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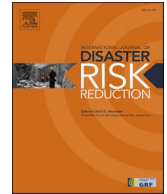
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Measuring and predicting supply chain resilience under disaster and pandemic disruptions: Evidence from Japan's automotive sector

Ikki Teshima , I Made Raditya Wicaksana, Zhujijie Cai, Xiaoyu Liu, Yen Chen , Yuanhong Tian, Enna Hirata 

Graduate School of Maritime Sciences, Kobe University, Japan

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ABSTRACT

This study investigates the supply chain resilience (SCR) of Japanese automotive manufacturers by integrating perspectives from disaster risk and operational disruption. A hybrid analytical framework that combines a logistic regression (LR) scorecard and a long short-term memory (LSTM) model is employed. This framework uses publicly available data from 2015 to 2024, which consists of information from seven major automakers. Resilience is assessed across internal and external dimensions in response to disruptions such as the COVID-19 pandemic and natural disasters. Explanatory variables include production volume, market concentration level, employee tenure, recall rate, exchange rate, and disaster indices. The LR scorecard identifies leading indicators of disaster resilience by estimating the probability of achieving post-disruption peak profitability (AUROC = 0.83), while the LSTM model captures time-series predictors of profit recovery (test MSE = 0.0194). Results show that long employee tenure, stable production, and strong quality control are the most critical enablers of supply chain continuity. The findings highlight the importance of operational resilience as a foundation for reducing disaster risk in Japan's automotive sector. Future research should extend the analysis to global supply chains and explore causal inference approaches to better guide policy and strategic decision-making.

1. Introduction

Modern supply chains are critical infrastructures that bolster national economies and social well-being. However, they are increasingly vulnerable to complex risks stemming from natural disasters and operational disruptions [1,2]. In an era marked by recurrent disasters such as earthquakes, tsunamis, and global pandemics, enhancing supply chain resilience (SCR) has become a corporate imperative and a central pillar of disaster risk reduction (DRR) policy, as outlined in the Sendai Framework for DRR. The Sendai Framework for DRR highlights the importance of resilient infrastructure and businesses in reducing economic losses, maintaining societal stability, and ensuring the continuity of essential services in the wake of natural and anthropogenic hazards [3,4]. Within this context, resilient supply chains function as critical buffers that mitigate cascading effects of disasters, including earthquakes, tsunamis, pandemics, and other extreme events, by sustaining goods flows, preserving employment, and supporting the broader economy.

* Corresponding author.

E-mail address: enna.hirata@platinum.kobe-u.ac.jp (E. Hirata).

Supply chain is a logistic network with multiple facilities starting from creating the product from companies to delivering it to the customers [5]. A supply chain operates as a complex logistical network, linking multiple facilities and stakeholders from product creation to final delivery. The objective of supply chain management is to maximize value creation while minimizing costs [6]. However, efficiency-driven optimization can also heighten vulnerability, as demonstrated during the COVID-19 pandemic, when globalized, streamlined networks lacked the elasticity needed to recover quickly [7]. This trade-off between efficiency and resilience is at the core of ongoing debates: while leaner supply chains help firms reduce costs, they can also amplify the consequences of disruption [8]. Consequently, strengthening SCR, which is defined as the ability to anticipate, withstand, and recover from adverse events with minimal performance loss, has become a critical priority.

Resilient supply chains are now recognized as adaptive systems capable of anticipating, absorbing, and rapidly recovering from adverse events [9,10], thus ensuring functional continuity of essential goods and services across society. The Sendai Framework explicitly calls for strengthening business continuity, critical infrastructure resilience, and collaborative risk governance between private and public sectors. Against this backdrop, it is crucial to empirically identify which operational and structural factors most influence a firm's ability to restore profitability, functionality, and employment following severe disruptions.

Existing studies on SCR have heavily relied on qualitative methods, such as expert interviews and post-event surveys, offering rich insights but limited cross-case comparability [11,12]. Emerging DRR-oriented works, including recent DRR studies, emphasize the need for data-driven approaches, leveraging longitudinal operational data and advanced predictive modeling [1,13]. Such methodologies enable more rigorous, policy-relevant resilience assessments, informing both corporate strategy and national disaster preparedness plans [14]. In recent years, the relevance of SCR has expanded beyond the pursuit of private sector efficiency to align with the broader objectives of DRR. This shift reflects the increasing recognition that SCR is not only a matter of corporate competitiveness but also a crucial element of national disaster preparedness.

In the automotive sector, strengthening SCR is not just a matter of firm competitiveness, but also a national imperative closely tied to disaster risk reduction (DRR) policy. This policy emphasizes multi-hazard preparedness, capacity building, and collaborative risk governance, all of which are in line with the Sendai Framework [15].

The Japanese automotive industry, the world's third largest and a contributor to nearly one-tenth of national employment [16], stands as a vital case where disaster resilience intersects with international economic stability and public safety. The sector's highly optimized, lean supply networks, while effective under normal conditions, have repeatedly revealed vulnerabilities during major disruptive events, notably the COVID-19 pandemic and the 2011 Great East Japan Earthquake, resulting in sharp declines in output, employment, and cascading impacts throughout global markets [17]. Toyota's global production fell 14 percent, Honda's production more than quarter, and Nissan dropped nearly 30 percent [16]. This may indirectly affect the Japanese economy, which in turn showed the importance of maintaining the automotive supply chain resilience. Therefore, this study will focus on Japanese automobile companies supply chain analysis to understand their resilience effort against risks. Through resilience, a company may be able to quickly recover from a disruptive event but also could improve market positions.

In real world supply chain activities, there are different types of risks that disrupt the stability of businesses. For instance, operational risks including delays, production bottlenecks and inventory mismanagement can result in the inability to meet the demand. Strategic risks such as over-reliance on a single supplier or a specific geographic area will lead to inflexible systems. Environmental risks such as natural disasters or political instability will reduce the responsiveness to the market. From private organizations' perspectives, to minimize the impact of disruptions and ensure customer satisfaction, increasing SCR has become one of the most important priorities in recent years. As a result, a scientific approach needs to be introduced to measure these risks and enhance the supply chain reliability.

Given these stakes, strengthening supply chain resilience in the automotive sector is not merely a corporate concern but a national imperative tied to disaster risk reduction, economic security, and social stability. Understanding the operational and structural drivers of SCR can inform both industry practice and public policy, ensuring that critical sectors maintain functionality and accelerate post-disaster recovery.

Building on this need, this study systematically investigates the determinants of SCR in Japan's automotive industry, highlighting their significance in mitigating disruption and advancing disaster risk management objectives. We adopt a hybrid analytic framework, which integrates logistic regression (LR) scorecard and long short-term memory (LSTM) neural networks, on publicly available, multi-dimensional data from Japan's automotive sector for the period of 2015–2024. By analyzing both internal factors (e.g., production stability, employee tenure) and external conditions (e.g., disaster indices, currency volatility) factors, we aim to generate empirical insights into recovery trajectories aftershocks. Grounding this analysis within DRR policy frameworks enables us to link industry practices with broader disaster resilience strategies.

To address these gaps, this study pursues three specific objectives. First, it identifies the key operational and structural determinants of supply chain resilience in Japan's automotive sector using a multi-firm longitudinal dataset from 2015 to 2024. Second, it evaluates a dual-model framework that integrates a logistic regression scorecard with a long short-term memory (LSTM) model to measure and predict post-disruption recovery, thereby comparing an interpretable statistical approach with a high-capacity sequence model. Third, it derives policy-relevant implications by situating the empirical findings within DRR and Sendai Framework discussions, showing how firm-level resilience indicators can inform disaster risk governance and business continuity strategies.

The novelty of this study lies in its quantitative, transparent, and policy-relevant approach. By combining methodologies for measuring and predicting supply chain resilience with open access data, we offer actionable insights for firms, policymakers, and researchers engaged in strengthening supply chain resilience. This contribution advances both theoretical understanding and practical governance of SCR in an era of growing systemic risk.

This study treats firm-level continuity metrics, such as the probability of achieving peak operating profit after a disruption and the

trajectory of profit recovery, as operational proxies for DRR outcomes emphasized in the Sendai Framework. These outcomes include dampened cascading economic losses, faster sectoral recovery, maintained employment and livelihoods, and reduced secondary impacts on dependent firms and regions. When major automotive manufacturers quickly restore profitability and stabilize operations after disasters or pandemics, they can sustain production, protect jobs, and preserve upstream and downstream transactions. This limits the propagation of shocks through the wider economy. Thus, our analysis addresses business continuity at the firm level by identifying internal and external drivers of post-disruption performance and risk governance at the sector and policy levels. Aggregated continuity indicators for leading automakers can inform DRR strategies for a nationally critical industry.

The remainder of this paper is structured as follows: Section 2 reviews existing studies, Section 3 describes data and methodology, Section 4 presents results and discussion, and Section 5 concludes.

2. Literature review

Recent literature increasingly recognizes SCR as a critical foundation for DRR and sustainable socioeconomic stability [1,2,13]. The Sendai Framework for DRR calls for strengthening the resilience of business and critical infrastructure as central DRR priorities. In this context, supply chains, especially those underpinning essential sectors like automotive manufacturing, are viewed not only as economic entities but as “lifelines” important for post-disaster recovery, long-term risk management, and national security [17].

