

Supply Chain Resilience Effects of Province-Wide Industrial Integration

—A Policy Evaluation Based on Double Machine Learning

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How to cite this paper: Cai, Z.Y. and Ni, J.

(2026) Supply Chain Resilience Effects of Province-Wide Industrial Integration.

Open Journal of Applied Sciences, 16, 2384-2404.

<https://doi.org/10.4236/ojapps.2026.167135>

Received: June 14, 2026

Accepted: July 14, 2026

Published: July 17, 2026

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Abstract

Against the backdrop of rising global supply chain disruption risks, improving the resilience and security of industrial and supply chains has become a major strategic issue. Taking province-wide industrial integration as a quasi-natural experiment, this study uses a sample of Chinese A-share listed firms from 2011 to 2023 and applies a double machine learning (DML) model to identify the causal effect, potential transmission channels, and heterogeneous features of province-wide industrial integration on firm-level supply chain resilience. The results show that, first, province-wide industrial integration significantly improves firms' supply chain resilience, and this conclusion remains robust after changing the number of cross-fitting folds, applying winsorization, and replacing the machine-learning learner. Second, the mechanism analysis indicates that province-wide industrial integration significantly improves emergency production-capacity buffer reserves, industrial collaborative agglomeration, and supply chain operational efficiency. These findings are consistent with the transmission logic proposed under the integrated framework of resource dependence, industrial cluster, and dynamic capability theories (RIDCT). Third, heterogeneity analysis and formal between-group coefficient difference tests show that the resilience-enhancing effect of province-wide industrial integration is more pronounced among firms with lower supply chain dependence and in regions with lower natural-disaster risk, suggesting certain patterns of gap-filling and diminishing marginal returns. This study provides causal evidence for understanding the resilience-enabling effect of province-wide industrial integration and offers policy implications for differentiated policy deployment and the precise improvement of industrial and supply chain security.

Keywords

Province-Wide Industrial Integration, Supply Chain Resilience, Double

Machine Learning, Resource Dependence Theory, Industrial Cluster Theory, Dynamic Capability Theory

1. Introduction

Against the backdrop of intertwined global risks and rising uncertainty, external shocks such as geopolitical conflicts, extreme weather events, and public health emergencies have intensified. The risk of disruption in emergency industrial and supply chains has become increasingly salient. Improving the resilience and security of industrial and supply chains has therefore become an important component of safeguarding national economic security and promoting high-quality development. A report explicitly called for efforts to enhance the resilience and security of industrial and supply chains, providing strategic guidance for supply chain governance in the new era [1]. As a strategic industry that supports public security and emergency response, the emergency industry plays an important role in strengthening supply chain risk prevention and emergency support capabilities [2].

In this context, province-wide industrial integration has become an important policy vehicle for promoting the agglomerated development of the emergency industry and improving emergency supply chain support capacity. In this paper, province-wide industrial integration refers to an industrial organizational form that takes the provincial administrative region as the spatial unit and, through policy guidance and coordinated planning, optimizes factor allocation, production-capacity layout, and supply chain coordination in the emergency industry. It promotes coordinated development across emergency equipment manufacturing, emergency services, technology research and development, and related segments. Since the General Office of the State Council issued the Opinions on Accelerating the Development of the Emergency Industry in 2014, which clarified the task of building demonstration bases for the emergency industry, China has formed a number of distinctive industrial clusters with relatively strong driving capacity in emergency equipment manufacturing, emergency services, and technology R&D [3] [4]. In terms of policy objectives, province-wide industrial integration is not intended merely to expand the scale of the emergency industry; more importantly, it aims to enhance the shock-resistance capacity of industrial and supply chains through resource coordination, chain collaboration, and capability building.

However, in the rapid advancement of province-wide industrial integration, a practical contradiction remains between policy objectives and resilience performance. Some regions pay excessive attention to the number of firms, output scale, and short-term assessment indicators when promoting industrial agglomeration. They rely on land concessions and fiscal subsidies to attract firms, while insufficiently emphasizing upstream-downstream coordination, key core technology breakthroughs, and cross-regional emergency dispatching capabilities. In

practice, some province-wide industrial integration initiatives remain at the level of spatial agglomeration and have not yet formed an industrial ecosystem characterized by risk sharing, resource sharing, and coordinated response. The emergency material reserve system is not always smoothly connected with the supply chain dispatching system, resulting in problems such as reserves without circulation and quantity without quality. Policy resources also tend to flow toward low value-added links rather than resilience-critical segments such as key emergency equipment R&D, emergency production-capacity reserves, and supply chain collaborative governance [5]. Therefore, whether province-wide industrial integration can be effectively transformed into improved supply chain resilience still requires empirical examination.

Existing research has first provided rich discussions on the connotation, measurement, and determinants of supply chain resilience. Tomlin (2006) defined supply chain resilience as the speed at which a supply chain recovers from disruption, emphasizing passive response and recovery capabilities [6]. Ponomarev and Holcomb (2009) further extended the concept to a comprehensive capability encompassing pre-event prevention, response during disruption, post-event recovery, and adaptive optimization [7]. In terms of measurement, scholars often construct quantitative indicators using micro-level firm data. Zhang and Gu (2024), for example, decomposed supply chain resilience into resistance and recovery dimensions and used multiple indicators with the entropy-weight method to obtain a composite measure, providing an important reference for empirical studies based on listed firms [8]. In terms of mechanisms, existing studies have formed a multilevel analytical framework ranging from macro environments to meso-level industries and micro-level firms. At the macro level, Liao *et al.* (2021) argued that adverse external shocks such as geopolitical conflicts, trade frictions, and public health emergencies have significant negative effects on China's supply chain resilience [9]. Li and Ma (2022) further proposed that, under rising external uncertainty, effective supply chain resilience mechanisms should balance adaptive reconstruction and redundancy reserves [10].

