Asia Pacific Academy of Science Pte. Ltd.

Mathematics and Systems Science 2025, 3(1), 3033.
https://doi.org/10.54517/mss3033

Article

Supply chain resilience in the semiconductor manufacturing industry: A dynamic simulation Bayesian network analysis of Taiwan semiconductor manufacturing Co

Brandon Leeroy Glass, Hongzhuan Chen*, Yule Ren*

College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China
*** Corresponding authors:** Hongzhuan Chen, chz-hhu@163.com; Yule Ren, 1911708249@qq.com

CITATION

Glass BL, Chen H, Ren Y. Supply chain resilience in the semiconductor manufacturing industry: A dynamic simulation Bayesian network analysis of Taiwan semiconductor manufacturing Co. Mathematics and Systems Science. 2025; 3(1): 3033. https://doi.org/10.54517/mss3033

ARTICLE INFO

Received: 1 November 2024
Accepted: 16 January 2025
Available online: 13 February 2025

Abstract: This paper examines the supply chain resilience of Taiwan Semiconductor Manufacturing Co. (TSMC) using a Bayesian network (BN) model developed from the Supply Chain Operations Reference (SCOR) framework. This hybrid model allows for an integrated analysis of various key performance indicators (KPIs) across TSMC's supply chain, providing a comprehensive view of its resilience. By simulating multiple disruption scenarios, the study captures the dynamic interactions and cascading effects of disruptions, such as inventory shortages, transportation delays, and labor cost fluctuations. This approach offers a quantitative analysis of TSMC's resilience under varied scenarios, revealing critical strengths, such as flexibility in resource allocation, as well as vulnerabilities, particularly in response to high-impact events like geopolitical tensions and natural disasters. Insights from this model highlight the areas where strategic improvements can further strengthen resilience. Overall, the research demonstrates the applicability of Bayesian networks as a powerful tool for resilience assessment, not only in TSMC's context but also as a scalable solution for other high-complexity, high-dependency supply chains within the semiconductor industry. This study contributes valuable knowledge to the broader field of supply chain resilience and advances the methodologies available for industry practitioners and researchers alike.

Keywords: Bayesian network; supply chain resilience; SCOR framework; key performance indicators; semiconductor manufacturing industry

1. Introduction

The semiconductor manufacturing industry has faced significant disruptions in recent years, ranging from global supply chain (SC) bottlenecks due to the COVID-19 pandemic to geopolitical tensions affecting key supply routes. These challenges have highlighted the vulnerability of even the most advanced supply chains, as evidenced by the widespread chip shortages that impacted various industries worldwide. The ripple effects of these disruptions have underscored the critical need for robust supply chain resilience strategies. The semiconductor manufacturing industry is a critical pillar of the global economy, underpinning innovations in technology, telecommunications, and automotive sectors, among others. Central to this industry is Taiwan Semiconductor Manufacturing Company (TSMC), the world's largest dedicated semiconductor foundry. TSMC plays a pivotal role in supplying high-performance chips to global tech giants. However, the semiconductor supply chain is highly complex, spanning multiple stages of design, production, and distribution, and is vulnerable to disruptions from geopolitical tensions, natural disasters, and market volatility. Supply chain resilience, defined as the capacity to absorb, recover from, and adapt to disruptions, has emerged as a key strategic priority for firms like TSMC [1]. Recent research highlights the importance of dynamic simulations and predictive modeling, such as Bayesian Networks (BNs), to evaluate and strengthen supply chain resilience in volatile environments [2]. By applying these methods, organizations can mitigate risks and ensure business continuity in the face of unforeseen challenges.

The main contributions of this paper are as follows:

1) Development of a hybrid Bayesian network model: A hybrid BN model is constructed, based on the SCOR (Supply Chain Operations Reference) concept, to simulate and analyze the resilience of TSMC's supply chain. The model captures the complex interdependencies among suppliers, manufacturers, and distributors across multiple tiers, combining SCOR's process-oriented approach with probabilistic analysis.
2) Dynamic time-series analysis integration: The model integrates dynamic time-series analysis to simulate and evaluate how various disruptions propagate through the supply chain over time.
3) Scenario analysis and quantitative insights: Scenario analysis is employed to simulate disruptions and assess their impacts on TSMC's supply chain. The analysis provides quantitative insights into the system's vulnerabilities and strengths, offering actionable recommendations to enhance overall supply chain resilience.

Including the current section, the paper structure contains a total of 6 sections. A brief literature review makes up section 2, while in section 3 the basic theories of the proposed methodology are discussed, i.e., Bayesian networks and SCOR. The construction of the dynamic model is covered in the next section, detailing the merging of the two concepts in building the model as well as incorporating the dynamic effect into the supply chain model. Section 5 outlines the comprehensive quantitative analysis of the simulations before the paper then concludes with the key findings and limitations faced during the study.

2. Materials and methods

Dubey et al. [3] carried out an extensive study of the literature on managing supply chain risks globally. They looked at different approaches to risk management and emphasized that in order to improve supply chain resilience, firms must proactively identify, evaluate, and reduce risks. A workable supply chain model that incorporates resilience, agility, and sustainability viewpoints was put forth by Ivanov [4]. His study highlighted the value of creative technology and flexible approaches in creating robust supply chains that can function in changing and unpredictable conditions. Ivanov and Dolgui [1] analyze the weaknesses made apparent by the recent pandemic and suggest methods to strengthen resilience, such as supplier diversification, digitization, and cooperation amongst supply chain participants. Another study, Chhimwal et al. [5] employed a BN approach to investigate how risk propagation occurs in a circular supply chain network of an automobile business. The concept of adopting circularity in the supply chain is unique and dynamic in nature, and it carries certain risks. Jeff et al. [6] touch on the development of non-probabilistic resilience measures that can take dynamics into account, the extension of current bottleneck detection techniques to the network environment, and the more complex balancing of efficiency and resilience as examples of interesting research paths. Liu et al. [7] used a robust dynamic BN model with a bounded deviation budget for disruption risk evaluation because dynamic Bayesian networks, when combined with probability intervals, are a valid tool to estimate the risk of disruptions propagating along the supply chain (SC) under data scarcity. Recent studies are seeing BNs combined with other techniques, such as the Monte Carlo simulation, in which the integrated techniques would enable Qazi et al. [8] to capture the Risk Network Value at Risk (RNVaR). Jamil and Asrol [9] used the analytical hierarchy process (AHP) on the SCOR-associated metrics of assets, cost, reliability, responsiveness, and agility, enabling the study of the supply chain performance of the palm oil industry in Indonesia.

Propagation in Bayesian networks is generally conducted through forward, backward, and mixed (bidirectional) mechanisms, which allow evidence to spread through both direct and indirect dependencies. The study by Liu et al. [10] emphasizes how minimal strong triangulation supports propagation computation, especially in mixed BNs with both discrete and continuous variables. This approach ensures that the network remains computationally efficient while accurately representing dependencies through triangulated junction trees, which are instrumental in managing propagation across complex BNs. Another approach to enable efficient propagation in BNs is max-product belief propagation. Dedieu et al. [11] introduce max-product belief propagation as an alternative to variational inference, particularly for noisy-OR BNs. By adopting parallelized computations, max-product algorithms scale well with large datasets, providing faster and more accurate propagation outcomes compared to traditional variational inference methods. Propagation is highly relevant in real-world applications such as risk analysis in supply chains. For example, Bugert and Lasch [12] explore propagation in supply networks using BNs to assess both upstream and downstream risk flows. This study combines Bayesian networks with agent-based modeling, allowing the simulation of dynamic interactions within supply chains and addressing propagation's bidirectional effects. Their work provides quantitative insights into how disruptions can cascade through network layers, influencing both direct and indirect risk factors. Constantinou [13] further discusses how full propagation of evidence can be achieved in BNs, with an emphasis on structure learning algorithms that maintain network connectivity under constraints. By adopting a hybrid learning algorithm, BNs can maximize evidence propagation, facilitating robust inference and enabling applications across domains where evidence consistency is critical. Bayesian networks' propagation mechanisms are also applied in the robustness certification of Bayesian neural networks (BNNs). Adams et al. [14] present BNN-DP, a dynamic programming approach designed to ensure BNN robustness through bound propagation techniques. By interpreting BNNs as dynamic systems, this framework supports rigorous evaluation of risk propagation bounds, which is vital in scenarios where adversarial attacks could alter inference outcomes.