Existing SCR research covers a broad range of geographies, industries, and hazard contexts (Table 1). Many foundational studies have focused on operational, strategic, and environmental risks, consistently highlighting flexibility, redundancy, and adaptive capacity as drivers for post-disruption recovery, whether the threat is from natural hazards or global shocks such as pandemics [18–20].

Methodological approaches to measuring SCR span from qualitative (expert interviews, case studies, and surveys) to quantitative (data-driven and modeling) paradigms [11,12]. Qualitative methods enrich understanding of context, human factors [25], and policy barriers but can be limited by subjective perception bias and insufficient comparability across cases, especially internationally. This limitation is visible in automotive sector studies that depend on expert judgment to identify SCR barriers and enablers in regions such as India paradigms [11,23] and Europe [26].

Beyond structural and technological measures, recent studies underscore the role of internal capabilities – such as employee retention, organizational learning, and knowledge transfer – in shaping how firms absorb and adapt to disruptions [27]. This perspective affirms the legitimacy of treating people-based factors as components of SCR alongside physical exposure and network structure indicators. Recent work emphasizes that resilience is not only a structural or technical property of supply chains, but also a function of organizational agility and adaptive leadership capabilities, especially in volatile and uncertain conditions [15].

In response to growing academia and policy demands for measurable, reproducible, and predictive assessments of resilience, there is a clear methodological shift toward leveraging publicly available data and advanced analytics. Related journals highlight the value of machine learning and time-series analysis for capturing the temporal and structural complexity of supply chain disruptions [1,2,14]. For instance, Liu et al. [22] modeled China’s cobalt supply chains using public data to quantify resilience against geopolitical risks, mirroring the global push for reproducible, scalable, and actionable DRR research. Haraguchi et al. [1] introduced the “conversion strategy” as a novel supply chain adaptation in multi-hazard environments, while Dixit et al. [13] synthesized thematic findings on healthcare supply chain preparedness. Despite these advances, coverage of the Japanese automotive sector as a globally critical supply chain remains limited. Case studies on natural disaster impacts, especially the 2011 Great East Japan earthquake, emphasize the ripple effects of disruptions, the need for network-wide risk mapping, and geographic clustering’s role in risk propagation [17]. However, few studies systematically leverage public longitudinal data and predictive analytics to identify the operational and structural determinants of resilience within this sector, underlining the research gap this study addresses.

Despite the growing body of work on supply chain resilience, three important gaps remain in the existing literature. First, many DRR and SCR studies rely on qualitative case analyses, survey-based indices, or single-method statistical models, with relatively few data-driven, reproducible assessments of resilience in the Japanese automotive sector, even though it is a globally critical supply chain. Second, prior quantitative contributions rarely combine interpretable scorecard approaches with sequence-learning models, and typically underutilize publicly available longitudinal firm data to link operational indicators with DRR policy agendas such as the

Table 1
Overview of previous research on SCR by geography.

Author(s), year	Variables	Supply Chain Issue	Target Area
Scavarda et al., 2015 [21]	Three Brazilian Automotive SCs as the subject of analysis using multi-tier case study approach using interview as well as direct observation.	Lack of flexibilities in supply chains	Brazilian Automotive Supply Chain
Agarwal & Seth, 2021 [11]	10 resilience barriers that preventing resilience analysis using TISM to understand their relationship through discussion with experts	Resilience barriers	Indian Automotive Company
Liu et al., 2023 [22]	Geopolitical risks and demand shocks of EVs	Cobalt Supply Chain System	China Electric Vehicles
Chukwuka et al., 2024 [12]	28 specific risk factors grouped into 11 risk types, four risk subcategories and two main categories.	Emergency supply chains	General disaster relief operations
Agarwal & Seth, 2024 [23]	8 Supply chain enablers, 3 business outcomes (business continuity, market share growth, financial performance), and their relationship using Fuzzy ISM and MICMAC with experts and researchers	Supply chain resilience enablers/abilities affect to business outcomes	Indian Automobile Industry
Li & Sukhotu, 2025 [24]	Digital capabilities and their sub-dimensions digital infrastructure capability, digital analytics capability, and strategic support capability.	Visibility, collaboration, and resilience	China’s electric vehicle industry

Sendai Framework. Third, there is limited empirical guidance on how firm-level operational and structural metrics can be translated into actionable insights for DRR-oriented policy and governance, including business continuity planning.

To address this gap, this study contributes to the literature by applying a dual-model quantitative approach, combining LR scorecards with LSTM neural networks, using an original publicly sourced longitudinal dataset.

3. Methodology

In this study, a dual-model framework is adopted in which a LR scorecard and a LSTM neural network are applied to the same longitudinal dataset. The LR scorecard provides an interpretable, policy-oriented view of resilience drivers by transforming multidimensional risk factors into transparent scores, while the LSTM captures non-linear and temporal dependencies in profit dynamics that traditional regression models may miss. Rather than assuming that model integration automatically increases “robustness” or “generalizability,” the two models are used in a complementary way: the LR scorecard highlights which operational and structural variables are statistically associated with post-disruption peak profitability, and the LSTM is used to test whether similar factors are important when forecasting recovery trajectories over time. The dual-model approach has been previously applied in domains such as crisis prediction and management, where Ayvaz et al. [28] reported that their dual-model system achieved an accuracy of 95.41% in predicting the 2002 and 2008 crises.

To operationalize supply chain resilience, this study uses firm-level operating-profit trajectories – specifically, the probability of reaching a post-disruption peak in profits and the speed of profit recovery – as a financially oriented proxy for the continuity of production, employment, and upstream and downstream transactions in the automotive supply chain. We acknowledge that this proxy does not directly measure other important resilience dimensions, such as service levels, lead-time recovery, and the pace of supplier and logistics restoration. Therefore, we interpret our results as capturing a profit- and continuity-focused facet SCR rather than its full, multidimensional character.

For external shocks, including the pandemic, we use a simple, transparent coding scheme to avoid ambiguity and temporal leakage. Pandemic exposure is represented by a binary dummy that clearly distinguishes between pandemic and non-pandemic observations. Where needed, this is complemented by intensity or disruption indicators (e.g., disaster indices), whose coding and value ranges are described in the data table and accompanying text in Tables 3 and 4.

This design follows emerging recommendations in resilience and risk analytics to combine interpretable indicators with high-capacity predictive models, using triangulation across methods to strengthen empirical claims. By comparing feature importance patterns, partial dependence behavior, and out-of-sample performance across the LR and LSTM models, the analysis can identify drivers that are consistently influential under different modeling assumptions and data structures. In this sense, the hybrid framework enhances the credibility and practical usefulness of the findings, not by relying on a single “best” model, but by leveraging the complementary strengths of both approaches for understanding and predicting supply chain resilience.

The LR scorecard transforms multidimensional risk factors, including both operational indicators and structural variables, into an interpretable scoring system. This method enables a granular analysis of the contribution of individual variables to supply chain resilience, helping to identify critical determinants such as employee tenure, production stability, and recall rates. Importantly, the scorecard produces outputs that are directly actionable for industry practitioners and policymakers, offering tools for risk ranking, threshold setting, and the communication of resilience factors in terms of probabilities of post-disruption profitability. Its reliance on Weight of Evidence (WoE) transformation and optimal binning further enhances analytical transparency while reducing the risk of overfitting.

The integration of the two models is implemented through triangulation rather than algorithmic coupling. First, feature importance patterns from the LR scorecard (e.g., signs and magnitudes of coefficients, WoE-based variable rankings) are compared with permutation importance rankings and partial dependence plots from the LSTM to assess whether the same drivers – such as production stability, employee tenure, and recall performance – emerge as influential across methods. Second, agreement between the direction and shape of effects (for example, the positive association between firm scale and profit, or the non-linear negative impact of high disaster exposure) is used as evidence that the identified mechanisms are robust to different modeling assumptions. Third, discrepancies between the models highlight areas where dynamic interactions or non-linearities matter beyond what the static scorecard can capture, informing both interpretation and future model development. In this sense, the hybrid framework does not involve a direct information feedback loop between LR and LSTM; instead, it combines an interpretable risk-scoring tool with a high-capacity sequence model to obtain a more comprehensive understanding of resilience. The LR scorecard addresses the question of which firm-level conditions are associated with achieving high post-disruption profitability, whereas the LSTM addresses how profit responds over time to shocks under those conditions. Together, these perspectives support both theory building and practical decision-making by aligning transparent indicators with richer dynamic forecasts.

While the scorecard emphasizes interpretability, the LSTM model captures the complex temporal dynamics that are intrinsic to supply chain disruption and recovery. Because past events and sequential patterns influence current outcomes, LSTMs are well-suited

Table 2
A comparison of the two models.

Model	Key Strength	Limitation	Research Contribution
LR Scorecard	Transparency, interpretability, policy linkage	Linear, limited time modeling	Variable importance, operational insights
LSTM	Temporal sequence modeling, non-linear learning	Less interpretable	Dynamic prediction, time-based inference

Table 3
Data and explanations.