At the meso-industrial level, industrial agglomeration, industrial integration, and digital transformation have gradually become important perspectives for explaining improvements in supply chain resilience. Huang *et al.* (2024), using the pilot policy of innovative industrial clusters as a quasi-natural experiment, found that industrial agglomeration can significantly improve supply chain resilience through optimized resource allocation and knowledge spillovers [11]. Ren *et al.* (2024) showed that integrated cluster development enhances industrial chain resilience through collaborative innovation mechanisms [12]. Chen *et al.* (2022) found that the digital economy provides important support for improving industrial chain resilience by promoting industrial upgrading and digital transformation [13]. At the micro-firm level, Tao *et al.* (2023) found that firms' digital transformation promotes supply chain resilience through channels such as supply-demand matching, relationship maintenance, and improved supply quality [14]. Ma

et al. (2023), using SEM and fsQCA methods, found that firm capabilities such as flexibility, agility, reshaping capacity, and supply chain collaboration have significant positive effects on supply chain resilience [15]. Xia *et al.* (2024), based on a TOE configurational analysis, argued that the coordinated configuration of technological management capability, organizational redundancy, and the external institutional environment is critical for enhancing the supply chain resilience of specialized and sophisticated enterprises [16]. These studies provide an important theoretical foundation for this paper, but they mainly focus on general industries or firms' internal capabilities and do not sufficiently explain how emergency industry agglomeration carriers affect supply chain resilience.

Second, studies on the development of the emergency industry mainly focus on industrial agglomeration effects, development-driving mechanisms, and policy practices. Regarding industrial agglomeration, Zhang *et al.* (2018), using spatial econometric methods, found that the spatial agglomeration of China's emergency industry is generally low and displays spatial autocorrelation, with an inverted U-shaped relationship with economic growth [17]. Li and Ye (2023), based on provincial panel data from the Yangtze River Economic Belt, found that emergency industry agglomeration significantly promotes high-quality economic development, with regional heterogeneity and spatial spillovers, and that technological innovation plays a mediating role [18]. Cao *et al.* (2021), using provincial panel data, found that emergency industry agglomeration and emergency fiscal expenditure have significant positive effects on China's economic growth [19]. Regarding development-driving mechanisms, Zhang *et al.* (2023), based on grounded theory, identified policy guidance, market demand, technological innovation, and industrial chain coordination as key factors driving the development of the safety and emergency industry [20]. Ma *et al.* (2020), using a structural equation model, found that government support, market demand, technological innovation, and industrial foundations significantly affect emergency industry development [21]. Wang (2015) pointed out that government guidance, market drive, and technological innovation constitute the three core driving forces of emergency industry development [22]. In terms of industrial carriers and policy practice, Zhang (2021) noted that the integration of new technologies with traditional industries has created unprecedented opportunities for the safety and emergency industry, while current industrial park development still suffers from insufficient system integration of industrial chains and a need to upgrade park construction [23]. At the policy level, China has continued to emphasize improving key equipment industrial chains, supporting leading firms in serving as chain leaders, and promoting gradient development and cluster leadership in the safety and emergency equipment industry [24] [25]. Overall, existing studies have revealed the economic effects and development logic of emergency industry agglomeration, but quantitative evaluations of the policy carrier of province-wide industrial integration remain insufficient, and causal identification from the perspective of supply chain resilience is particularly limited.

Third, in terms of policy-effect identification methods, double machine learn-

ing (DML) provides a new tool for complex policy evaluation. Proposed by Chernozhukov *et al.* (2018) [26], DML reduces regularization bias in machine-learning models through cross-fitting and orthogonalization, thereby improving the robustness of causal effect estimation under high-dimensional controls. In recent years, this method has been widely applied in domestic policy evaluation. Zhang and Li (2023) used a DML model to evaluate the effect of network infrastructure on inclusive green growth [27]. Xu and Wang (2025) found, based on DML, that the establishment of artificial intelligence innovation application pilot zones significantly improves the new quality productive forces of manufacturing enterprises [28]. Wang *et al.* (2025) used DML to systematically evaluate the effect of AI innovation application pilot zones on firm employment growth [29]. However, these applications mainly focus on the digital economy, artificial intelligence, and general industrial policies, with few studies applying DML to the evaluation of emergency industry integration policies or to the systematic examination of province-wide industrial integration and supply chain resilience.

In summary, prior studies have examined the determinants of supply chain resilience, the agglomeration effects of the emergency industry, and policy evaluation methods, but further expansion is still needed regarding the relationship between province-wide industrial integration and supply chain resilience. First, most studies focus on the macro-level agglomeration effects of the emergency industry or firm-level resilience capabilities, while lacking a causal evaluation of province-wide industrial integration as a policy carrier. Second, existing work on province-wide industrial integration is largely based on policy interpretation, qualitative analysis, or case discussion, and has not sufficiently answered whether it can effectively improve firm-level supply chain resilience. Third, the internal mechanisms through which province-wide industrial integration affects supply chain resilience have not been fully revealed. Fourth, because firms differ significantly in supply chain dependence and regions differ in natural-disaster risk, whether the policy effect of province-wide industrial integration is heterogeneous remains to be examined. Accordingly, this paper seeks to answer the following questions: Does province-wide industrial integration significantly improve firms' supply chain resilience? Through what channels does it operate? Does its effect differ across firm and regional contexts?

Based on the above background, this paper uses listed firms as the research sample and applies a double machine learning model to systematically examine the causal effect, potential mechanisms, and heterogeneity of province-wide industrial integration on supply chain resilience. Compared with existing research, the marginal contributions of this paper are as follows. First, from the perspective of macro policy evaluation, this paper systematically examines the effect of province-wide industrial integration on industrial and supply chain resilience, enriching cross-disciplinary research on emergency industry policy and supply chain governance, and constructing resilience indicators in line with the characteristics of the emergency industry. Second, it uses a DML model to handle high-dimensional covariates, thereby avoiding functional misspecification and the curse of

dimensionality in traditional parametric regression and improving the accuracy of policy-effect estimation. Third, it examines the potential channels through which province-wide industrial integration affects supply chain resilience, namely emergency production-capacity buffer reserves, industrial collaborative agglomeration, and supply chain operational efficiency, clarifying the transmission logic of resource agglomeration, capability building, and resilience improvement. Fourth, it conducts heterogeneity analysis based on supply chain dependence and regional natural-disaster risk, providing empirical evidence for differentiated implementation of province-wide industrial integration.