The reviewed literature emphasizes the significance of probabilistic models, particularly Bayesian networks, in supply chain resilience analysis due to their ability to capture both static and dynamic disruptions. Prior studies have demonstrated the effectiveness of BNs for modeling uncertainty and risk propagation across complex systems. However, a noticeable gap persists in the integration of dynamic simulation techniques with standardized supply chain performance metrics such as the SCOR framework. To address this limitation, this study develops a hybrid BN model grounded in the SCOR framework. This model introduces dynamic time-series analysis, enabling a more detailed examination of how supply chain disruptions evolve over time and impact key performance indicators. Limited studies have explored the combination of SCOR with dynamic BNs for supply chain resilience analysis. This allows not only the assessment of disruptions but also tracking their temporal progression and cascading effects. The main innovation lies in this combination of SCOR and BNs. This approach offers both theoretical advancements and practical tools for resilience assessment in complex supply chains, as demonstrated through the case of Taiwan Semiconductor Manufacturing Company (TSMC).

3. Theory and methodology

3.1. Bayesian networks

Using a directed acyclic graph (DAG), Bayesian networks are graphical models that display a set of potential variables along with their conditional dependencies. Variables are represented by nodes in the network. These variables may be unidentified parameters, concealed variables, or observable quantities. Dependencies are shown by the edges between the nodes in the network. Every node has a probability function that is made up of conditional probabilities relating to various combinations of parent nodes or initial probabilities for root nodes (nodes without parents), well described by Jensen and Nielsen [15]. As Neapolitan [16] highlighted, BNs facilitate decision-making under uncertainty by representing and quantifying probabilistic relationships within a system [16]. Bayes' theorem describes how the dependent variables relate to one another. The hypothesis of the Bayes theorem is given an estimated number following observations, based on probabilistic knowledge of the hypothesis prior to any observations. Bayes theory is expressed as seen in Equation (1):

$$P(H|E) = \frac{P(E|H) \cdot P(H)}{P(E)}, P(E) \neq 0 \tag{1}$$

For data E and variable H, $P(H|E)$ is the posterior probability of H in light of the observed data E, $P(H|E)$ is the likelihood function of the probability of new data E given H, $P(H)$ is the prior (unconditional) probability distribution of parameter H, and $P(E)$ is marginal likelihood (evidence). With the use of Bayes' rule and in light of the data, we are able to update our beliefs about the variable H to a posterior belief. BNs can be used for representing the impact of evidence on existing data through probabilistic expressions describing the causal relationship among variables, as seen in an extension by Murphy [17].

3.2. Supply chain operations reference

The Supply Chain Operations Reference (SCOR) model is a globally recognized framework that provides a standardized methodology for evaluating and improving supply chain performance. Developed by the Supply Chain Council, SCOR serves as a comprehensive tool to map, measure, and optimize supply chain processes. It categorizes the supply chain into five primary processes: Plan, Source, Make, Deliver, and Return. These processes encompass the entire flow of goods and services, from the procurement of raw materials to the final delivery of products to the customer. At the first level of the Supply Chain Operations Reference model, companies define fundamental strategic objectives for their operational areas, setting the overall scope and framework for their supply chain. At this level, competitive performance targets are established while considering the five primary processes as shown in **Figure 1**.

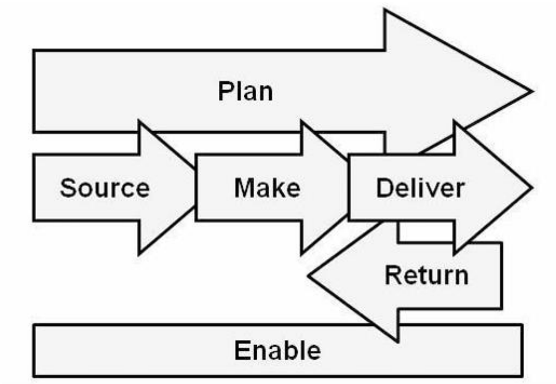


Figure 1. SCOR performance targets.

SCOR offers a common language for organizations to assess their supply chains and identify areas for improvement, allowing for better alignment of operational strategies with business goals. The model is designed to help companies streamline their processes, reduce costs, enhance customer satisfaction, and adapt to changing market conditions. One of its strengths is its versatility. It can be applied to different industries and across various sectors of the supply chain, making it an essential tool for both manufacturers and service providers. SCOR breaks down supply chain performance into measurable components, known as performance attributes, which are critical to achieving operational excellence. These five key attributes are: Asset management efficiency, cost, agility, responsiveness, and reliability. These attributes help organizations focus on the most important aspects of their supply chain performance and provide a structured way to assess how well they are managing resources, meeting customer needs, controlling costs, and adapting to disruptions or changes in demand. The model is classified into 3 levels, one to three, respectively, with each level defined by its own metrics, as can be seen in **Figure 2**. The first level (highest level), defined by m0 metrics, evaluates the performance of the organization as a whole and represents the overall effectiveness of its supply chain. These metrics are known as the internal-facing metrics. The m2 metrics assess the performance of individual Level 2 processes within the supply chain, such as the source, make, and deliver processes. Lastly, m3 metrics evaluate specific activities or sub-processes within a Level 2 process, providing a detailed view of individual components within each major process.

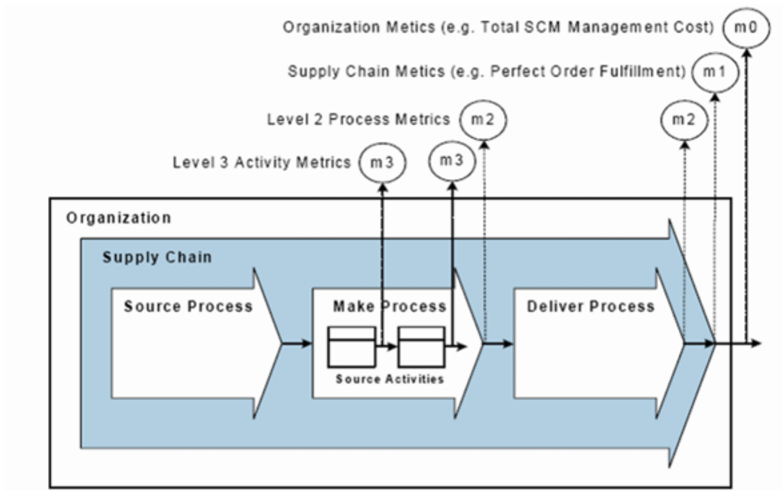


Figure 2. SCOR performance attributes.

In total, SCOR includes over 250 distinct metrics, each of which can be traced back to one of these five primary attributes, providing companies with detailed insights into their supply chain operations and enabling them to track and improve performance at a high level. In the following sections, the methodology approach will see these two theories and concepts merged to build a model that represents the research objectives. This approach leverages Bayesian inference, updating probabilities across the network as new evidence is introduced, thus providing a dynamic tool for simulating and analyzing potential outcomes. The insights gained offer valuable decision support for risk mitigation and identifying areas of vulnerability or strength within the supply chain, contributing to a deeper understanding of its adaptive capacity in the face of uncertainties. [18].