No.	Variable	Explanation
(1)	Production volume	This measure captures a company's manufacturing scale and its capacity to allocate resources. Examining changes in production highlights the speed of recovery after disruptions, making it a key indicator.
(2)	HHI	Herfindahl-Hirschman Index (HHI) measures market concentration on a scale from 0 to 10,000, serving as an indicator of monopolistic risk. A lower HHI reflects a competitive landscape where firms manage risks independently, whereas a higher HHI points to oligopolistic structures with greater interdependence, heightening vulnerability to cascading systemic failures. It highlights the pathways of risk transmission among firms and offers a structural foundation for cross-sectional resilience assessments. The formula is as follows: $HHI = \sum_{i=1}^n s_i^2 \times 10,000$ $s_i = \text{Market share of company } i \left(s_i = \frac{\text{Sales Volume}}{\text{Global Sales Volume}} \right)$ $n = \text{total number of companies in the market}$
(3)	Number of employees	Workforce size determines operational elasticity. Large-scale employers incur greater losses during strikes or pandemics but benefit from labor redundancy for faster recovery. Smaller firms demonstrate adaptability yet possess lower tolerance to sustained disruptions.
(4)	Employee tenure	Indicates employee stability and experience. Longer tenure may support smoother operations and quicker recovery during disruptions due to institutional knowledge. Higher values indicate robust institutional knowledge transfer, enabling efficient crisis decision-making. Lower values imply reliance on external recruitment, prolonging recovery.
(5)	Employee wages	Reflects labor cost structure and competitiveness. Higher wages might imply reliance on skilled labor; disruptions in such labor pools can strongly affect supply continuity. Automation-intensive enterprises face lower impacts. This indicator evaluates potential threats to production continuity from labor market volatility.
(6)	Annual recall rate	Serves as a key indicator of supply chain robustness, where higher recall frequencies often reveal underlying weaknesses in quality control systems, supplier reliability, or manufacturing processes, directly impacting operational continuity and brand reputation.
(7)	Exchange rate fluctuation	Influences the competitiveness of goods in international trade, both imports and exports. Consequently, it can serve as an indirect indicator of market conditions, reflecting how external shocks affect supply chain strategies. The annual exchange rate is computed as the average of the monthly exchange rates for each year. The formula is as follows. $\frac{\text{annual average exchange}_i - \text{annual average exchange}_{i-1}}{\text{annual average exchange}_i}$
(8)	Natural disasters	Earthquakes and tsunamis are chosen because these are the two most common natural disasters in Japan. We choose to record an earthquake greater than magnitude 4 and tsunami greater than 3 m because a disaster warning is issued and activities may be halted.
(9)	Factory concentration	Evaluates geographic risk exposure, as production facilities clustered in specific regions become vulnerable to localized disruptions. Geographic clustering amplifies localized risks. Spatial density of factory clusters is calculated using GPS coordinates.
(10)	Operating profit	This financial metric serves as a critical buffer capacity indicator for supply chain resilience. Higher operating profits enable firms to allocate emergency funds for risk mitigation. Declining profits signal weakened shock-absorption capabilities, making it essential for assessing long-term strategic adaptability. Data sourced consistently from securities reports ensures cross-firm comparability.

Sources: (1) – (5) and (10) are obtained from the corporate reports of each company including Toyota, Honda, Nissan, Subaru, Mazda Mitsubishi, and Suzuki. (6) is taken from the website of Japan's Ministry of Land, Infrastructure, Transport [29]. (7) is sourced from International Monetary Fund (IMF) [30]. (8) comes from the from Japan Meteorological Agency [31]. (9) is gathered from the official websites of each corporation, with the corresponding geographic coordinates (latitude and longitude) identified using Google Maps.

Table 4
Data description for the LSTM model.

No.	Data Type	Unit
1.	Production volume in Japan	1,000,000
2.	Sales volume in Japan	1,000,000
3.	Production volume in worldwide	1,000,000
4.	Sales volume in worldwide	1,000,000
5.	Automobile sales in Japan	1,000,000
6.	Automobile sales in worldwide	1,000,000
7.	HHI	1000
8.	Number of employees	10,000
9.	Employee wages in Japanese yen	1,000,000
10.	Pandemic (COVID-19)	−1 or 1 (−1 means no pandemic and 1 means positive)
11.	EI	0 or greater

to handle such long-term dependencies. By integrating longitudinal company indicators, disaster events, and other time-varying factors, the LSTM model can uncover non-linear relationships and forecast future profitability under varying shock scenarios. This data-driven approach complements the scorecard by identifying patterns or interactions, such as the compounding effects of multiple disruptions, that traditional regression models may not fully capture.

The integration of both models enhances the robustness and generalizability of the research. The logistic regression scorecard provides interpretability and domain insight, though it has limitations in managing non-linearities and temporal intricacies.

Conversely, the LSTM offers predictive strength in complex, real-world time series contexts but often lacks transparency regarding individual variable contributions. By combining the two, we are able to validate findings across approaches, ensuring that insights from one model can reinforce or clarify results from the other. Table 2 presents a comparative summary of the strengths and limitations of the two models.

For the LR scorecard, the final sample included 70 firm-year observations. These observations were divided into temporally ordered training and test sets to maintain the panel structure and prevent look-ahead bias. We evaluated the model using a time-based train-test split (training on earlier years and testing on later years). In addition to examining discrimination (AUROC), we used a calibration plot and Brier score to confirm that the predicted probabilities were reasonably aligned with the observed post-disruption peak profitability frequencies.

For the LSTM, we conducted model estimation and evaluation in a strictly forward-looking manner within each firm. This approach used only past and current information to predict future operating profit trajectories, thereby ruling out temporal leakage. We defined a forecasting horizon of h periods ahead, addressed missing values and irregular reporting intervals using interpolation, carry-forward rules, or exclusion criteria, and ensured a consistent time grid across firms for training and testing the sequence model.

Ultimately, this dual-model strategy produces a more comprehensive assessment that is both analytically rigorous and practically relevant. It aligns with emerging best practices in DRR and resilience analytics, which increasingly emphasize the importance of blending interpretable indicators with high-accuracy predictive models to support decision-making in dynamic, data-rich environments. The research process is presented in Fig. 1.

3.1. Data curation

Resilience has a broad definition that applies to many fields, including engineering, psychology, and health care. Weid et al. [32] distilled this broad concept into three core questions: “resilience of what?”, “resilience of how?” and “resilience to what?”. Most interpretations agree that resilience reflects how a system functions to recover from disruptions. Conceptual framework of studying resilience made by mapping a performance degradation after disruption over time. The capabilities of the system, in this case supply chain, to cope with disruptions can be done by absorption, adaptation, or restoring the status quo [9]. Thus, to measure resilience, system performance over time and disruptions is needed. In this study, we will use company operating profit for the resilience metrics. Meanwhile the disruption will focus on natural causes.

Seven of Japan’s largest and most influential automakers (Toyota, Honda, Nissan, Subaru, Mazda, Mitsubishi, and Suzuki) were selected for this study. Together, these companies account for a substantial share of both the domestic and global automotive markets. Operating within the same competitive environment leads them to share overlapping supply chains, meaning that a disruption in one firm often affects the others. At the same time, variations in company size, production scale, and strategic approaches create a valuable opportunity to examine how different business models shape supply chain resilience. The disruptions discussed in this study include COVID-19 pandemic and natural disasters. The pandemic is considered a major systemic shock that spread through demand and supply channels. Recovery trajectories are shaped by firm-level actions, broader institutional responses, and crisis governance arrangements [33]. The specific types of data also chosen to be related with resilience of the company, such as internal risks (e.g., employee numbers, length of service, wages, recall rates) and external risks (e.g., exchange rates, natural disasters, factory concentration). Because the selected companies are publicly traded, their data sources are publicly accessible, providing consistent financial, operational, and recall information. This ensures reliable comparisons both across firms and over time.

The variable set was developed through a deductive approach, drawing on (i) established SCR and DRR literature addressing operational and structural drivers – such as production stability, employee tenure, product quality and recalls, market concentration, exchange rate exposure, and disaster frequency, and (ii) the requirement that all variables be consistently observable in public reports for all seven automakers from 2015 to 2024. Each of the ten variables is explicitly linked to the resilience dimensions outlined in the literature review, e.g., buffer capacity, exposure, and adaptive capability as discussed in Section 2, with additional references to prior studies supporting their relevance. Table 3 presents a detailed explanation of data used in the study.

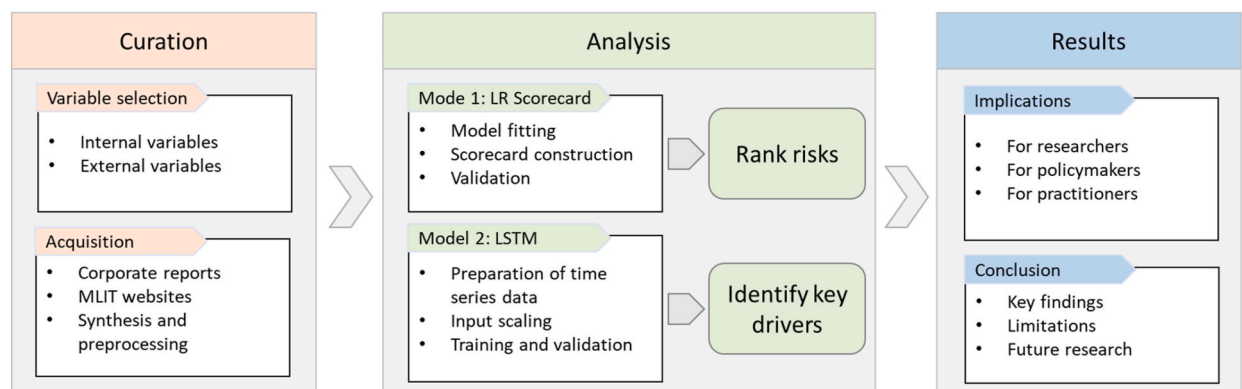


Fig. 1. Research process.