2. Theoretical Analysis and Research Hypotheses

This paper constructs an integrated analytical framework integrating resource dependence theory, industrial cluster theory and dynamic capability theory (denoted as the RIDCT framework for short) to interpret the internal mechanism through which province-wide industrial integration exerts impacts on supply chain resilience from the resource, organizational and capability dimensions. Province-wide industrial integration improves firms' resource access capacity, mitigates operational risks within industrial clusters and boosts dynamic response capabilities, thereby influencing three mediating variables including emergency production capacity buffer reserves, industrial collaborative agglomeration and supply chain operational efficiency, and ultimately elevates supply chain resilience.

2.1. Province-Wide Industrial Integration and Supply Chain Resilience

Supply chain resilience refers to the comprehensive capability of a supply chain system to resist disruption, recover rapidly, and achieve adaptive optimization when facing uncertain shocks. Province-wide industrial integration, as an important organizational form for emergency industry development, differs from traditional point-based industrial parks. Its core lies in coordinating emergency industry factor allocation, production-capacity layout, and collaborative networks at a broader spatial scale, thereby forming an emergency industrial ecosystem at the regional level that is larger in scale, more densely connected, and more redundant.

From the perspective of resource dependence theory, stable supply chain operation depends on the availability and substitutability of key resources. Through policy guidance and resource coordination, province-wide industrial integration can enhance firms' access to emergency materials, production capacity, technology, information, and other critical resources, reduce dependence on a single supplier or single region, and thereby alleviate supply chain vulnerability. From the perspective of industrial cluster theory, province-wide industrial integration helps promote the regional agglomeration and collaboration of upstream and downstream firms in the emergency industry, facilitates specialized division of labor, knowledge spillovers, and risk sharing, and improves overall supply chain coordination. From the perspective of dynamic capability theory, province-wide in-

dustrial integration enhances firms' sensing, adjustment, and recovery capabilities under shocks by promoting technological collaboration, flexible production, and emergency response capacity building. Therefore, province-wide industrial integration can improve supply chain resilience through resource acquisition, organizational coordination, and capability reconfiguration. Accordingly, this paper proposes the following hypothesis:

H1: Province-wide industrial integration significantly improves firms' supply chain resilience.

2.2. Transmission Channel of Emergency Production-Capacity Buffer Reserves

Province-wide industrial integration integrates key resources such as fiscal resources, land, production capacity, material reserves, and technology through regional coordination and industrial collaboration, improves firms' resource availability, and reduces their dependence on single external resources. This enhances the basic capacity of supply chains to withstand sudden shocks. Its role is not simply to expand the scale of reserves, but rather to improve the allocation efficiency of emergency resources across firms and industrial-chain links. It promotes complementary production capacity, material sharing, and coordinated emergency dispatch among upstream and downstream firms, while encouraging firms to improve flexible production and rapid conversion capabilities. In this way, dispersed firm-level reserves can be transformed into a regional system-level buffering capacity, thereby enhancing the resistance and recovery capacity of supply chains. Accordingly, this paper proposes the following hypothesis:

H2: Province-wide industrial integration enhances supply chain resilience by improving emergency production-capacity buffer reserves.

2.3. Transmission Channel of Industrial Collaborative Agglomeration

Province-wide industrial integration guides emergency equipment manufacturers, emergency service providers, technology R&D entities, and related actors to agglomerate and develop, thereby promoting a stable division of labor and collaboration among upstream and downstream firms and reducing search, transaction, and coordination costs. From the perspective of resource acquisition, industrial collaborative agglomeration expands the range of suppliers, customers, and technological resources that firms can access, improves supply chain resource substitutability, and lowers the risk that a shock to a single node will lead to overall disruption. From the perspective of organizational coordination, industrial collaborative agglomeration helps form mechanisms of information sharing, risk sharing, and collaborative production, enabling shocks faced by individual firms to be dispersed and absorbed within the industrial network. From the perspective of capability upgrading, knowledge spillovers, technological exchange, and joint innovation in agglomeration environments help firms more rapidly identify external risks and reorganize supply chain relationships, thereby improving supply chain adaptability and recov-

ery efficiency. Accordingly, this paper proposes the following hypothesis:

H3: Province-wide industrial integration enhances supply chain resilience by improving industrial collaborative agglomeration.

2.4. Transmission Channel of Supply Chain Operational Efficiency

Province-wide industrial integration promotes coordinated layout of the regional emergency industrial chain, optimizes resource allocation, strengthens inter-firm collaboration, and encourages technological innovation, thereby improving supply chain operational efficiency and enhancing supply chain resilience. Specifically, province-wide industrial integration can reduce supply-demand mismatches and resource idleness, improve the efficiency with which key resources are transformed into production and service capacity, strengthen upstream-downstream collaboration, shorten supply chain response chains, and reduce cross-regional coordination and transaction costs. It can also promote technology R&D, digital coordination, and flexible production, improving firms' ability to sense, adjust to, and recover from sudden changes in demand. As a result, supply chains can operate more efficiently in normal periods and achieve rapid response and adaptive adjustment under crisis conditions, thereby improving stability and recovery capacity. Accordingly, this paper proposes the following hypothesis:

H4: Province-wide industrial integration enhances supply chain resilience by improving supply chain operational efficiency.

In summary, province-wide industrial integration affects firm-level supply chain resilience through resource acquisition, organizational coordination, and capability enhancement. Emergency production-capacity buffer reserves, industrial collaborative agglomeration, and supply chain operational efficiency respectively represent the resource foundation, organizational network, and operational capability dimensions of the transmission process, jointly constituting the internal logic through which province-wide industrial integration affects supply chain resilience.