4. Proposed BN-SCOR hybrid model

4.1. Problem description

The semiconductor industry, particularly the supply chain of Taiwan Semiconductor Manufacturing Company (TSMC), is a highly complex, interdependent system where disruptions can propagate through multiple tiers of suppliers, manufacturers, and distributors. These disruptions, whether natural or man-made, introduce significant risks to the stability of the system. The challenge lies in understanding how disruptions propagate structurally and temporally through the supply chain and in quantifying the likelihood of these cascading failures. In this research, the interdependencies within TSMC's supply chain are modeled using a hybrid BN, where each node X_i represents a supply chain entity, and the directed edges represent conditional dependencies between these nodes. The probabilistic relationships are defined as:

$$P\big(X_i \big| \text{Parents}(X_i)\big) = P(X_i | X_1, X_2, \dots, X_n) \tag{2}$$

where $P\big(X_i \big| \text{Parents}(X_i)\big)$ denotes the conditional probability of node X_i being affected, given the state of its parent nodes $X_1, X_2, \dots, X_n$. This enables the calculation of the joint probability distribution over the entire network:

$$P(X_1, X_2, \dots, Xn) = \prod_{i=1}^{n} P(X_i|\text{Parents}(X_i)) \tag{3}$$

This formulation allows us to model how disruptions propagate through the system, capturing both direct and indirect effects across multiple tiers of the supply chain. Additionally, the time aspect is incorporated using dynamic time-series analysis, where disruptions evolve over time. The state of each node at time t, $X_i(t)$, is dependent not only on its current conditions but also on its previous states:

$$X_i(t) = f(X_i(t-1), \epsilon_t) \tag{4}$$

where ε_t represents a stochastic term accounting for random fluctuations or unforeseen events. This dynamic relationship allows for the modeling of disruption propagation across both time and space, providing insights into how quickly and to what extent disruptions spread through the network. By integrating these probabilistic and temporal components, the research quantifies both the structural and temporal resilience of TSMC's supply chain.

4.2. Simulation model

When combined with BNs, the SCOR model enhances the ability to simulate various operational scenarios and their impacts on supply chain resilience, enabling a more robust evaluation of potential risks and the development of strategies to mitigate them. The SCOR model acts as the foundational structure of the BN, providing a comprehensive framework to model the complexities of the supply chain. It allows for a standardized approach to evaluating performance across various dimensions of supply chain management. By breaking the supply chain into key attributes, SCOR offers a holistic view of the operational processes that affect both upstream and downstream activities. In the established model, the SCOR elements serve as the central or "middle" nodes in the network because they bridge the gap between the key performance indicators (KPIs) at the top level and the overall resilience at the base. These nodes are essentially the "body" of the network, ensuring that every action or event in the supply chain is captured, processed, and reflected in the overall resilience of the network. The BN allows for probabilistic reasoning of all the metrics necessary to achieve the desired objectives.

In this BN, the resilience of TSMC's semiconductor supply chain is conceptualized through the integration of three key capacities. Absorptive, adaptive, and restorative, each influencing the overall resilience of the system. These capacities are represented by parent nodes that encapsulate the supply chain's ability to absorb, adapt, and recover from various disruptions. Each capacity functions in binary states, i.e., True (positive outcome) or False (negative outcome), to denote whether TSMC's supply chain is effectively managing disruptions or failing to do so. Key performance indicators (KPIs), such as inventory cost, labor cost, and lead time shortness, serve as critical inputs to these capacities. Each KPI is categorized into three states: low, medium, and high, to quantify the performance levels and their impact on the supply chain's resilience. The three capacities are modeled to interconnect and influence overall resilience, with the understanding that under normal or disrupted conditions, the states of these KPIs directly inform the supply chain's ability to either continue operations smoothly or to recover post-disruption.

The absorptive capacity refers to the ability of TSMC's supply chain to withstand disruptions without significant degradation in performance. It is primarily determined by asset management efficiency and total cost, both of which are influenced by KPIs like inventory days, warranty cost, and cash cycle time. The more efficiently TSMC manages its assets and keeps costs low, the higher the absorptive capacity will be, and the system is more likely to remain in a positive state (True) despite external disruptions. Absorptive capacity, as discussed by Sheffi [19], plays a foundational role in building a resilient supply chain that can maintain steady-state operations even under stress.

The adaptive capacity of the network represents TSMC's ability to adjust or respond to unexpected changes, which is crucial in maintaining operational fluidity in the face of volatile supply and demand conditions. Adaptive capacity is informed by flexibility, responsiveness, and delivery reliability, which are derived from KPIs such as processing speed, order completeness, and filling order accuracy. Notably, while delivery reliability could be associated with both adaptive and restorative capacities, it is modeled as part of the adaptive capacity in this network because of its direct influence on TSMC's ability to adjust and respond in real time to disruptions. This decision aligns with Ponomarov and Holcomb's framework [20], which emphasizes the necessity for flexibility and quick response as part of adaptive resilience.

The restorative capacity, which measures TSMC's ability to recover from disruptions and return to normal operations, is defined by the parameters of recovery time and cost, resource reallocation, and backup suppliers. These elements are, in turn, influenced by KPIs such as labor cost, unplanned ability, and quick ship ability, which determine how quickly and effectively TSMC can reallocate resources or rely on alternative suppliers to restore lost capacity. In this network, restorative capacity focuses on post-disruption recovery, ensuring that lost production or capacity is mitigated through effective recovery strategies. Together, these three feed into the overarching node of resilience, representing TSMC's ability to withstand, adapt to, and recover from disruptions.

The network acknowledges that while some KPIs may be relevant to multiple capacities, their placement has been optimized for best fit. For instance, delivery reliability, which impacts both adaptive and restorative functions, is placed under adaptive capacity due to its stronger alignment with real-time adjustments in production and delivery schedules. This alignment allows for a clearer interpretation of the supply chain's resilience in specific contexts. The integration of KPIs from the SCOR model into this Bayesian framework strengthens the network's applicability in analyzing and quantifying resilience within a manufacturing context. The SCOR model is widely recognized for linking operational activities with supply chain performance, making it an ideal foundation for modeling resilience. By doing so the network holistically captures the multi-dimensional nature of resilience within TSMC's supply chain, providing a structured approach to understanding how the system absorbs shocks, adapts to changing conditions, and restores lost capacity following disruptions.

Table 1. Influence between nodes.

Parent	**Child**	**Weighted**	**Maximum**
Inventory days	Asset management efficiency	0.3520	0.6062
Cash cycle time	Asset management efficiency	0.2620	0.5220
Asset management efficiency	Absorptive capacity	0.2778	0.5
Quick ship ability	Backup suppliers	0.2556	0.5
Total cost	Absorptive capacity	0.2333	0.5
Processing speed	Responsiveness	0.2834	0.4583
Restorative capacity	Resilience	0.3750	0.45
Unplanned ability	Resource reallocation	0.2556	0.45
Lead time	Recovery time & cost	0.2667	0.45
Flexibility	Adaptive capacity	0.2363	0.4
Absorptive capacity	Resilience	0.3250	0.4
Providing specific needs	Restorative capacity	0.3	0.4
Resource reallocation	Backup suppliers	0.2333	0.4
Responsiveness	Adaptive capacity	0.2104	0.4
Delivery reliability	Restorative capacity	0.25	0.35
Inventory cost	Resource reallocation	0.2111	0.35
Labor cost	Adaptive capacity	0.1993	0.35
Labor cost	Total cost	0.1557	0.35
Recovery time & cost	Total cost	0.1557	0.35
Transportation cost	Total cost	0.1494	0.35
Warranty cost	Total cost	0.1405	0.35
Cash cycle time	Recovery time & cost	0.2111	0.35
Order completeness	Delivery reliability	0.1337	0.35
Backup suppliers	Restorative capacity	0.2	0.3
Adaptive capacity	Resilience	0.175	0.3
Filling order accuracy	Delivery reliability	0.1406	0.2784
Order consistency	Delivery reliability	0.1318	0.2784
Lead time	Responsiveness	0.1234	0.2646
Providing specific needs	Flexibility	0.1333	0.2
Quick ship ability	Flexibility	0.1333	0.2
Unplanned ability	Flexibility	0.1333	0.2

In the BN model, the strength of influence between nodes is depicted by the arcs connecting them, with Euclidean distance and arc weights serving as key measures to quantify these relationships. Euclidean distance, in this context, reflects the degree of similarity or dissimilarity between the probability distributions of connected nodes, capturing how closely their outcomes align. Arc weights further quantify the magnitude of these influences, with higher weights indicating a stronger causal effect from parent to child nodes. In this model, these weights were determined automatically by the GeNIe software based on the input conditional probabilities, which encode the conditional dependencies between variables. The visual representation of the model uses arc thickness to illustrate the strength of influence, where thicker arcs signify stronger dependencies, indicating that variations in the parent node exert a more substantial impact on the child node's probabilistic outcomes. This approach integrates both Euclidean distance and weight to offer a detailed representation of the interdependencies within the supply chain system. The described network can be seen in **Figure 3**. The influence between the nodes can also be seen in **Table 1**.