3.2. Logistic regression scorecard

A LR scorecard method is an approach used to create interpretable scoring models, commonly in areas like credit risk, lending, and customer behavior analysis, by converting the results of a logistic regression model into a scorecard format. This format assigns point values to various predictor attributes, and the total score, obtained by summing these points, reflects the risk or probability of a specific outcome. Historical data on client behavior or risk events is processed by selecting and transforming relevant variables, commonly through methods like binning and WoE [34]. These techniques improve the interpretability of the variables, making them more suitable for use in developing scorecards.

In this method, LR is used to train the model. The regression coefficients are scaled or converted into “points” for each predictor bin or category using methods min-maxing. The resulting scorecard is validated with measures AUROC (area under the ROC curve) to ensure it performs adequately. The scorecard offers a transparent, business-friendly tool for decision-making in credit assessment, or risk classification tasks. The process flow for the LR scorecard model is presented in Fig. 2.

As shown in Fig. 2, the first step involves data preprocessing. This includes applying first-order differencing to achieve stationarity for variables such as “number of production units,” “number of employees,” and “average wage.” Standardization is then performed to ensure comparability across variables with different scales, while the variance inflation factor (VIF) is used to check for multi-collinearity among other categories. Additional data transformations are also applied to enable comparison. For example, “production volume difference” is calculated as the change in the number of units produced relative to the previous year. Similarly, “factory concentration” is derived by converting factory latitude and longitude into measures of spatial dispersion, using standard distance (SD)

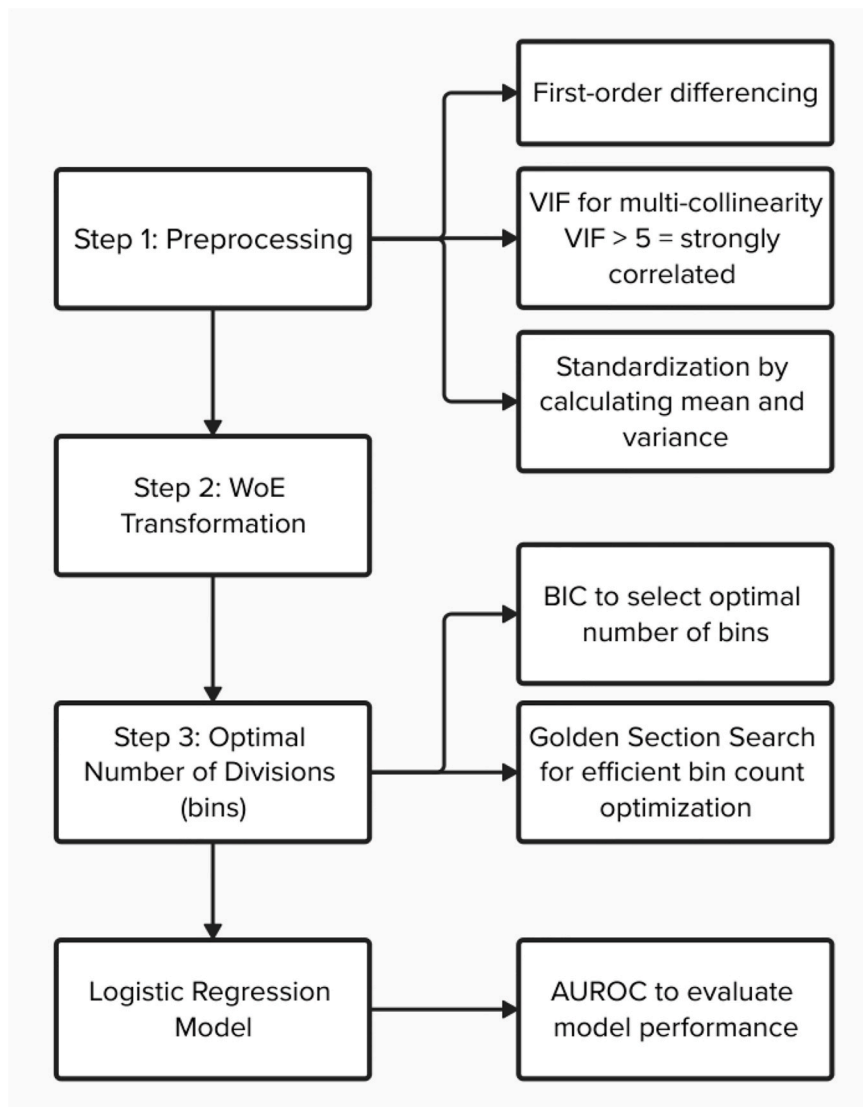


Fig. 2. Logistic regression model analysis flow.

as defined in Equation (1).

$$SD = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n} + \frac{\sum_{i=1}^n (y_i - \bar{y})^2}{n}} \quad (1)$$

3.2.1. LR equation

LR is a statistical method used to analyze the relationship between a dependent qualitative variable, either binary or multiple categories, and one or more independent explanatory variables [35]. In this study, the dependent variable indicates whether a company achieves its highest profit, serving as an indicator of its ability to strive or recover to new heights, which reflects resilience. The LR model estimates the probability that a company achieves post-disruption peak profitability (resilience “event”) based on several explanatory variables. S as summed input of the linear score $Logit(p)$ is obtained as follows.

$$Logit(p) = \ln \frac{p}{1-p} = \beta_0 + \sum_{i=1}^n \beta_i WoE_i \quad (2)$$

where p is probability of the event (e.g., resilience), β_0 is the intercept, β_i is the coefficient for the i th variable/bin. WoE_i is the weight of evidence for the i th variable/bin.

3.2.2. Weight of evidence

WoE transformation (Equation (3)) is applied within the scoring method to evaluate the discriminatory power of each attribute. WoE transforms each variable/bin to reflect its information value with respect to distinguishing events from non-events. In this context, an “event” refers to firms achieving their highest profits (classified as robust), while a “non-event” refers to firms that do not. A positive WoE value indicates that companies in the corresponding interval are classified as “resilient,” a negative value indicates “non-resilient,” and values near zero suggest that the attribute contributes minimally to identifying resilience.

$$WoE = \ln \left(\frac{D_e}{D_{ne}} \right) = \ln \left(\frac{N_e/N_t + 0.5}{N_{ne}/N_t + 0.5} \right) \quad (3)$$

where D_e indicates the distribution rate of events and D_{ne} indicates the distribution rate of nonevents; N_e is the number of events, N_{ne} is the number of nonevents, and N_t total number of events.

3.2.3. Scorecard calculation

Each bin (for each variable) is assigned a score based on its WoE and the variable’s regression coefficient, scaled by a factor to create practical score ranges.

$$Points_i = factor * \beta_i * WoE_i \quad (4)$$

where β_i is the coefficient from LR for the i th variable/bin. WoE_i is the weight of evidence for the i th variable/bin. Factor is a scaling parameter, typically set as $\frac{20}{\ln 2}$ (≈ 28.85), to convert log-odds into score points.

3.2.4. Total score

Total score is sum as all the bin scores for a specific observation (company/year).

$$Score = factor * s = \frac{20}{\ln 2} * s \quad (5)$$

here, s is the sum of $\beta_i * WoE_i$ across all bins for the observation.

3.2.5. Score to probability mapping

Convert total score or linear predictor back to a probability (through inverse logit):

$$p = \frac{1}{1 + e^{-y}} \quad (6)$$

Or in terms of score:

$$p = \frac{1}{1 + \exp \left(-\frac{\ln 2}{20} * Score \right)} \quad (7)$$

where y is the logit output (sum of all $\beta_i * WoE_i$ terms + intercept).

Additionally, variables are optimally binned with the number of divisions determined using the Bayesian Information Criterion (BIC) to enhance stability and interpretability of the model. For each explanatory variable, a LR model was estimated under varying

binning settings, with the number of bins ranging from 2 to 10. Model quality was then evaluated using the BIC. In general, BIC is defined by Equation (8), where H denotes the maximum log-likelihood of model n , k the number of parameters, and n the sample size. The second term acts as a penalty, reducing the risk of overfitting.

$$BIC = -2H + k \ln n \quad (8)$$

In this study, resilience in the LR scorecard is operationalized as a binary outcome indicating whether a firm ultimately attains its post-disruption peak operating profit within the defined recovery horizon. This measure is not intended as an exhaustive definition of resilience but as a specific, observable manifestation of the extent of financial recovery after major shocks. Conceptually, a firm that regains or surpasses its historical best operating profit can be regarded as having restored its economic functionality to a high level, which is particularly relevant for assessing long-term continuity and investment capacity in a disaster-prone context. Operating profit is chosen because it is consistently reported across all seven automakers and over time, enabling a reproducible and policy-relevant outcome variable in the absence of more granular process metrics such as service levels or lead times.

At the same time, the broader process dimension of resilience – how quickly and smoothly firms recover after disruptions – is captured through the LSTM model, which focuses on the dynamics of profit trajectories rather than a single end-state indicator. Together, the LR and LSTM components provide complementary perspectives: the LR scorecard emphasizes whether firms eventually reach a high post-disruption performance level, while the LSTM assesses the temporal pattern of recovery.