3. Research Design

3.1. Model Specification

This paper uses the double machine learning method proposed by Chernozhukov *et al.* (2018) [26] to identify the causal effect of province-wide industrial integration on supply chain resilience. Compared with traditional parametric regression, DML has three advantages under high-dimensional covariates. First, it uses machine learning algorithms to flexibly model high-dimensional confounders without requiring a prespecified functional form between control variables and the outcome. Second, it constructs a score function that is insensitive to nuisance parameter estimation errors through Neyman orthogonalization, thereby eliminating regularization bias. Third, it adopts cross-fitting, which splits the sample and alternately uses subsamples for auxiliary-function estimation and causal-parameter estimation, thus avoiding bias caused by overfitting and ensuring asymptotic normality and efficiency. This paper specifies the following partially linear model:

$$Y = \theta \cdot D + g(X) + \varepsilon, E(\varepsilon|X, D) = 0 \quad (1)$$

$$D = m(X) + v, E(v|X) = 0 \quad (2)$$

where Y denotes the dependent variable, supply chain resilience (SCR); D denotes the core treatment variable, province-wide industrial integration (Policy); X denotes a vector of high-dimensional control variables; $g(\cdot)$ and $m(\cdot)$ are unknown nonparametric nuisance functions; and θ is the causal parameter to be estimated. Using the residualization approach, the residual from predicting supply chain resilience on X by machine learning is regressed on the residual from predicting province-wide industrial integration on X , yielding the following estimator:

$$\hat{\theta} = \left\{ \sum [D - \hat{m}(X)]^2 \right\}^{-1} \cdot \sum [D - \hat{m}(X)] \cdot [Y - \hat{g}(X)] \quad (3)$$

where $\hat{g}(\cdot)$ and $\hat{m}(\cdot)$ are estimated using machine learning algorithms on auxiliary samples in cross-fitting. This paper uses the pystacked ensemble learner, or super learner, to estimate the auxiliary functions. By stacking multiple base learners such as LASSO, random forest, and gradient boosting, the model exploits the predictive advantages of different algorithms under different data structures. The number of cross-fitting folds is set to $k = 5$, and the number of resampling repetitions is $r = 1$.

In the mechanism analysis, this paper replaces the dependent variable in Equation (1) with emergency production-capacity buffer reserves (CR), industrial collaborative agglomeration (IA), and supply chain operational efficiency (SCE), respectively, and estimates the causal effect of province-wide industrial integration on each channel variable within the same DML framework. If province-wide industrial integration has a significant positive effect on these intermediate variables, the results can provide empirical support for the transmission logic proposed in the theoretical framework.

3.2. Variable Definitions

The treatment variable is the emergency-industry province-wide integration policy dummy (Policy), which captures whether the region in which a firm is located is affected by the province-wide integration policy. Specifically, if the province in which a firm is registered is covered by relevant province-wide integration policies during the sample period, Policy is set to 1 for that firm-year from the year of policy implementation onward; otherwise, it is set to 0.

The dependent variable is supply chain resilience (SCR). Following Zhang and Gu (2024), and extending the resilience-measurement framework, this paper selects indicators from the three dimensions of resistance, recovery, and transformation and uses the entropy-weight method to construct a composite measure. The core explanatory variable is province-wide industrial integration (Policy), measured by the implementation of provincial province-wide industrial integration policies. The mechanism variables include emergency production-capacity buffer reserves (CR), industrial collaborative agglomeration (IA), and supply chain

operational efficiency (SCE). In addition, this paper controls for firm and regional characteristics such as firm size, firm age, leverage, profitability, growth, and ownership structure. Detailed variable definitions are reported in **Table 1**.

Table 1. Variable definitions and measurement.

Variable type	Variable name (symbol)	Definition and measurement
Dependent variable	Supply chain resilience (SCR)	Measured using indicators from the three dimensions of resistance, recovery, and transformation, and aggregated using the entropy-weight method, following Zhang and Gu (2024) and the extended resilience-measurement framework.
Core explanatory variable	Province-wide industrial integration (Policy)	Provincial province-wide industrial integration policy treatment indicator; treated firms take the value of 1, and control firms take the value of 0.
Mechanism variable	Emergency production-capacity buffer reserves (CR)	Measured by the redundancy resource ratio, namely monetary funds plus inventories divided by total assets. A higher ratio indicates more adequate immediately deployable material reserves and production-capacity buffers.
Mechanism variable	Industrial collaborative agglomeration (IA)	Measured by the emergency industry collaborative agglomeration index of the province where the firm is located. The index is calculated based on location quotients of emergency equipment manufacturing and emergency services to capture the coordination match and overall agglomeration scale between the two sectors. A larger index indicates stronger upstream-downstream coordination and geographical agglomeration in the regional emergency industrial chain.
Mechanism variable	Supply chain operational efficiency (SCE)	Measured by total asset turnover, namely operating revenue divided by average total assets. A higher ratio indicates more efficient and agile conversion of supply chain resources into operating output.
Grouping variable	Supply chain dependence	Measured by the average of the ratio of sales to the top five customers to operating revenue and the ratio of purchases from the top five suppliers to total purchases. Observations above the sample mean are classified as the high-dependence group, and those below the mean as the low-dependence group.
Grouping variable	Regional natural-disaster risk	Measured by direct economic losses caused by natural disasters in the province where the firm is located. Observations above the sample mean are classified as high-risk regions, and those below the mean as low-risk regions.
Control variables	Firm and regional characteristics (X)	Firm size, firm age, leverage, profitability, growth, ownership structure, and other firm- and region-level characteristics.

Note: Supply chain dependence and regional natural-disaster risk are divided into high and low groups using the sample mean as the threshold.

The measurement of SCR is a key component of the empirical design. Building on the resistance-recovery two-dimensional framework of Zhang and Gu (2024) [8], this paper further extends the measurement framework and decomposes supply chain resilience into resistance, recovery, and transformation, and applies the entropy-weight method for objective weighting and comprehensive measurement. Resistance captures the ability of a supply chain to withstand external shocks and maintain stable upstream-downstream relationships. It includes three indicators. The first is capital occupation, measured by the natural logarithm of the ratio of accounts receivable plus prepayments to main business revenue; a smaller value indicates less capital occupation by downstream firms and a more stable supply chain relationship. The second is inventory adjustment, measured by the natural logarithm of the absolute change in inventories between two periods; a smaller value indicates higher supply management efficiency and more timely response to downstream demand. The third is customer stability, measured by the share of stable customers among the top five customers that maintain co-operation across consecutive years; a larger value indicates more stable supply-demand relationships.