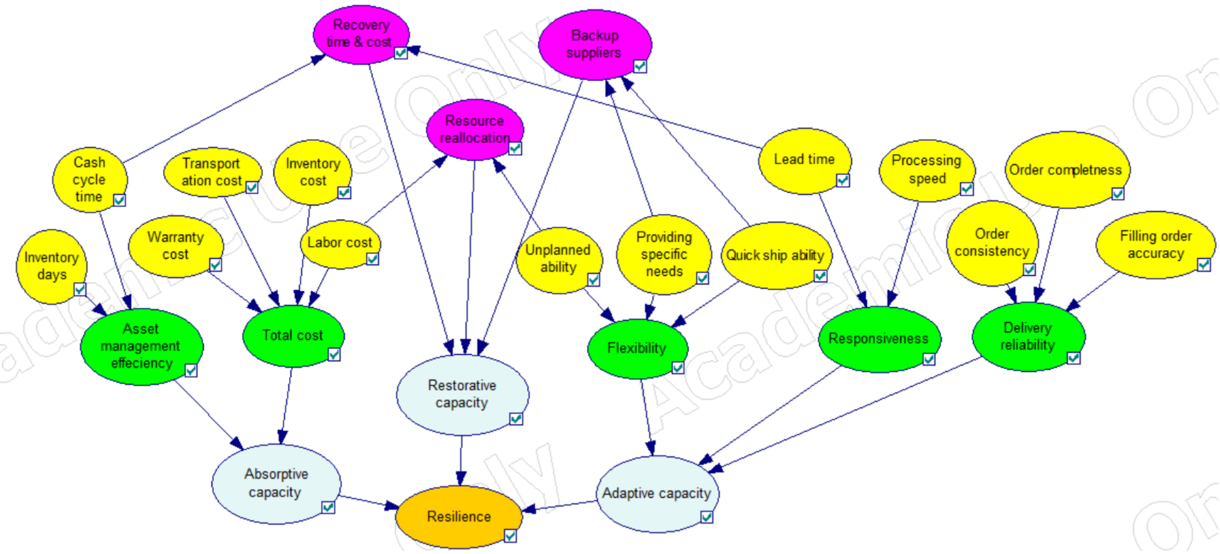


Figure 3. TSMC SCOR-BN resilience model.

To identify the most critical KPIs for evaluating supply chain resilience, the study began with a comprehensive literature review to explore widely used metrics associated with the SCOR model's attributes. This review identified over 250 potential KPIs commonly utilized to monitor supply chain performance and resilience. From this extensive list, an initial set of 30 KPIs was developed, encompassing the five SCOR attributes: Reliability, Responsiveness, Agility, Cost, and Asset Management. A structured survey was then distributed to 87 supply chain experts, who evaluated each KPI based on three criteria: relevance, impact, and feasibility, using a 1–5 Likert scale. In addition to scoring the KPIs, respondents selected their top five metrics and provided qualitative feedback to offer further insights. After collecting responses, a data-cleaning process was conducted to ensure validity and consistency, resulting in the exclusion of five incomplete or inconsistent submissions. A total of 82 valid responses were analyzed. The quantitative analysis involved calculating weighted scores for each KPI, with relevance given a 50% weight, impact 30%, and feasibility 20%. This provided an objective basis for ranking the KPIs, while the frequency of top five selections highlighted consensus among respondents. The qualitative feedback was also analyzed to support the quantitative findings and to justify the exclusion of less impactful metrics.

The combined analysis of weighted scores, top five frequency selections, and qualitative feedback led to the final selection of 14 KPIs. These metrics were chosen for their consistent performance across all evaluation criteria and their alignment with the SCOR attributes. Metrics related to financial efficiency, such as inventory days and cash cycle time, emerged as critical, alongside delivery reliability and lead time shortness, which reflected the importance of ensuring consistent and timely operations. Agility metrics, such as quick ship ability and providing specific needs, stood out for their relevance in dynamic supply chain environments. Cost-related metrics, including labor cost and warranty cost, underscored the significance of financial resilience in planning. The weighted scores of these 14 KPIs were visualized in a bar chart in **Figure 4**, providing a clear representation of their relative importance.

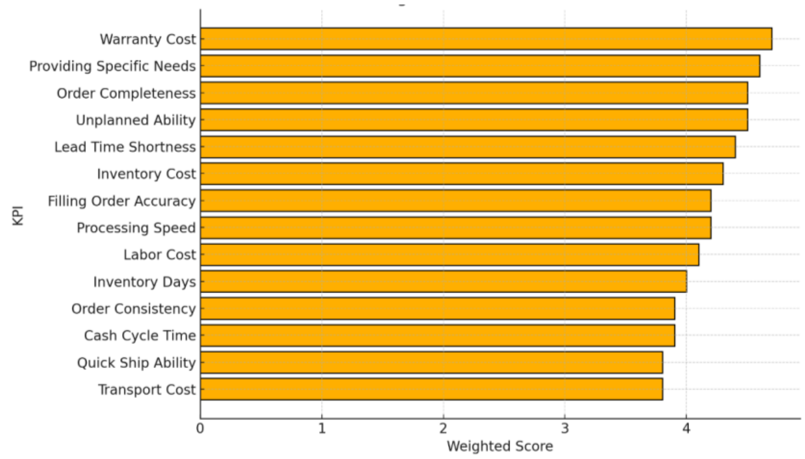


Figure 4. Weighted scores for selected KPIs.

Subsequently, upon reaching out to a few experts, their feedback process pushed the list to the 17 KPIs, with the addition of supplementary KPIs namely, recovery time and cost, backup suppliers and resource reallocation. These were seen as crucial to further enhance the model as one capable of yielding reasonable results. This final selection offers a focused, yet comprehensive set of metrics tailored to TSMC's unique needs and the complexities of semiconductor manufacturing. It is important to note that specific data related to each KPI was obtained by analyzing open-source industry data. Given TSMC accounts for well over 80% of global chips, this approach is justified as reasonable for this study.

The entire network is placed in the temporal plate of GeNIe's dynamic simulation interface because every node can be seen as a parameter or variable that changes with time. The time step is set to 12, representing a 12-month period that will see numerous disruptions introduced in order to understand how the resilience responds with time. In dynamic simulation, time steps simply represent the number of iterations being considered. However, the network being in the temporal plate was not enough to capture the dynamic element of a real-life supply chain. In a dynamic system such as a supply chain, resilience is not static; it evolves as a function of past states and external conditions. The temporal arc of order 1 signifies that the state of resilience at any given time step (e.g., month t) depends on its state in the previous time step (e.g., month $t-1$). This reflects how historical performance, disruptions, and recovery efforts influence future resilience levels, which is critical in capturing real-life dynamics of supply chain operations. Therefore, the resilience node was modeled to have a temporal arc to itself of order 1, as per **Figure 5**.

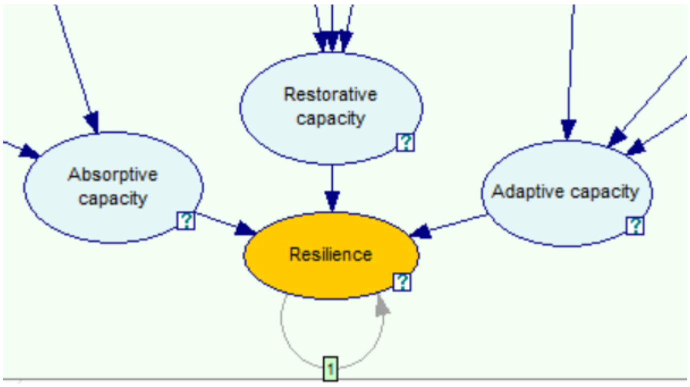


Figure 5. Order 1 feedback modelling.