3.3. Long short-term memory

LSTM is a type of Recurrent Neural Network (RNN) designed to retain relevant information over long sequences, addressing the vanishing gradient problem that traditional RNNs face [36]. This method is used for classification or prediction [37]. This study uses a LSTM model to predict future operating profit from financial time-series data. The model includes an input layer, one or more LSTM layers, dropout layers to reduce overfitting, and a final dense layer that outputs a single profit value.

The initial step of this method involves data preprocessing. The Japanese automotive supply chain was significantly affected by specific natural disasters, notably the 2016 Kumamoto Earthquake. To capture this, we designed the earthquake index (EI). Using earthquake intensity data (JMA seismic intensity [31]) and factory location information, we construct EI that quantifies the extent to which factory areas are impacted by each seismic event. The JMA seismic intensity quantifies the level of ground shaking at multiple observation points within the affected area and has long served as a key indicator of strong motion in Japan. It is also correlated with other strong-motion indices such as Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), and Spectrum Intensity (SI) [38]. The EI for each company is calculated using proportion of production volumes of each site, multiplies the areas of the site in square meters, and the occurrence of earthquake in the site location. Earthquakes significantly affect a company's production activities, and the impact tends to increase with the total area of its production sites. The EI (Equation (9)) is calculated as the product of the “ p ”: proportion of the area of production site i relative to the total area of all factory sites,” the “ s ”: factory area in square meters,” and an earthquake dummy variable E_{dummy} , which indicates the number of earthquakes with a JMA seismic intensity greater than 4 during the corresponding period.

$$EI = p * s * E_{dummy} \quad (9)$$

The aggregation value of all production sites' EI for each year is then used as EI for calculation in the LSTM model. Other variables are unit-scaled to enhance comparability. The global-level disruption represented by COVID-19 is coded as 1 for positive impacts and -1 for negative impacts during the corresponding period. The details of variable name and unit applied in the LSTM model are presented in Table 4.

The model is subsequently set up with defined input size, hidden size, output size, and the number of LSTM layers. For regression applications, mean squared error (MSE) is chosen as the loss function, complemented by the Adam optimizer to enhance training efficiency. The input features comprise financial metrics, and the output represents predicted operating profit. Training proceeds for 100 epochs, during which predictions are generated, losses calculated, and model weights updated through backpropagation. Hidden states are detached at each step to avoid memory accumulation. The architecture is implemented as a custom PyTorch class which

Table 5
Configuration of LSTM model.

Parameter	Definition
Input	Time series sequences of variables described in Table 3
LSTM layer	A specialized component designed for sequence prediction tasks (50, 100)
Dropout layer	To reduce overfitting
Dense layer	Output layer to produce a single value (operating profit)
Constructor	Interpolation or imputation
Forward function	Used check if hidden states are provided.
Loss function	MSE
Optimizer	Adam optimizer
Input dimension	Numbers of input variables (11)
Hidden dimension	Size of the model (16)
Output dimension	Number of output variable (1)

provides the essential framework for constructing, training, and managing neural network models in PyTorch. The forward function method initializes hidden states when absent and routing the LSTM output into a fully connected layer for prediction. Training progress is monitored by printing the loss at regular intervals. Table 5 summarizes the configuration details.

4. Results and discussion

To enhance coherence and readability, this section is organized to progress from model performance to driver interpretation and finally to broader implications. Subsection 4.1 presents the predictive performance of the LR scorecard and LSTM models; Subsection 4.2 interprets the key resilience determinants identified by both models; Subsection 4.3 details the sensitivity test; Subsection 4.4 examines implications for DRR policy and managerial practice; Subsection 4.5 outlines the study's novelty; and Subsection 4.6 summarizes the main contributions.

4.1. Logistic regression scorecard model

For each explanatory variable, a LR model was constructed under various binning configurations, with the number of bins ranging from 2 up to 10, and WoE values were calculated for each bin. The optimal setting was identified by a minimum BIC value of -62.138 , resulting in two bins for all variables. The WoE values are obtained through optimal binning. The intervals for each variable's bins, along with the corresponding WoE and scores, are as follows (Table 6). The cut-points reported in Table 6 (e.g., production drop ≥ 5764 units) were derived using an optimal binning algorithm guided by the BIC. This approach imposes a strong penalty on model complexity, thereby reducing the likelihood of overfitting. Although the algorithm considered multiple bin configurations during the search process, a parsimonious two-bin structure (High/Low) achieved the lowest BIC for most variables. Consequently, the identified thresholds represent statistically optimal split points that maximize information value while maintaining an appropriate level of segmentation for the sample size.

Higher scores indicate a stronger likelihood of the positive outcome predicted by the model (e.g., strong resilience or lower financial risk). Lower scores reflect higher risk or lower likelihood of the positive event (e.g., non-resilience or higher risk of default). The difference between scores for various bins/attributes demonstrates their impact and can be used for benchmarking or strategy. The score range (minimum and maximum) and the intervals are critical for risk interpretation; businesses often standardize score ranges for comparison across models.

The results reveal that the most influential risk factors are employee tenure, production volumes, and exchange rates, each showing a strong link to resilience outcomes. In contrast, variables such as market concentration (HHI), the number of employees, and employee wages demonstrate weaker associations with risk. This suggests that market concentration does not play a decisive role in a company's ability to recover from disruptions. The likely reason lies in Japan's mature and stable automotive market, where long-term relational contracting and keiretsu-style networks mitigate the short-term effects of competitive concentration in downstream product markets. Furthermore, the HHI applied here measures concentration in final vehicle markets rather than in upstream tiers or critical component segments, making it too coarse to capture vulnerabilities rooted in specialized suppliers or geographically clustered sub-networks. Consequently, the weak HHI effect should not be viewed as evidence that concentration is irrelevant to resilience, but rather that aggregate product-market concentration is an imperfect proxy for underlying structural risks in this sector.

From an internal and controllable standpoint, increasing employee tenure, boosting production volumes, and minimizing recall incidents are key to enhancing organizational resilience. Among these, production volume exhibited one of the most significant effects: a year-on-year drop of 5764 units or more resulted in a significant penalty, highlighting the importance of maintaining stable production during external shocks, such as the pandemic caused by the COVID-19 virus. Firms such as Suzuki and Mitsubishi, which sustained or increased output, were more likely to achieve record profitability, highlighting the value of robust supply chain management.

Employee tenure also stood out as a major contributor to organizational performance. Companies with an average service length above 16.8 years tended to perform better, likely benefiting from the organizational knowledge and crisis management capacity provided by longer-tenured workforces. Honda, for example, maintained consistently high tenure and delivered strong financial results, while Nissan, with declining tenure, lagged behind. The observed importance of variables related to tenure and workforce stability aligns with the argument that resilience is based on human resource and knowledge management capabilities, such as retention, learning, and knowledge sharing [27]. This suggests that resilience is not solely dependent on physical assets or network topology.

Table 6
WoE result.

Variables	Low interval	WoE	Score	High interval	WoE	Score
Production volumes	≤ 5764	0.8408	-25	>5764	-0.6513	19
Number of employees	≤ 267	-0.2399	-4	>267	0.1278	2
Employee wages	$\leq 103,282$	0.4643	3	$>103,282$	-0.4761	-3
HHI	≤ 137	-0.1547	0	>137	0.0347	0
Employee tenure	≤ 16.8	0.8408	-29	>16.8	-0.6513	22
Total recalls	≤ 198	-0.3395	9	>198	0.3337	-9
Exchange rate	≤ 111	0.5798	-12	>111	-0.6513	14

Exchange rate movements were also found to influence profitability. A weaker yen (over 111 JPY/USD) often corresponded with better financial results for firms that rely heavily on exports.

Quality management, as reflected by the frequency of vehicle recalls, also played a notable role. Firms with fewer than 198 recalls attained higher resilience scores. This suggests that maintaining product quality and limiting recalls during times of supply chain stress is crucial for sustaining financial health.

On the other hand, fluctuations in employee numbers, changes in wages, had little to no effect on firm profitability. These patterns suggest that short-term human resource measures and wage manipulation do not significantly impact firms' performance in the mature Japanese automotive sector during times of disruption.

Table 7 presents the VIF values for the variables examined in this study. As all values are below 5, multicollinearity was not detected.

Finally, the model was evaluated over the same period using the derived scorecard values, with the results presented in Fig. 3. The AUROC achieved a value of 0.83.

Overall, the LR scorecard successfully transformed multidimensional operational and structural indicators into an interpretable resilience scoring framework. The model demonstrated robust predictive performance, with goodness-of-fit statistics and classification accuracy indicating that the probability estimates were reliable for distinguishing between resilient and non-resilient firms. Several variables emerged as statistically significant predictors of resilience outcomes. In particular, employee tenure, production stability, and recall frequency, were identified as critical determinants. Their WoE transformations and contributions to the scorecard highlight the extent to which both organizational stability and operational reliability influence the likelihood of achieving post-disruption profitability.

4.2. LSTM model

Data from six companies (Toyota, Honda, Nissan, Subaru, Mazda, and Mitsubishi) are used for training, while one company (Suzuki) is reserved for testing. Fig. 4 illustrates the influence of each variable on operating profit. The results show that factors such as production volume and workforce size (numbers of employees) positively affect operating profit, whereas variables like sales volume, pandemic impacts, and the EI exert negative effects.