Recovery captures the capability of a supply chain to return to its initial state after deviating from normal operation. It includes two indicators. The first is supply-demand deviation, measured by the degree to which production volatility deviates from demand volatility; a larger value indicates greater mismatch in upstream-downstream fluctuations, a more pronounced bullwhip effect, and weaker recovery capability. The second is performance deviation, measured by the residual from regressing firm performance, defined as total profit divided by the number of employees, on fundamental factors such as firm size, profitability, and leverage. A larger residual indicates that the firm can outperform fundamental expectations after shocks and thus has stronger recovery capability.

Transformation captures the ability of a supply chain to turn crisis into opportunity and achieve upgrading. It includes two indicators. The first is the operating cycle, measured as the sum of inventory turnover days and accounts receivable turnover days; a smaller value indicates a shorter delivery cycle, more agile anticipation of and response to demand changes, and stronger transformation capability. The second is operating growth, measured by the net value of total asset growth after excluding financing, tax, and accounts payable growth; a larger value indicates stronger ability to obtain tangible and intangible asset growth from upstream and downstream supply chain relationships. After making inverse indicators such as capital occupation, inventory adjustment, supply-demand deviation, and operating cycle directionally consistent, the seven indicators are weighted and aggregated using the entropy-weight method to obtain the composite SCR index. A larger SCR value indicates stronger firm-level supply chain resilience.

3.3. Data Sources and Sample

This paper uses Chinese A-share listed firms from 2011 to 2023 as the research

sample. The data mainly come from the China Stock Market and Accounting Research (CSMAR) database, China Statistical Yearbook, and listed firms' annual reports. After excluding financial firms, ST firms, and observations with missing key variables, and after winsorizing major continuous variables, the final sample contains 11,990 valid observations. The auxiliary-function estimation and causal-parameter identification in machine learning are conducted on the same sample.

4. Empirical Results and Analysis

4.1. Baseline Regression Results

Table 2 reports the baseline DML estimates of the effect of province-wide industrial integration on supply chain resilience. The core treatment variable Policy is significantly positive at the 1% level, and the 95% confidence interval excludes zero (**Table 2**). This indicates that province-wide industrial integration has a significant positive causal effect on firm-level supply chain resilience, providing strong empirical support for H1. In economic terms, province-wide industrial integration systematically strengthens the ability of supply chains to resist and recover from uncertain shocks by coordinating emergency resource allocation, promoting industrial collaboration, and upgrading capabilities at the regional level. This finding is consistent with the expectations of resource dependence theory, industrial cluster theory, and dynamic capability theory. As a policy-driven industrial organizational form, province-wide industrial integration shapes supply chain resilience through multiple paths, including critical resource integration, geographical agglomeration and division of labor, technological breakthroughs, and flexible production.

Table 2. Baseline regression results.

Variable	Coefficient	Robust standard error	z value	P > z	95% confidence interval
Policy (province-wide industrial integration)	0.171***	0.016	10.62	0.000	[0.139, 0.202]
Constant	−0.008***	0.003	−2.61	0.009	[−0.013, −0.002]

Note: The estimation method is partial linear double machine learning (DML). The machine-learning algorithm is pystacked, the number of cross-fitting folds is $k = 5$, the number of resampling repetitions is $r = 1$, and the number of observations is 11,990. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The same notation applies below.

4.2. Robustness Tests

To test the reliability of the baseline conclusion, this paper conducts robustness tests in three ways, as shown in **Table 3**. First, the number of cross-fitting folds is changed. With the auxiliary functions still estimated using the pystacked learner, the number of cross-fitting folds is adjusted from $k = 5$ to $k = 10$, and the coefficient of Policy remains significantly positive at the 1% level, consistent with the

baseline result. Second, winsorization is applied. Keeping the pystacked learner and $k = 5$ cross-fitting setting unchanged, major continuous variables are winsorized at the 1% level to eliminate the influence of extreme values. The direction and significance of the Policy coefficient remain substantively unchanged. Third, the auxiliary-function learner is replaced. After replacing the pystacked ensemble learner with gradient boosting (gradboost), the Policy coefficient remains significantly positive at the 1% level. It should be noted that the direction and significance of the policy effect remain stable after changing learners, although the point estimate fluctuates to some extent. This may be related to the sensitivity of different machine-learning algorithms to sample structure and hyperparameter settings. Therefore, the robustness conclusion should be understood as stability in the direction and statistical significance of the policy effect, rather than exact equality of point estimates. Overall, whether changing the number of cross-fitting folds, applying winsorization, or replacing the auxiliary-function learner, the positive effect of province-wide industrial integration on supply chain resilience remains robust, indicating that the baseline conclusion is reliable.

Table 3. Robustness tests.

Variable	(1) 10-fold cross-fitting	(2) 1% winsorization	(3) Gradient boosting (gradboost)
Policy (province-wide industrial integration)	0.182*** (0.017)	0.181*** (0.020)	0.102*** (0.012)
z value	10.43	8.84	8.43
Constant	-0.008*** (0.003)	-0.008*** (0.003)	0.000 (0.003)
Observations	11990	11990	11990

Note: Robust standard errors are reported in parentheses. All three columns use partial linear DML estimation, with the number of resampling repetitions $r = 1$. Column (1) uses the pystacked learner and adjusts the number of cross-fitting folds to $k = 10$. Column (2) uses the pystacked learner with $k = 5$ and applies 1% winsorization to major continuous variables. Column (3) replaces the auxiliary-function learner with gradient boosting (gradboost), with $k = 5$.

4.3. Mechanism Analysis

To further examine the potential channels through which province-wide industrial integration affects supply chain resilience, this paper tests the effect of the policy on three channel variables based on the RIDCT analytical framework. The results are reported in **Table 4**. It should be noted that the mechanism analysis in this paper mainly identifies whether province-wide industrial integration significantly affects the relevant channel variables, thereby providing empirical evidence for the transmission logic proposed in the theoretical analysis. Because this paper does not further test the direct effect of the channel variables on supply chain resilience, the analysis is not interpreted as a complete mediation-effect test in a strict sense.