In dynamic BNs, temporal feedback is crucial for capturing time-evolving dependencies. The feedback loop of order 1 is designed to represent the fact that the current state of supply chain resilience is influenced by its prior state in the previous time step (e.g., previous month). the temporal arc from supply chain resilience back to itself models this. Mathematically, this can be represented by a Markov process, where the state at time t, $S(t)$, is conditioned by the state at $t-1$, $S(t-1)$. The recursive dependency can be expressed as:

$$P(S(t)|S(t-1),\boldsymbol{X}(t))P(S(t)|S(t-1),\boldsymbol{X}_{\text{internal}}(t),\boldsymbol{X}_{\text{external}}(t)) \tag{5}$$

where $S(t)$ is the supply chain resilience at time t, $\boldsymbol{X}_{\text{internal}}(t)$ refers to internal-facing factors and $\boldsymbol{X}_{\text{external}}(t)$ refers to customer-facing factors. The Markov property assumption simplifies the model by limiting the influence to only the previous time step (first-order). This temporal feedback structure enables the resilience level from the previous period to carry forward into the next period. It helps in modeling path-dependent outcomes, which is crucial for real-world systems where conditions accumulate over time.

5. Simulation, analysis and discussion

5.1. Analyzing the static network resilience

5.1.1. Causal reasoning

In reference to **Figure 6**, the absorptive capacity, as previously discussed, is largely determined by the firm's ability to efficiently manage its assets and costs. Asset management efficiency represents how well TSMC is able to manage its supply chain resources, including inventory and working capital, and is directly impacted by KPIs such as cash cycle time and inventory days. These two factors are further governed by KPIs like cash cycle time, inventory days, and transportation cost. A high probability of cash cycle time in a low state suggests that TSMC is efficient in managing its cash flow, converting resources into revenue quickly, and maintaining operational flexibility during supply chain disruptions. In the model, the probability distribution for asset management efficiency is skewed towards the medium and high states, with 47% for medium and 27% for high, which indicates that TSMC tends to operate at optimal levels most of the time, allowing for resilience when disruptions occur. Total cost, on the other hand, encompasses the financial aspects of maintaining supply chain operations and is influenced by factors such as transportation cost, inventory cost, labor cost, and warranty cost.

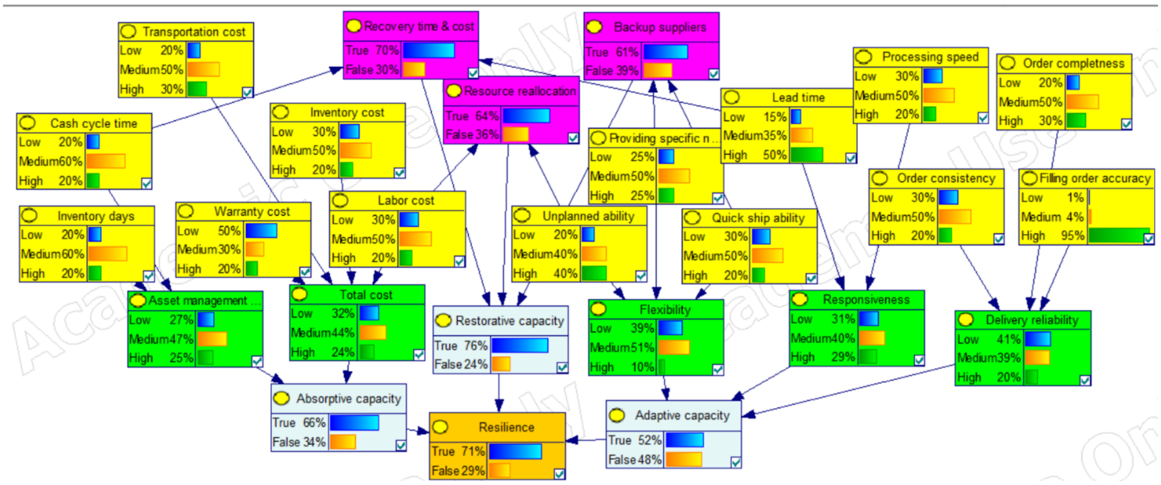


Figure 6. TSMC supply chain resilience static network.

The current model gives a 32% probability for low total cost, 44% for medium, and 24% for high. This suggests that while TSMC can often manage costs efficiently (evident by the relatively high chance of low and medium costs), there are occasions where costs can escalate, potentially affecting the company's ability to absorb supply chain shocks. Importantly, total cost directly feeds into TSMC's absorptive capacity, which has a 66% probability of being true, signaling a strong likelihood that the company can absorb disruptions without dramatically increasing operational costs. Lower costs typically imply that TSMC is effectively using resources to mitigate disruptions, allowing it to maintain flexibility in response to sudden changes, such as spikes in labor or transportation expenses. When costs are higher, however, the company may face challenges in reallocating resources, impacting its overall absorptive capacity. In an industry as cost-sensitive as semiconductor manufacturing, the balance between minimizing costs and maintaining sufficient buffer resources is essential. Thus, TSMC's absorptive capacity is reinforced by its ability to keep costs manageable while ensuring that operational efficiency does not suffer under disruption, further enhancing the company's overall resilience.

Restorative capacity within TSMC's supply chain is crucial for its ability to bounce back after disruptions by leveraging existing resources and backup plans. This capacity is dependent on three core components, i.e., recovery time and cost, resource reallocation, and backup suppliers. Each of these parameters has direct KPIs that influence the overall performance of TSMC's resilience in a crisis. Recovery time and cost in this model represent how quickly and cost-effectively TSMC can resume normal operations following a disruption. The node for this parameter depends on cash cycle time and lead time shortness, with probabilities distributed based on historical data and industry benchmarks. Cash cycle time is crucial, as it reflects how fast TSMC can convert resources into cash, which directly affects recovery speed. The CPT suggests a 70% probability of true recovery capability, supported by medium to high efficiency in lead time shortness and cash cycle time. This aligns with the semiconductor industry's need for quick lead times due to high customer demand and rapid technological evolution. Also, resource reallocation plays a significant role in ensuring that during disruptions, TSMC can effectively shift resources (such as labor or equipment) to mitigate loss of productivity. This node is influenced by labor costs and unplanned ability, both of which reflect the company's flexibility in mobilizing internal resources under stress. With labor cost often fluctuating in relation to market dynamics, the model shows a 64% chance of successful resource reallocation, a figure supported by efficient workforce planning and cross-training of employees that help maintain operations even in difficult circumstances. However, this also indicates room for improvement in managing costs when reallocating resources during high-stress periods. Finally, backup suppliers add an external layer to restorative capacity, allowing TSMC to ensure continuity even if a primary supplier fails. The providing specific needs and quick ship ability KPIs are key here, with TSMC's diverse and global supplier network contributing to a 61% probability of true backup supplier capability. While TSMC has strategically diversified its supply chain to avoid over-reliance on any single supplier, there are still risks inherent in the global nature of the semiconductor industry, where raw material shortages or geopolitical issues can cause delays. By maintaining strong relationships with backup suppliers and prioritizing flexibility in procurement, TSMC has a robust but not infallible restorative capacity.

On the other hand, adaptive capacity, defined by the three nodes of flexibility, responsiveness, and delivery reliability, each of which plays a critical role in determining TSMC's overall ability to adapt to new circumstances. Flexibility, influenced by unplanned ability and quick ship ability, shows a 39% chance of achieving high flexibility, highlighting the challenges of adapting quickly in an industry where manufacturing processes are complex and highly specialized. However, flexibility is bolstered by the company's investment in advanced manufacturing technologies that allow for some degree of process modification, albeit with certain limitations in terms of cost and time. Responsiveness, driven by KPIs such as order consistency and order accuracy, has a 31% probability of being highly responsive. TSMC is generally able to maintain its order commitments, though it faces some difficulties in maintaining accuracy during periods of extreme demand fluctuations. The company's strong customer relationships and emphasis on forecasting allow it to remain responsive to changes, though delays in certain areas of the supply chain can still cause disruptions. Finally, delivery reliability, which evaluates how consistently TSMC meets its delivery targets, has a 41% probability of being high under normal operating conditions. Influenced by order completeness, processing speed, and filling order accuracy, delivery reliability is essential for TSMC to maintain its reputation as a trusted supplier in the global semiconductor market. The model suggests that TSMC is generally reliable in meeting its delivery goals, but external factors like shipping delays and global trade barriers occasionally affect performance.