Fig. 5 presents a comparison between the original operating profit data and the values predicted by the LSTM model. The blue line denotes the actual data, while the orange dashed line indicates the model's predictions. The LSTM model, trained on data from six companies, achieves a test performance of $MSE = 0.0194$, which is considered acceptable.

The LSTM model effectively captured temporal dynamics and non-linear interactions among variables influencing operating profit. Notably, production volume and the number of employees were positively associated with higher operating profits, underscoring their importance as key drivers of firm performance. In contrast, sales volume, pandemic events, and the EI exhibited negative correlations with operating profit, demonstrating the model's capacity to reflect the impact of real-world shocks on financial outcomes. Overall, the model exhibited strong predictive performance, achieving a MSE of 0.0194 on the test dataset, which indicates a good fit and reliable forecasts of profitability. Our results for the pandemic period align with accounts that highlight the impact of crisis depth and duration on supply-chain structures and the surrounding governance environment, including policy interventions and coordination mechanisms [33].

To ensure the reproducibility of the LSTM model, we have specified the core hyperparameters and data preprocessing details. The core hyperparameters and settings are summarized in Table 8.

Furthermore, to demonstrate that the model's generalization capability is not idiosyncratic to a single firm (Suzuki), we conducted a leave-one-firm-out (LOFO) cross-validation across all seven firms. In this validation, we add a LOFO evaluation where each firm is held out in turn. In addition, because the data are time-series, we apply a time-based split within each firm (earlier years for training, later years for validation) to avoid future-to-past leakage. If requested, we can further include a rolling-origin evaluation (expanding/rolling window) to confirm robustness across different forecast origins.

To improve interpretability of the LSTM model and to triangulate the results with the LR scorecard, additional model-agnostic diagnostics are conducted, namely permutation importance and partial dependence plots (PDPs). The permutation importance analysis indicates that macro-trend and firm-scale variables, such as worldwide sales volume and number of employees, exert the largest influence on predicted operating profit, whereas HHI, the EI, and the COVID-19 dummy contribute relatively little to the model's predictive performance. This pattern is consistent with the LR findings, which also highlight core production and sales activities, rather than market concentration or specific hazard indicators, as the primary determinants of profit structures.

Table 7
VIF result.

Variables	VIF
Production volumes	1.4872
Number of employees	1.0909
Employee wages	1.6643
HHI	1.2433
Employee tenure	1.0444
Total recalls	1.2639
Exchange rate	1.6990

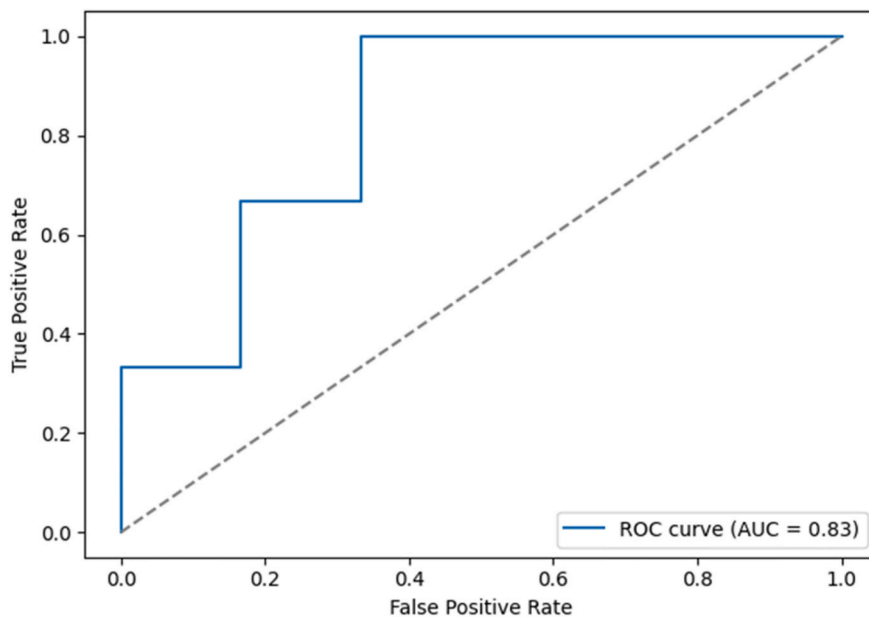


Fig. 3. Area under the curve.

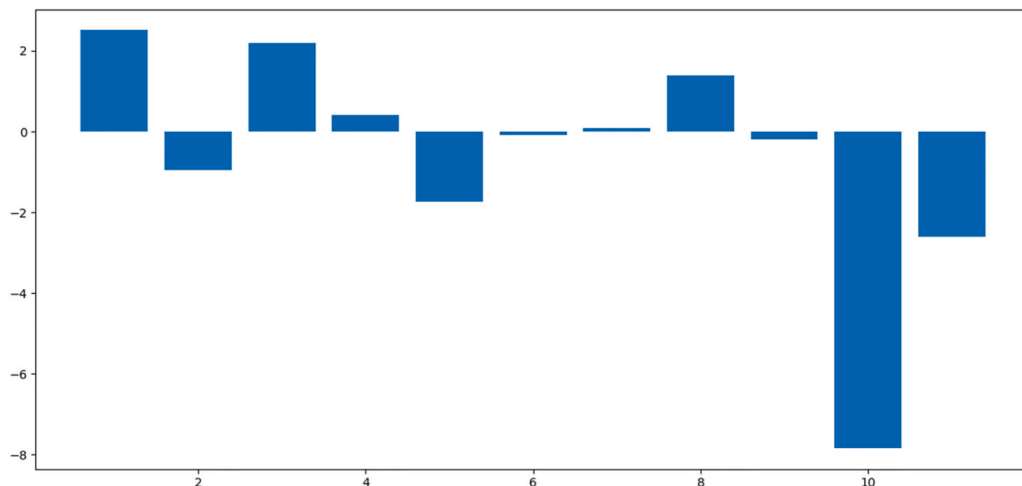


Fig. 4. Correlation analysis between input and output variables. The input variables in X-axis are listed in the same order as Table 4, and the output variable in Y-axis corresponds to operating profit.

To visualize non-linear effects, PDPs are generated for the most influential inputs (production volume and number of employees) and for EI. For production volume and employees, the PDPs show a positive monotonic relationship with predicted profits, confirming the economic intuition that expansion in macro-level demand and increased corporate scale are associated with higher profitability. Although the global importance of EI is relatively low, its PDP reveals that higher EI values – corresponding to more frequent or severe disaster conditions – have a non-linear, increasingly negative effect on predicted profits, suggesting that the LSTM successfully captures the adverse impact of extreme shocks even when their average contribution is modest.

These interpretability analyses are implemented under the same LOFO cross-validation framework used for the baseline LSTM evaluation. This additional validation yielded an overall average RMSE of 0.60 across firms. For six companies (all except Toyota), the model achieved low prediction errors, with an average RMSE of 0.25 (MSE 0.018), indicating good generalization to typical automotive firms in the sample. Toyota (Firm ID 1) exhibited a much higher error (RMSE 2.6379), which feature-importance analysis links to a different profit structure: for most firms, global/domestic sales and number of employees dominate, whereas for Toyota the EI is the most influential predictor and macro sales variables are less important (Table 9). For the remaining six firms, error levels are low and the qualitative patterns in the PDPs. For example, the positive association between firm scale and profit remain consistent, supporting the general validity and cross-firm robustness of the LSTM-based resilience assessment.

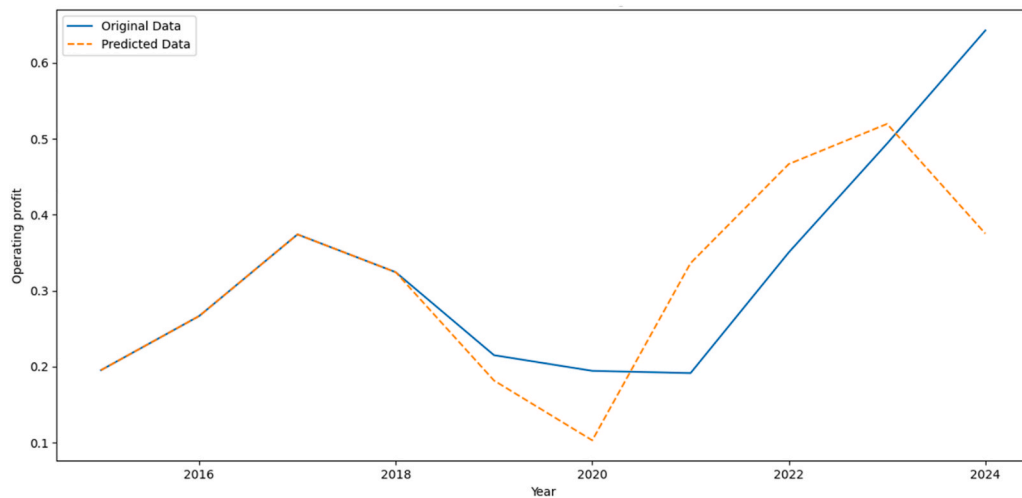


Fig. 5. Prediction accuracy.

Table 8

Hyperparameters and data preprocessing details.