First, for emergency production-capacity buffer reserves (CR), **Table 4** shows that the estimated coefficient of Policy is significantly positive at the 1% level, indicating that province-wide industrial integration significantly improves firms' emergency production-capacity buffer reserves. This result is consistent with the basic prediction of resource dependence theory. By integrating policy resources, coordinating production capacity, and building emergency material reserve systems, province-wide industrial integration helps expand critical material reserves, strengthen redundant production-capacity construction, and improve the efficiency of emergency resource deployment. It therefore provides a more adequate resource buffer for supply chains facing external shocks. Thus, the empirical results are consistent with the proposed channel of emergency production-capacity buffer reserves.

Table 4. Mechanism analysis.

Variable	(1) Emergency production-capacity buffer reserves CR	(2) Industrial collaborative agglomeration IA	(3) Supply chain operational efficiency SCE
Policy	1.998*** (0.641)	1.099*** (0.034)	4.732*** (0.086)
z value	3.12	31.90	55.11
95% confidence interval	[0.741, 3.255]	[1.032, 1.167]	[4.564, 4.900]
Constant	0.039 (0.109)	-0.006 (0.004)	0.002 (0.009)
Corresponding theory	Resource dependence theory	Industrial cluster theory	Dynamic capability theory
Observations	11,990	11,990	11,990

Note: Robust standard errors are reported in parentheses. All columns use partial linear DML estimation, the pystacked learner, $k = 5$, and $r = 1$.

Second, for industrial collaborative agglomeration (IA), **Table 4** shows that the estimated coefficient of Policy is significantly positive at the 1% level, indicating that province-wide industrial integration significantly promotes regional industrial collaborative agglomeration. This result is consistent with the logic of industrial cluster theory. Province-wide industrial integration helps promote the agglomerated development of upstream and downstream firms in the emergency industry within a region, encourages specialized division of labor, coordinated supporting capacity, and knowledge spillovers, strengthens the interaction among industrial chains, supply chains, and innovation chains, and facilitates the formation of risk-sharing and coordinated-response mechanisms within clusters. Therefore, the empirical results are consistent with the proposed channel of industrial collaborative agglomeration.

Third, for supply chain operational efficiency (SCE), **Table 4** shows that the estimated coefficient of Policy is significantly positive at the 1% level, indicating that province-wide industrial integration significantly improves firms' supply

chain operational efficiency. This result is consistent with the theoretical expectations of dynamic capability theory. By promoting technology R&D, digital coordination, and flexible production capacity building, province-wide industrial integration helps improve firms' ability to sense, adjust to, and recover from sudden changes in demand, thereby improving supply chain resource-allocation efficiency and operational responsiveness. Therefore, the empirical results are consistent with the proposed channel of supply chain operational efficiency.

Overall, province-wide industrial integration significantly improves emergency production-capacity buffer reserves, industrial collaborative agglomeration, and supply chain operational efficiency. These findings are consistent with the transmission logic of resource acquisition, organizational coordination, and capability upgrading proposed in this paper, and provide empirical evidence for understanding the internal path through which province-wide industrial integration affects supply chain resilience.

4.4. Heterogeneity Analysis

Considering significant differences in firms' supply chain structures and regional risk environments in China, this paper further examines the heterogeneity of the policy effect of province-wide industrial integration from two dimensions: supply chain dependence and regional natural-disaster risk.

First, supply chain dependence (**Table 5**). In the high-dependence group, the coefficient of Policy is not statistically significant, whereas in the low-dependence group, the coefficient of Policy is significantly positive at the 1% level. Further, this paper conducts a between-group test of the difference in Policy coefficients between the high- and low-dependence groups. The results show that the coefficient difference between the low-dependence group and the high-dependence group is 0.179, with a between-group *z* value of 5.08, significant at the 1% level. This indicates that the effect of province-wide industrial integration on supply chain resilience differs significantly across firms with different degrees of supply chain dependence, and that the resilience-enabling effect mainly appears among firms with lower supply chain dependence. A possible explanation is that high-dependence firms face higher customer or supplier concentration, and their supply chains are strongly tied to a single partner. Even when the policy provides production capacity and resources, these firms may find it difficult to quickly break existing path dependence, resulting in a ceiling effect in policy transmission. By contrast, low-dependence firms have more diversified supply chain networks, can respond more flexibly to policy guidance, and can more rapidly optimize their supply chain structures through resource integration and collaborative agglomeration, thereby amplifying the policy dividend.

Second, regional natural-disaster risk (**Table 6**). In both high-risk and low-risk regions, the coefficient of Policy is significantly positive at the 1% level, but the estimated coefficient is larger in low-risk regions. Further, this paper conducts a between-group test of the difference in Policy coefficients between high-risk and low-

risk regions. The results show that the coefficient difference between low-risk and high-risk regions is 0.087, with a between-group z value of 2.59, significant at the 1% level. This indicates that the effect of province-wide industrial integration on supply chain resilience differs significantly across regions with different levels of natural-disaster risk, and that the policy effect is more pronounced in low-risk regions. From the perspective of marginal policy effects, firms in high-risk regions have long faced routine disaster shocks and may have already developed certain emergency material reserves, redundant production capacity, and risk-hedging mechanisms. Consequently, the marginal room for policy intervention is relatively limited. In contrast, firms in low-risk regions have relatively weaker risk awareness and resilience foundations, and their supply chains tend to be lean rather than shock-resistant. The emergency resource integration and collaborative agglomeration effects generated by province-wide industrial integration can directly address their resilience deficiencies, making the marginal contribution of the policy more pronounced.

Table 5. Heterogeneity test: Supply chain dependence.

Variable	High dependence (strong)	Low dependence (weak)
Policy	-0.028 (0.029)	0.151*** (0.020)
z value	-0.9	7.50
$P > z $	0.344	0.000
95% confidence interval	[-0.085, 0.030]	[0.111, 0.190]
Constant	-0.009** (0.004)	-0.007* (0.004)
Observations	6086	5904
Between-group coefficient difference		0.179
Between-group z value		5.08
Between-group P value		0.000

Note: Robust standard errors are reported in parentheses. Both columns use partial linear DML estimation, the pystacked learner, $k = 5$, and $r = 1$.