All three capacities are the parameters that directly influence TSMC's overall resilience, which measures the company's ability to withstand, adapt to, and recover from disruptions. The network's analysis shows a 71% probability of TSMC achieving true resilience, a figure that reflects the company's strong operational foundations but also underscores the ongoing need for optimization in areas such as cost management and global supply chain coordination.

5.1.2. Diagnostic reasoning

Diagnostic reasoning, conducted by setting resilience to a failure state, reveals adaptive capacity as the primary bottleneck, with a 61% probability of failure. Key contributing factors include poor delivery reliability (43% low), limited flexibility (49% medium), and low responsiveness (40% medium). Restorative capacity issues were also identified, with inefficiencies in resource reallocation (44% false probability) and prolonged recovery timelines (37% false probability). Absorptive capacity weaknesses, such as suboptimal asset management efficiency (47% medium) and high total cost (45% medium), further reduce resilience. These findings are represented in **Figure 7**.

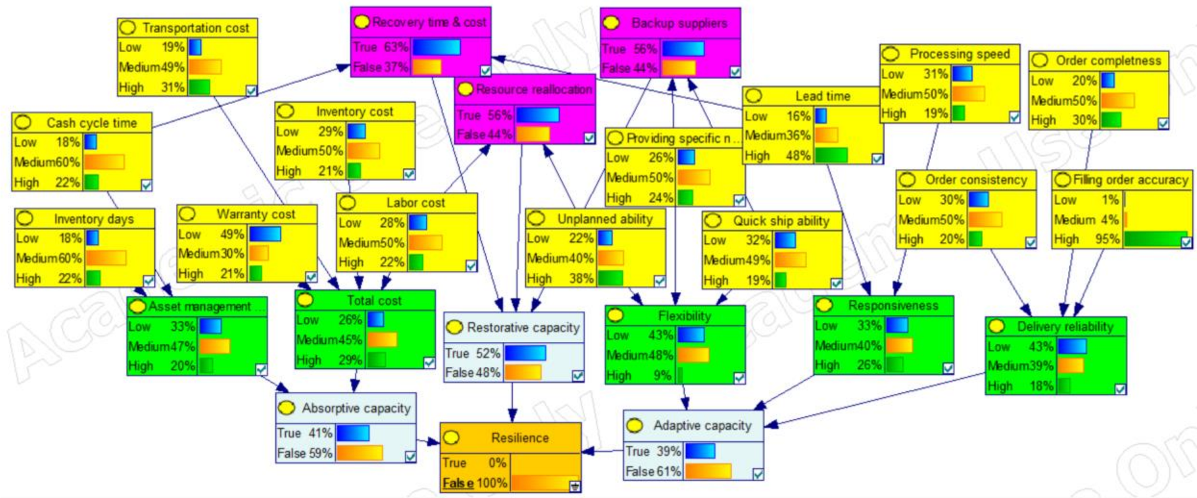


Figure 7. Diagnostic reasoning results.

5.1.3. Causal chain analysis

The causal chain analysis identifies key pathways affecting TSMC's resilience. The most critical chain contributing to resilience failure includes labor cost → resource reallocation → restorative capacity → resilience. An alternative pathway based on average influence involves cash cycle time → recovery time & cost → restorative capacity → resilience. These findings highlight areas where strategic interventions, such as improving cost management and enhancing backup supplier relationships, can improve resilience.

5.2. Forward propagation–GeNIe dynamic simulation

Propagation in BNs is central to the inference process, allowing probability distributions to update dynamically in response to new evidence. This process enables decision-making under uncertainty, where BNs offer a structured approach to managing interdependencies between variables. Bayesian networks utilize directed acyclic graphs (DAGs) to represent conditional dependencies, with propagation mechanisms facilitating inference across the network.

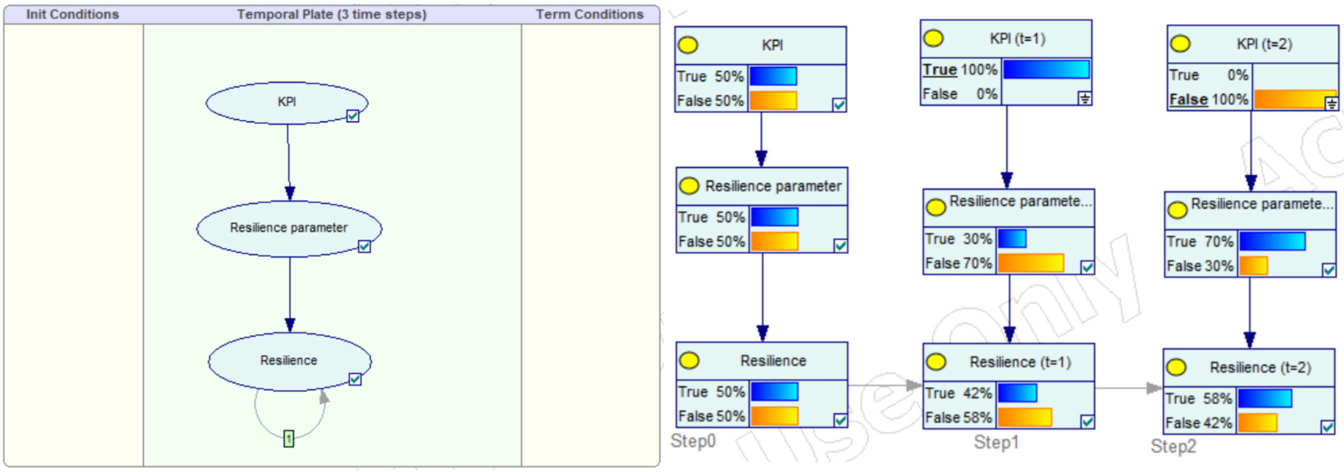
Despite the entire disruption scenarios being hypothetical, by incorporating some of the patterns of modern challenges faced by today's supply chains in the industry (including TSMC), which include geopolitical tensions, pandemics, and technological failures, to name a few. This ensures the study is a close representation of the risks that exist in the real world. **Table 2** shows the month-by-month (in order from 1–12) disruptions to TSMC's supply chain, the affected KPIs, and how their respective states change as a result.

Table 2. Disruption events to TSMC's manufacturing supply chain.

Disruption	KPIs affected	State change
Earthquake in Taiwan	Lead time shortness, inventory cost and cash cycle time	All change to high due to severe disruptions in operations and infrastructure
Trade war escalation	Transport and inventory cost	Transport changes to high due to increased tariffs; inventory remains high from previous disruption.
Supplier quality issues	Warranty cost, order completeness and order consistency	Warranty costs change to high; order completeness and consistency drop to low, reflecting the effect of receiving substandard materials.
Major port strike	Transport cost, lead time shortness and cash cycle time	Transport and lead time shortness remain high; cash cycle time changes to high due to significant delays in shipments.
Increase in demand for semiconductors	Inventory days, quick ship ability, filling order accuracy	Inventory days change to low as stock turns over quickly, quick ship ability changes to high to meet fast shipping demands, and filling order accuracy changes to medium, balancing increased demand pressures.
Raw material shortage	Inventory cost, unplanned ability, cash cycle time	Inventory cost remains high, unplanned ability changes to high, reflecting strong downside flexibility; cash cycle time changes to high due to production delays.
Pandemic outbreak	Labor cost, lead time shortness, inventory days	Labor cost and lead time shortness remain high; inventory days remain low due to ongoing disruptions.
New technology implementation	Processing speed, order completeness	Both change to medium as the firm adjusts to new technology and initial disruption.
Geopolitical tensions in Asia-Pacific region	Transport and Labor costs	Both remain high, reflecting continued pressures from external tensions.
Major customer contract loss	Providing specific needs, order completeness, cash cycle time	Providing specific needs and order completeness changes to low due to reduced demand; cash cycle time changes to high, reflecting slower revenue streams.
Supplier bankruptcy	Warranty cost, inventory days	Warranty costs remain high due to challenges in securing quality materials; inventory days change to medium as efforts are made to secure alternative suppliers.
Recovery and stabilization	Lead time shortness, unplanned ability, inventory cost	All change to medium as attempts to stabilize operations are made.