Configuration	Value
Look-back window (SEQ_LEN)	5 years
Structure	LSTM (2 layers, 32 hidden units)
Dropout rate	0 (Regularized via Weight Decay)
Optimizer	AdamW
Learning Rate	1e-3 (Weight Decay: 1e-2)
Training	Max 4000 epochs (Early-stopping patience: 150)
Loss Function	MSE
Scaling	Standardization (Z-score normalization) applied per firm/feature

4.3. Sensitivity test

To assess robustness to confounders and overlapping industrial shocks, an additional sensitivity analysis is conducted for the global semiconductor shortage, which represents a major non-disaster shock during the study period. A binary dummy variable for the semiconductor shortage is introduced, taking the value 1 for 2021Q1–2022Q2 and 0 otherwise, and incorporated into both the LR scorecard and the LSTM model. The objective is to test whether controlling explicitly for this period-specific supply constraint alters the estimated driver structure, including the signs (LR) and the relative importance or rankings of key predictors (LR and LSTM).

For the LR scorecard, augmenting the model with the semiconductor-shortage dummy leaves the test AUROC unchanged at 0.7778 (difference 0.0000 between the baseline and augmented specifications), and the signs and rankings of the main coefficients remain stable. The variance inflation factor for the shortage dummy remains below 2.0, indicating no serious multicollinearity issues. Together, these results imply that the impact of the semiconductor shortage is already largely mediated through fluctuations in operational variables such as production and wages, and that the inferred resilience drivers are robust to this prominent non-disaster shock. As an additional robustness check, the Appendix reports re-estimated models that exclude all observations from 2021Q1–2022Q2; the qualitative signs and rankings of key drivers remain substantively unchanged in these subsamples.

For the LSTM, the semiconductor-shortage dummy attains a mid-range permutation importance (ranked sixth, importance score 3.03), indicating that the model recognizes the associated supply constraint as a relevant but secondary factor (Table 10). Crucially,

Table 9

LOFO performance by firm.

Firm_id	Firm name	RMSE	MAE	MSE
1	Toyota	2.6379	2.3064	6.9584
2	Honda	0.6922	0.5525	0.4791
3	Nissan	0.5007	0.3952	0.2507
4	Subaru	0.1021	0.0648	0.0104
5	Mazda	0.1108	0.0949	0.0123
6	Mitsubishi	0.1526	0.1244	0.0233
7	Suzuki	0.0984	0.0761	0.0097
Average		0.6135	0.5163	1.1063

even after adding this control, the core fundamentals – domestic and global automobile sales, production volume, and number of employees – remain concentrated among the top drivers, suggesting that the LSTM's profit predictions are primarily governed by persistent demand–supply fundamentals rather than by a single overlapping shock.

4.4. Implications

When interpreting the empirical findings, we consider variables such as workforce tenure, production stability, and product quality (i.e., recalls) to be predictors or indicators of the likelihood of stronger post-disruption profit recovery rather than definitive causal drivers of SCR. These signals may reflect underlying factors, such as firm maturity, employment systems, capital intensity, or product mix, that are not fully identified in our design. Therefore, we frame any managerial implications in predictive terms and explicitly view causal claims about specific practices or configurations as hypotheses for future research.

4.4.1. Implications for researchers

Future research on SCR would benefit from hybrid analytical frameworks that integrate interpretable models, such as logistic regression scorecards, with advanced time-series approaches like LSTM. Such combinations allow researchers to capture both the relative importance of explanatory variables and the dynamic, temporal effects that shape resilience outcomes. Additionally, applying causal inference and machine learning techniques can move beyond identifying correlations, enabling the elucidation of the precise mechanisms that drive resilience or vulnerability within supply chains.

Expanding SCR research beyond Japan and the automotive sector is essential for enhancing the generalizability of findings. Comparative studies across different countries and industries can support the identification of resilience indicators that are transferable across diverse regulatory, cultural, and operational contexts, thereby improving benchmarking practices and the broader applicability of resilience strategies.

Future studies should differentiate between internal factors, such as employee tenure and production stability, and external factors, including natural disasters and exchange rate fluctuations, recognizing their distinct and interactive influences on resilience. Leveraging public longitudinal datasets can further enhance the objectivity, reproducibility, and methodological rigor of SCR research, providing a stronger empirical foundation for both theoretical and practical insights.

4.4.2. Implications for policymakers

Policymakers should embed operational resilience, such as workforce stability and consistent production practices, at the core of national DRR strategies, in alignment with international frameworks like the Sendai Framework. Policies that incentivize longer employee tenure, rigorous quality control, and production continuity can serve as effective mechanisms to buffer supply chains against disaster-related shocks. Policymakers can support more proactive, multi-hazard governance mechanisms by embedding firm-level resilience indicators, such as profit recovery speed and continuity of operations, into regulatory frameworks and disaster risk reduction (DRR) planning, which is consistent with recent DRR policy design recommendations under the Sendai Framework [15].

Not all commonly considered factors, such as wages or market concentration, contribute equally to supply chain resilience. Policy interventions should therefore prioritize support for proven resilience drivers. In addition, promoting the public availability of operational and risk-related data can enhance the accuracy of resilience assessments and enable informed decision-making at both macro and micro levels.

SCR indicators should be systematically incorporated into industrial safety regulations and disaster response plans. Such integration helps protect critical infrastructure, maintain employment stability, and ensure continuity of operations during periods of disruption.

4.4.3. Implications for practitioners

Investing in employee retention and skill development is essential for preserving institutional knowledge, which directly supports a company's capacity to recover rapidly from disruptions. Regular monitoring and proactive management of employee tenure and

Table 10
Feature importance analysis results.

Feature	Mean	STD
Automobile sales in Japan	4.1392	0.9622
Automobile sales in worldwide	4.0266	1.2445
Production volume in Japan	3.4759	1.3383
Number of employees	3.3420	1.9083
Sales volume in Japan	3.2154	1.4360
Semiconductor shortage	3.0313	1.1220
Production volume in worldwide	2.6542	1.5581
Sales volume in worldwide	2.0228	1.0702
EI	1.5805	0.7143
HHI	1.3907	0.8884
Employee wages in Japanese yen	1.0494	0.7448
Pandemic (COVID-19)	0.9064	0.7246

engagement should be incorporated into broader resilience strategies to ensure organizational knowledge is maintained over time.

Maintaining consistent production volumes and minimizing recalls is critical, particularly during periods of external shocks, to safeguard profitability and sustain market position. Utilizing resilience scorecards and predictive analytics can help identify vulnerable points within the supply chain, allowing managers to strengthen weak links before they escalate into operational failures.

Practitioners should implement data-informed approaches that combine statistical methods and AI-based tools for forecasting and scenario analysis. This enables proactive risk management rather than reactive crisis response. Benchmarking against key indicators, such as production changes, employee tenure, and recall rates, can guide internal assessments and support continuous improvement in supply chain resilience.

4.5. Novelty

This study represents one of the first comprehensive, data-driven analyses of supply chain resilience in the Japanese automotive sector that combines interpretable scorecards with sequence-learning models on a common multi-firm longitudinal dataset. In contrast to prior SCR works that focus primarily on qualitative case studies or survey-based indices in automotive and DRR contexts, the present analysis uses publicly available operational, financial, and hazard-related indicators for seven major automakers from 2015 to 2024 to construct reproducible resilience measures and benchmarks. Methodologically, the study introduces a novel hybrid framework that combines an interpretable LR scorecard with LSTM neural networks. The LR scorecard provides transparent, actionable risk scores, while the LSTM model captures complex, non-linear temporal dynamics and interactions among risk variables. Such a dual-model approach is rarely applied in SCR research and enables the simultaneous delivery of both explainable and predictive insights. By integrating quantitative public data with this hybrid modeling framework, the study offers a transparent and replicable methodology for measuring and forecasting supply chain resilience, producing both theoretical contributions and practical tools for managers and policymakers in a previously under-examined context.

This study offers three specific contributions to the supply chain resilience and disaster risk reduction literature. First, while many prior SCR studies in automotive and DRR contexts rely on qualitative case analysis or survey-based indices (e.g., Scavarda et al., 2015; Agarwal & Seth, 2021, 2024), this paper provides a multi-firm, data-driven assessment of resilience in Japan's automotive sector using publicly available longitudinal indicators from 2015 to 2024. By focusing on seven major automakers, the analysis complements existing case-based evidence with reproducible, cross-firm comparisons grounded in operational and structural variables.

Second, quantitative resilience research typically employs a single modeling paradigm, such as regression or a specific machine-learning model, without systematically combining interpretable and sequence-learning approaches. This study introduces a dual-model framework that integrates a logistic regression scorecard with an LSTM network, allowing comparison between a transparent, policy-oriented scoring method and a high-capacity time-series model for predicting post-disruption recovery. The framework demonstrates how convergent patterns in feature importance and partial dependence across the two models can be used to triangulate key drivers of resilience in a complex, hazard-rich environment.

Third, existing empirical work on the Japanese automotive industry rarely links firm-level resilience metrics to broader DRR policy agendas, despite the sector's critical role in national and global supply chains. By grounding the analysis in the Sendai Framework and related DRR studies, the paper translates model-based findings on production stability, employee tenure, recalls, and disaster exposure into implications for disaster risk governance and business continuity planning. In doing so, it connects operational indicators commonly reported by firms with policy debates on critical infrastructure resilience, thereby bridging corporate SCR analysis and national-level DRR objectives.

4.6. Key contributions

This study makes three specific contributions to the supply chain resilience and disaster risk reduction literature.