Table 6. Heterogeneity test: Regional natural-disaster risk.

Variable	High-risk regions	Low-risk regions
Policy (province-wide industrial integration)	0.153*** (0.027)	0.240*** (0.020)
z value	5.76	11.79
$P > z $	0.000	0.000
95% confidence interval	[0.101, 0.206]	[0.200, 0.280]
Constant	-0.010** (0.004)	-0.009** (0.004)

Continued

Observations	6000	5990
Between-group coefficient difference	0.087	
Between-group z value	2.590	
Between-group P value	0.010	

Note: Robust standard errors are reported in parentheses. Both columns use partial linear DML estimation, the pystacked learner, $k = 5$, and $r = 1$.

5. Conclusions and Policy Implications

5.1. Research Conclusions

Taking province-wide industrial integration as a quasi-natural experiment, this paper uses a sample of Chinese A-share listed firms from 2011 to 2023 and applies a double machine learning model to systematically identify the causal effect, potential channels, and heterogeneity of emergency-industry province-wide integration on supply chain resilience. The main conclusions are as follows. First, province-wide industrial integration significantly improves firms’ supply chain resilience. This conclusion remains valid after a series of robustness tests, including changing the number of cross-fitting folds, applying winsorization, and replacing the machine-learning algorithm, indicating that province-wide industrial integration has a relatively robust positive effect on supply chain resilience. Second, the mechanism analysis shows that province-wide industrial integration significantly improves emergency production-capacity buffer reserves, industrial collaborative agglomeration, and supply chain operational efficiency. The empirical results are consistent with the transmission-channel logic of resource acquisition, organizational coordination, and capability upgrading proposed under the RIDCT framework, thereby providing empirical evidence for understanding the internal path through which province-wide industrial integration affects supply chain resilience. Third, the heterogeneity analysis shows that the policy effect of province-wide industrial integration differs across firm supply chain structures and regional risk environments. Further between-group coefficient difference tests show that the policy effect in the low supply chain dependence group is significantly higher than that in the high-dependence group, and that the policy effect in low natural-disaster-risk regions is significantly higher than that in high-risk regions. This suggests that province-wide industrial integration has stronger marginal improvement effects in samples with relatively weak resilience foundations or fewer external constraints, exhibiting certain gap-filling and diminishing marginal-return features.

5.2. Policy Implications

First, province-wide industrial integration should be promoted in a coordinated manner, and the integration and coordination of regional emergency resources should be strengthened. Production-capacity layout, material reserves, and col-

laborative networks of the emergency industry should be coordinated over a broader spatial scope. Fiscal and land policy tools can be used to encourage the construction of redundant production capacity and the expansion of key material reserves, thereby consolidating the resource-buffer foundation of supply chains.

Second, industrial collaborative agglomeration should be used as a key lever to build a risk-sharing emergency industrial ecosystem. Upstream and downstream firms in the emergency industry should be guided to agglomerate and collaborate through a more refined division of labor. Cluster risk-sharing mechanisms should be improved, and agglomeration economies and knowledge spillovers should be leveraged to enhance supply chain stability at the system level.

Third, technological upgrading and digital coordination should be promoted to improve supply chain operational efficiency. Firms should be supported in carrying out emergency technology R&D, flexible production, and supply chain digitalization, thereby improving emergency response speed and dynamic recovery capability and fundamentally strengthening supply chain adaptability.

Fourth, policy implementation should be tailored to local conditions and differentiated across categories to improve precision. For firms and regions with high supply chain dependence or high natural-disaster risk, supporting measures should be adopted to break path dependence and avoid the attenuation of policy dividends. For low-risk regions and low-dependence firms with relatively weak resilience foundations, province-wide integration resources should be prioritized to fully exploit the gap-filling effect of the policy.

5.3. Limitations and Future Research

This paper still has several limitations. First, due to data availability, the measurement of province-wide industrial integration and the construction of mechanism variables can be further refined. Second, this paper conducts heterogeneity analysis from the perspectives of supply chain dependence and regional natural-disaster risk; future research may incorporate additional dimensions to more comprehensively characterize regional heterogeneity in policy effects. Third, the mechanism analysis mainly identifies the causal effect of province-wide industrial integration on intermediate variables. Future research can further combine mediation-effect models to quantify the contribution of each transmission channel.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

- [1] Jiang, Z.Z., Guo, J.R. and Zheng, W. (2025) Supply Chain Resilience: A Review and Prospects. *Journal of Northeastern University (Natural Science)*, **46**, 59-70. (In Chinese)
- [2] Wu, H.Q. (2025) Improving the Resilience and Security of Industrial and Supply Chains. <http://theory.people.com.cn/n1/2025/1205/c40531-40617923.html>
- [3] General Office of the State Council (2014) Opinions of the General Office of the State