5.3. Dynamic supply chain results analysis

Upon running the simulation, the model is unrolled from the temporal plate over the stated time step; each individual time step will reveal its respective updated beliefs and evidence within the BN model. As the model progresses through each step, the probability distributions of nodes are recalculated based on the new evidence introduced, allowing us to observe how new data influences the network's state. Parent nodes update dynamically, transmitting causal effects to child nodes, enabling us to trace evolving dependencies and variable relationships in real time. Given the network's size and a larger time step of 12, a simplified model with a shorter time step of 3 (**Figure 8a**) can provide a clear illustration of the unrolling process and how evidence and beliefs propagate through each step (**Figure 8b**). For the full analysis, however, the results are presented and discussed ahead using line graphs showing each parameter and the overall resilience across the entire 12-time steps. This approach will allow for a comprehensive visual overview of resilience fluctuations and parameter evolution, highlighting both immediate and long-term impacts of disruptions within the simulated supply chain scenarios.



(a) **(b)**

Figure 8. GeNIe modelling of dynamic network, **(a)** dynamic 3-step illustration model; **(b)** unrolled 3-step illustration model.

5.3.1. Absorptive capacity

Consider **Figure 9**, the absorptive capacity saw notable declines during months 4 and 6, driven by significant disruptions such as the major port strike and raw material shortages. In month 4, the port strike disrupted transport and lead times, which strained the system's ability to absorb these impacts. The subsequent raw material shortage in month 6 compounded these issues, as the supply chain struggled to cope with increased costs and delays in production. The declines in absorptive capacity during these months corresponded with the dips in resilience, highlighting how the system's inability to manage these disruptions directly affected overall performance. By the end of the period, absorptive capacity improved as recovery measures took hold, contributing to the stabilization of resilience.

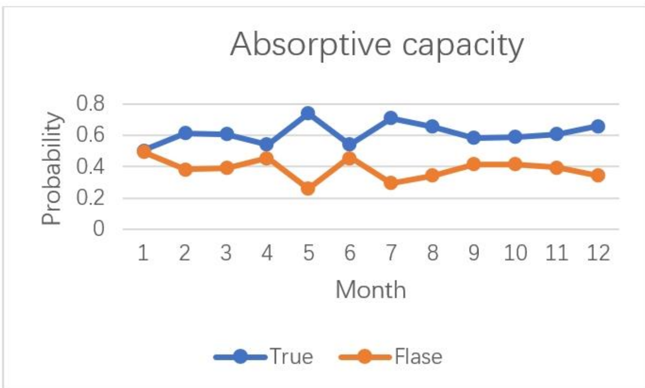


Figure 9. TSMC's absorptive capacity.

5.3.2. Restorative capacity

Moving onto the restorative capacity, this parameter remained consistently strong throughout the year, playing a crucial role in maintaining overall resilience during key disruptions such as the port strike and raw material shortages. Even during periods of strain, the system's ability to restore operations quickly helped prevent deeper declines in resilience. In month 8, during the implementation of new technology, restorative capacity supported resilience by enabling the system to adapt to operational changes and prevent disruptions from escalating. The strong performance in this area helped counterbalance the fluctuations in absorptive and adaptive capacities, ensuring that resilience was maintained at a relatively high level throughout most of the year. By the end of the period, continued recovery efforts allowed restorative capacity to further reinforce the system's resilience, particularly as the supply chain stabilized. The restorative capacity is represented by the graph in **Figure 10**.

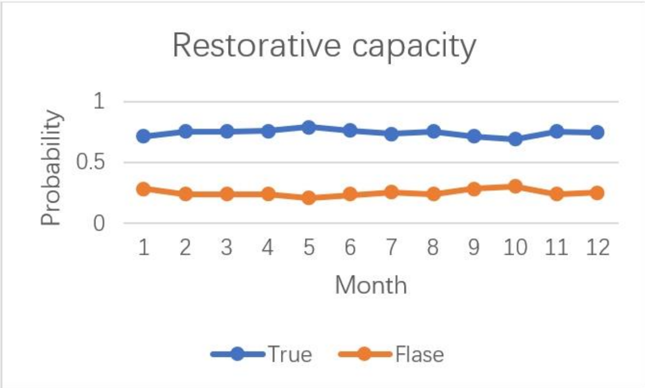


Figure 10. TSMC's restorative capacity.

5.3.3. Adaptive capacity

As seen in **Figure 11**, adaptive capacity exhibited variability throughout the year, reflecting the system's ability to adjust to different disruptions. During month 4, adaptive capacity's true value increased, showcasing the system's ability to adapt effectively to the major port strike by reallocating resources and managing transport and inventory challenges. In month 6, adaptive capacity remained stable with a slight increase, highlighting the system's continued flexibility in responding to the raw material shortage despite ongoing pressures. This variability underscores the system's capacity to handle sudden shifts and disruptions. Towards the later months of the year, adaptive capacity stabilized, reflecting a more consistent ability to manage disruptions and adapt to changing circumstances effectively.

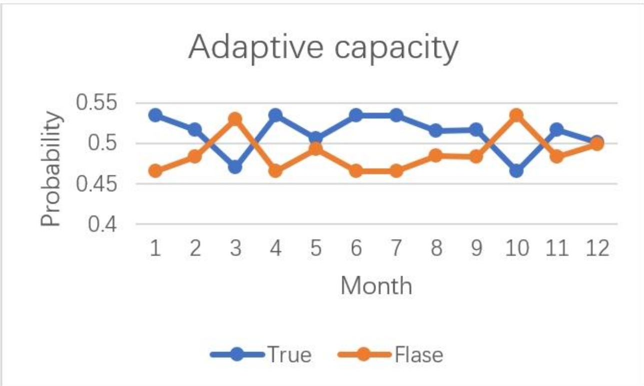


Figure 11. TSMC's adaptive capacity.

5.3.4. Supply chain resilience

The resilience of TSMC's supply chain, **Figure 12**, fluctuated throughout the 12-month period, reflecting its ability to handle disruptions and recover from them. During month 4, resilience dipped due to the major port strike, which disrupted transportation networks and led to delays in inventory movement. While adaptive capacity increased during this period, showcasing the system's flexibility to reallocate resources and manage disruptions, it was insufficient to fully counterbalance the strain on resilience caused by the extensive logistical challenges. By month 6, resilience experienced another significant decline due to raw material shortages, which extended lead times and increased operational costs. During this period, adaptive capacity increased slightly, reflecting the system's ability to remain flexible in adapting to the disruption, but this flexibility alone could not prevent the erosion of resilience under sustained external pressures. After month 6, resilience shows signs of stabilizing in months 7 and 8 but dips again in month 9, as geopolitical tensions in the Asia-Pacific region exerted further pressure on transport and labor costs. The system's resilience was weakened during this period due to difficulties in absorbing increased costs, as evidenced by a dip in absorptive capacity. However, the relatively stable restorative capacity during this period continued to cushion the impact of these external pressures, allowing the system to maintain a level of resilience despite the ongoing disruptions. By the final months, recovery and stabilization efforts led to a rebound in resilience, aided by improvements in lead times, unplanned ability, and better inventory management.

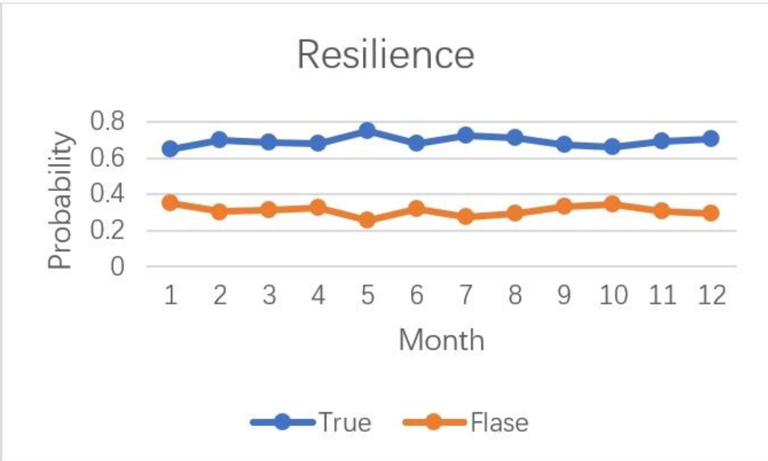


Figure 12. TSMC's supply chain resilience.