4.6.1. Multi-firm, data-driven resilience assessment in Japanese automotive

While many prior SCR studies in automotive and DRR settings rely on expert judgment, surveys, or single-case analyses, this paper develops a multi-firm, longitudinal assessment for seven major Japanese automakers using openly accessible operational, financial, and disaster-related indicators from 2015 to 2024. This design enables transparent replication, cross-firm comparability, and benchmarking of resilience outcomes in a globally critical but under-quantified supply chain.

4.6.2. LR-LSTM framework for interpretable and dynamic resilience modeling

Quantitative SCR research usually uses interpretable statistical models or black-box machine learning approaches separately. This study introduces a dual-model framework that integrates a logistic regression (LR) scorecard and a long short-term memory (LSTM) network using the same dataset. This framework compares an interpretable, policy-oriented scoring tool for post-disruption peak profitability with a high-capacity time-series model for profit-recovery trajectories. The framework triangulates feature importance, partial dependence patterns, and out-of-sample performance across the two models to show how convergent drivers, such as production stability, employee tenure, and recall performance, can be robustly identified in a hazard-rich environment.

Methodologically, the study demonstrates the value of combining explainable AI approaches with advanced machine learning to integrate interpretability and predictive power, offering a significant contribution to both academic research and industry practice. Finally, the study outlines directions for future research, including the use of broader international datasets, additional resilience-related variables, and causal machine learning techniques to further elucidate the mechanisms underlying SCR.

4.6.3. Operationalization of resilience drivers linked to DRR policy agendas

This study defines resilience in terms of post-disruption peak operating profit and explicitly models internal operational factors (e.g., production changes, workforce characteristics, and recall rates) and external risk indicators (e.g., earthquake exposure via the EI, exchange rate movements, and pandemic conditions in the LSTM) to derive interpretable resilience scores and dynamic predictions. By mapping these indicators to DRR and business continuity priorities, the analysis provides actionable guidance for corporate risk management and public policy. It also offers a replicable template that can be extended to other sectors and countries.

The study systematically identifies robust resilience drivers, including employee tenure, production volume stability, and quality control (measured by recall frequency). These factors emerge as critical predictors of profit recovery and peak profitability during disasters and pandemics, providing clear operational levers for both practitioners and policymakers. By differentiating internal (organizational and operational) from external (macroeconomic and disaster-related) risk factors, the analysis clarifies their distinct and sometimes interactive effects. Notably, traditional structural variables such as market concentration (HHI) and salary adjustments were found to have limited explanatory power in this mature sector. Our findings on the importance of internal, people-related factors align with perspectives on resilience that emphasize agility and adaptive leadership as fundamental organizational competencies for navigating environments with high levels of uncertainty and disruption [27].

Policy- and practice-relevant insights are also generated. The transparent LR scorecard framework facilitates the development of communicable metrics for corporate risk management and informs evidence-based DRR strategies, aligned with global frameworks such as the Sendai Framework. Moreover, the methodology establishes a foundation for benchmarking SCR performance across firms and over time. With suitable adaptation, it can be extended to other sectors and comparative international contexts, supporting broader cross-sectoral and transnational research in supply chain risk analytics.

5. Conclusion

This study examined the resilience of Japanese automotive supply chains to disaster and pandemic disruptions, utilizing a dual-model approach: a LR scorecard for interpretable factor analysis, and a LSTM neural network for dynamic profit prediction. By integrating ten years of publicly available operational and structural data, we systematically assessed both internal (e.g., employee tenure, production stability, quality control) and external (e.g., disaster indices, exchange rates) factors shaping resilience.

The LR scorecard results highlight several internal and structural factors consistently associated with higher resilience. These factors include long employee tenure, stable production, and strong quality control, as reflected by lower recall rates. In contrast, aggregate product-market concentration (HHI) shows a limited direct association with the resilience label. This suggests that downstream market structure is an imperfect proxy for the more granular network- and supplier-level vulnerabilities that shape disaster risk in this mature industry. These findings underscore the importance of internal operational robustness as a foundation for maintaining profitability and continuity amid shocks. They also motivate more detailed modeling of supply-network topology in future research.

The LSTM model supplements the scorecard by capturing the temporal dynamics of profit responses to shocks, such as pandemic conditions and natural disasters, among firms over time. Leave-one-firm-out validation shows that the model generalizes well for most automakers, but not for Toyota. Toyota's profit structure is more strongly influenced by earthquake exposure and regionally uneven disruptions than by aggregate sales and workforce indicators. This heterogeneity underscores the necessity of model designs that can accommodate exceptionally large, globally diversified firms and validation schemes that explicitly account for structural outliers.

From a policy and managerial standpoint, this study offers a transparent and replicable framework for converting multidimensional operational and hazard indicators into resilience scores and recovery forecasts. These scores and forecasts can inform disaster risk reduction and business continuity planning. The results indicate that investments in workforce stability, production smoothing, and quality management can yield resilience dividends. However, firm-level continuity remains intertwined with broader upstream and geopolitical risks, particularly in the context of the electric vehicle transition and critical mineral supply chains.

Lastly, as this study centers on Japanese manufacturers and their domestic operations, the broader generalizability and statistical significance of certain findings may be limited. Specifically, the analysis focuses on firm-level operational resilience within Japanese automakers, offering limited visibility into upstream supply chains for raw materials and components. This constraint is particularly relevant amid the ongoing electric vehicle (EV) transition, where securing supplies of critical minerals, such as cobalt, lithium, and nickel, and processing capacity has become a pressing issue for both industry stakeholders and policymakers. Recent studies on critical mineral and EV supply chains highlight that concentrated resource reserves, geographically clustered refining capacity, and geopolitical tensions create risks that extend beyond firm-level metrics [39,40]. These include exposure to export controls, sanctions, and environmental, social, and governance (ESG) disruptions in key producing regions. To address these gaps, future research could expand the analytical scope to upstream markets, incorporate additional resilience-related variables, and apply causal analytical techniques to enhance model robustness and interpretability. Broader extensions to global supply chains and diverse industrial contexts, complemented by advancements in causal machine learning, would further clarify the mechanisms driving resilient organizational behavior.

CRediT authorship contribution statement

Ikki Teshima: Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **I Made Raditya Wicaksana:** Writing – review & editing, Writing – original draft, Investigation, Data curation, Conceptualization. **Zhujie Cai:** Writing – original draft, Data curation. **Xiaoyu Liu:** Writing – original draft, Data curation. **Yen Chen:** Writing – original draft, Investigation. **Yuanhong**

Tian: Writing – original draft, Software, Methodology. **Enna Hirata:** Writing – review & editing, Writing – original draft, Validation, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Methodological robustness checks for resilience labeling and LR scorecard calibration

To facilitate replication, [Appendix A](#) provides a schematic example of the labeling procedure for a hypothetical firm. The example shows how disruption years are identified from the COVID-19 dummy and EI, how the three-year recovery window is constructed, and how the year in which peak operating profit is attained is mapped to the binary resilience label.

1. Justification of cut-points

The cut-points presented in [Table 6](#) (e.g., production drop ≥ 5764 units) were determined using a BIC-guided optimal binning algorithm. This method rigorously penalizes model complexity, thereby suppressing the risk of overfitting. While the algorithm allowed for multiple bins during the search process, for most variables, a parsimonious two-bin structure (High/Low) minimized the BIC. These thresholds represent the statistically optimal split points that maximize information value while avoiding excessive segmentation, given the sample size.

2. Sensitivity analysis (adaptive perturbation).

To verify the validity of the cut-points, we conducted a sensitivity analysis using adaptive perturbation, shifting each bin edge by $\pm 5\%$ and $\pm 10\%$ relative to the local data density.

- Results: The median change in test AUROC across all perturbations was 0.0000, confirming that the model's performance is centrally stable.
- Stability: 65.7% of the perturbed models remained within a negligible AUROC range (± 0.05).
- Note on Fluctuations: In specific edge cases, we observed larger fluctuations ($\text{Max } \Delta \text{AUROC} \cong 0.17$). We attribute this to the discreteness of the single-company test set (Toyota), where a change in the classification of a single year can cause a discrete jump in the evaluation metric. However, the signs and ranking of key variables remained consistent, confirming that the structural robustness of the model is maintained.

3. Verification of confidence intervals

Furthermore, we performed a bootstrap analysis ($N = 1,000$ iterations) on the training data to calculate the 95% Confidence Intervals for the logistic regression coefficients ([Appendix Table A1](#)). The analysis confirmed that key drivers such as *Average Service Years* are statistically significant, with confidence intervals that do not cross zero (CI: $[-1.50, 0.07]$).

Table A1

Bootstrap analysis results.

Feature	coef_mean	coef_ci_2.5%	coef_ci_97.5%	n_boot_valid
production_volume_diff	-0.7020	-1.4086	0.0278	1000
num_employees_diff	0.0858	-0.4571	0.6109	1000
employee_wages_diff	-0.0820	-0.8855	0.7419	1000
hhi	0.1099	-0.1287	0.3683	1000
avg_service_years	-0.8097	-1.4997	-0.0651	1000
total_recalls	-0.4146	-1.1270	0.2987	1000
exchange_rate	-0.5512	-1.2765	0.2028	1000
semiconductor_shortage	-0.3699	-1.2823	0.6507	1000

Data availability

Data will be made available on request.

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