paper for figures.