Throughout the year, restorative capacity played a critical role in cushioning these dips in resilience, allowing the system to recover and stabilize. By the final months, recovery efforts supported improvements in lead times, unplanned abilities, and inventory management, enabling resilience to rebound. The interaction between adaptive capacity and resilience highlights that while flexibility is essential for managing disruptions, resilience ultimately requires strong recovery mechanisms, supported by restorative capacity, to sustain performance through prolonged challenges.

5.4. Key findings from dynamic simulations

1) Temporal propagation of disruptions:
   - Disruptions originating at nodes with high interconnectivity, such as inventory days and lead time shortness, demonstrate rapid cascading effects throughout the network, as indicated by simulation results showing increased downstream impacts when these nodes experience disruptions. This highlights their critical role in maintaining supply chain stability.
   - Temporal analysis reveals that nodes like backup suppliers and resource reallocation significantly mitigate the spread of disruptions when their performance is optimized.
2) Performance under stress scenarios:
   - Scenarios involving simultaneous disruptions demonstrate the importance of adaptive capacity in maintaining operational continuity.
   - Nodes linked to restorative capacity, such as recovery time and cost, exhibit delayed responses under extreme conditions, indicating the need for proactive recovery planning.
3) Critical resilience enhancements:
   - Increasing flexibility in production scheduling and resource allocation improves the supply chain's ability to absorb shocks and maintain functionality.
   - Expanding quick ship ability and backup supplier availability reduces recovery times and prevents bottlenecks during high-stress scenarios.

6. Conclusion and limitations

The goal of this study was to test and assess the resilience of Taiwan Semiconductor Manufacturing Company's (TSMC) supply chain by simulating various disruption scenarios. The findings indicate that while TSMC's supply chain exhibits a degree of resilience, it is also susceptible to notable disruptions, particularly in scenarios involving natural disasters like earthquakes, geopolitical tensions, and critical supplier failures. These disruptions lead to extended lead times, depleted inventory levels, increased labor and operational costs, and reduced service levels. Based on the results analysis, what can be highlighted immediately is the importance of proactive measures such as diversifying suppliers, enhancing inventory management strategies, and investing in robust risk management practices to mitigate these impacts and ensure supply chain continuity.

However, certain limitations inherent in the modeling and simulation approach are evident. While the selected KPIs provided valuable insights into the supply chain's response to disruptions, the real-world complexity of TSMC's operations involves a far broader set of metrics that could also influence resilience. Factors such as environmental sustainability, ethical sourcing, cybersecurity, and technological advancements in manufacturing are just a few examples of additional dimensions that were not fully captured in this analysis due to limited access to data or just the complexity involved in incorporating them. Furthermore, the dynamic interactions between various supply chain components and external factors create effects that are difficult to predict and model comprehensively.

In conclusion, this study demonstrates the utility of simulation as a method for stress-testing supply chain resilience and highlights the critical areas where TSMC could focus its efforts to bolster its supply chain against future disruptions. The insights gained, while valuable, should be viewed as part of a broader, ongoing effort to continually monitor, evaluate, and enhance the robustness of the firm's global supply chain. Future research could expand on this work by incorporating a more extensive range of KPIs and by exploring the impact of emerging technologies and global trends on supply chain resilience.

Author contributions: Conceptualization, BLG and HC; methodology, BLG and HC; software, BLG; validation, BLG; formal analysis, BLG; investigation, BLG; resources, BLG; data curation, BLG; writing—original draft preparation, BLG; writing—review and editing, BLG, YR and HC; visualization, BLG; supervision, HC; project administration, HC; funding acquisition, HC. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported in part by "the Fundamental Research Funds for the Central Universities, NO. NP2024201"; General Project of the Humanities and Social Sciences Planning Fund of the Ministry of Education: Research on the Resilience Assessment and Improvement Strategy of the Equipment Manufacturing Industry Chain and Supply Chain under Sudden Risks (23YJA630009).

Conflict of interest: The authors declare no conflict of interest.

References

1. Ivanov D, Dolgui A. Viability of Intertwined Supply Networks: Extending the Supply Chain Resilience Angles towards Survivability. A Position Paper Motivated by COVID-19 Outbreak. International Journal of Production Research. 2020; 58(10): 2904–2915. doi: 10.1080/00207543.2020.1750727
2. Liu X. Viewpoints on Robust Supply Chain Network Risk Assessment Using Dynamic Bayesian Networks. Innovations in Applied Engineering and Technology. 2023; 2(1): 1–8. doi: 10.58195/iaet.v2i1.135.
3. Dubey R, Gunasekaran A, Childe SJ. Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility. Management Decision. 2019; 57(8): 2092–2112. doi: 10.1108/MD-01-2018-0119
4. Ivanov D. Viable supply chain model: Integrating agility, Resilience and Sustainability Perspectives—Lessons from and thinking beyond the COVID-19 Pandemic. Annals of Operations Research. 2022; 319: 1411–1431. doi: 10.1007/s10479-020-03640-6
5. Chhimwal M, Agrawal S, Kumar G. Measuring Circular Supply Chain Risk: A Bayesian Network Methodology. Sustainability. 2021; 13(15). doi: 10.3390/su13158448
6. Hong LJ, Li J, Wu X, Yi S. Future Research of Supply Chain Resilience: Network Perspectives and Incorporation of more Stakeholders. Fundamental Research. 2023; in press. doi: 10.1016/j.fmre.2023.07.012
7. Liu M, Lin T, Chu F, et al. A New Robust Dynamic Bayesian Network Model with Bounded Deviation Budget for Disruption Risk Evaluation. In: Proceedings of the IFIP International Conference on Advances in Production Management Systems (APMS); 5–9 September 2021; Nantes, France.
8. Qazi A, Simsekler MCE, Formaneck S. Supply chain risk network value at risk assessment using Bayesian belief networks and Monte Carlo simulation. Annals of Operations Research. 2023; 322: 241–272. doi: 10.1007/s10479-022-04598-3
9. Jamil M, Asrol M. An Integrated SCOR-AHP Framework for Evaluating Sustainable Supply Chain Performance of Palm Oil Mills. Journal of System and Management Sciences. 2024; 14(7): 72–87. doi: 10.33168/JSMS.2024.0704
10. Liu Y, Wang S, Zhou C, Wang X. Propagation Computation for Mixed Bayesian Networks Using Minimal Strong Triangulation. Mathematics. 2024; 12(13): 1925. doi: 10.3390/math12131925

11. Dedieu A, Zhou G, George D, Lázaro-Gredilla M. Learning noisy-OR Bayesian Networks with max-product belief propagation. In: Proceedings of the 40th International Conference on Machine Learning; 23–29 July 2023; Honolulu, HI, USA.
12. Bugert N, Lasch R. Analyzing upstream and downstream risk propagation in supply networks by combining Agent-based Modeling and Bayesian networks. Journal of Business Economics. 2023; 93: 859–889. doi: 10.1007/s11573-022-01128-2
13. Constantinou AC. Learning Bayesian networks that enable full propagation of evidence. IEEE Access. 2020; 8: 124845–124862. doi: 10.1109/ACCESS.2020.3006472
14. Adams S, Patanè A, Lahijanian M, Laurenti L. BNN-DP: Robustness certification of Bayesian neural networks via dynamic programming. In: Proceedings of the 40th International Conference on Machine Learning; 23–29 July 2023; Honolulu, HI, USA.
15. Jensen FV, Nielsen TD. Bayesian Networks and Decision Graphs, 2nd ed. Springer; 2007. doi: 10.1007/978-0-387-68282-2
16. Neapolitan RE. Learning Bayesian Networks. Prentice Hall; 2003.
17. Murphy KP. Dynamic Bayesian Networks: Representation, Inference and Learning [PhD thesis]. University of California; 2002.
18. Helbing D. Globally networked risks and how to respond. Nature. 2013; 497(7447): 51–59. doi: 10.1038/nature12047
19. Sheffi Y. The Resilient Enterprise: Overcoming Vulnerability for Competitive Advantage, 1st ed. The MIT Press; 2005.
20. Ponomarov SY, Holcomb MC. Understanding the concept of supply chain resilience. The International Journal of Logistics Management. 2009; 20(1): 124–143. doi: 10.1108/09574090910954873