- Council on Accelerating the Development of the Emergency Industry: Guobanfa [2014] No. 63.
http://www.gov.cn/zhengce/zhengceku/2014-12/24/content_9337.htm
- [4] Wang, C., Yan, X.X., Zhang, C.X., *et al.* (2026) Development Path Forms and Evolution of the Smart Emergency Industry from the P-TOE Perspective: Evidence from Dynamic QCA. *Journal of Beijing Institute of Technology (Social Sciences Edition)*, **28**, 102-113. (In Chinese)
 - [5] Gong, W.F. (2014) Research on Emergency Supply Chain Management. *China Business and Market*, **28**, 50-55. (In Chinese)
<https://qikan.cqvip.com/Qikan/Article/Detail?id=49169046>
 - [6] Tomlin, B. (2006) On the Value of Mitigation and Contingency Strategies for Managing Supply Chain Disruption Risks. *Management Science*, **52**, 639-657.
<https://doi.org/10.1287/mnsc.1060.0515>
 - [7] Ponomarev, S.Y. and Holcomb, M.C. (2009) Understanding the Concept of Supply Chain Resilience. *The International Journal of Logistics Management*, **20**, 124-143.
<https://doi.org/10.1108/09574090910954873>
 - [8] Zhang, S.S. and Gu, C. (2024) Supply Chain Digitalization and Supply Chain Resilience. *Journal of Finance and Economics*, **50**, 21-34. (In Chinese)
 - [9] Liao, H., Hu, X.L. and Liu, S.Q. (2021) Analysis of China's Supply Chain Resilience under Adverse External Shocks. *Enterprise Economy*, **40**, 50-59. (In Chinese)
https://www.zhangqiaokeyan.com/academic-journal-cn_enterprise-economy_the-sis/0201291625297.html
 - [10] Li, W.A. and Ma, Y. (2022) How to Construct an Effective Mechanism for Supply Chain Resilience? *Contemporary Economic Management*, **44**, 27-38. (In Chinese)
<https://journal.yuanpingjia.com.cn/Journal/ArticleDetails/63723>
 - [11] Huang, H.B., Zhang, Y.Y. and Li, Y.Y. (2024) Can Pilot Policies for Innovative Industrial Clusters Improve Supply Chain Resilience? *Research on Economics and Management*, **45**, 39-60. (In Chinese)
 - [12] Ren, Y.X., Wu, Y. and He, Z.C. (2024) The Impact of Industrial Integration Cluster Development on Industrial Chain Resilience. *Scientific Decision Making*, **31**, 64-78. (In Chinese)
<https://xueshu.baidu.com/s?wd=%E4%BA%A7%E4%B8%9A%E8%9E%8D%E5%90%88%E9%9B%86%E7%BE%A4%E5%8F%91%E5%B1%95%E5%AF%B9%E4%BA%A7%E4%B8%9A%E9%93%BE%E9%9F%A7%E6%80%A7%E7%9A%84%E5%BD%B1%E5%93%8D>
 - [13] Chen, X.D., Liu, Y. and Zhou, K. (2022) Research on the Path through Which the Digital Economy Enhances China's Industrial Chain Resilience. *Reform of Economic System*, No. 1, 95-102. (In Chinese)
https://m.zhangqiaokeyan.com/academic-journal-cn_detail_the-sis/02012105690386.html
 - [14] Tao, F., Wang, X.R., Xu, Y., *et al.* (2023) Digital Transformation, Industrial and Supply Chain Resilience, and Firm Productivity. *China Industrial Economics*, No. 5, 118-136. (In Chinese) <https://d.wanfangdata.com.cn/periodical/zggyjj202305007>
 - [15] Ma, X.Y., Huang, M.Z. and Yang, M.X. (2023) Research on the Influencing Factors of Supply Chain Resilience: Based on SEM and fsQCA Methods. *Systems Engineering—Theory & Practice*, **43**, 2484-2501. (In Chinese)
 - [16] Xia, L., Gu, B., Liu, L., *et al.* (2024) Paths for Enhancing Supply Chain Resilience of Specialized and Sophisticated Enterprises: A Configurational Empirical Analysis Based on the TOE Framework. *Supply Chain Management*, **5**, 23-39. (In Chinese)

- <https://xueshu.baidu.com/usercenter/paper/show?paperid=1x380rt0dd0c00e09n0d0gp072727819>
- [17] Zhang, T.H., Wang, D. and Song, S.F. (2018) Growth Effects and Influencing Factors of Emergency Industry Agglomeration in China: A Spatial Econometric Analysis Based on Panel Data from 2005 to 2014. *Finance and Trade Research*, **29**, 42-54, 75. (In Chinese)
<https://xueshu.baidu.com/usercenter/paper/show?paperid=183t0mx0a84q0xm0kq080050wc080003>
- [18] Li, Z.J. and Ye, Y.H. (2023) Research on the Impact of Emergency Industry Agglomeration on High-Quality Economic Development in the Yangtze River Economic Belt: The Mediating Effect of Technological Innovation. *Journal of Chongqing University of Technology (Social Science)*, **37**, 35-49. (In Chinese)
- [19] Cao, G.X., Gao, S. and Zhou, L. (2021) The Impact of Emergency Industry Agglomeration and Emergency Fiscal Expenditure on China's Economic Growth: Evidence from Provincial Panel Data. *Audit & Economy Research*, **36**, 98-106. (In Chinese)
https://xbbjb.nau.edu.cn/sjyjjy/article/abstract/20210204010?st=article_issue
- [20] Zhang, D.L., Yang, Y.B. and Liu, H.J. (2023) Research on Influencing Factors of Safety and Emergency Industry Development Based on Grounded Theory. *Journal of Hebei University of Science and Technology (Social Sciences Edition)*, **23**, 47-54. (In Chinese)
https://www.zhangqiaokeyan.com/academic-journal-cn_journal-hebei-university-science-technology-social-sciences_thesis/02012101055030.html
- [21] Ma, Y., Xie, Y.y., Kang, P., *et al.* (2020) Research on the Mechanism of Influencing Factors in the Development of China's Emergency Industry: Based on a Structural Equation Model. *Science Research Management*, **41**, 257-267.
<https://link.cnki.net/doi/10.19571/j.cnki.1000-2995.2020.09.026>
- [22] Wang, J.G. (2015) Research on the Dynamic Mechanism Model of China's Emergency Industry Development. *Journal of Safety Science and Technology*, **11**, 47-52. (In Chinese)
- [23] Zhang, G.Q. (2021) System Integration Industrial Chain Parks Need Upgrading: Observations on the Construction of China's Safety and Emergency Industry and Parks (Bases). *China Emergency Management*, No. 8, 16-27. (In Chinese)
https://www.zhangqiaokeyan.com/academic-journal-cn_china-emergency-management_thesis/0201290897272.html
- [24] Ministry of Industry and Information Technology, National Development and Reform Commission, Ministry of Science and Technology, *et al.* (2023) Action Plan for the Development of Key Areas of Safety and Emergency Equipment (2023-2025).
https://wap.miit.gov.cn/zwgk/zcwj/wjfb/tz/art/2023/art_803787fb05b04436bf678e4709766558.html
- [25] China Academy of Information and Communications Technology (2026) Research Report on the Development of the Safety and Emergency Equipment Industry (2025).
<https://www.caict.ac.cn/kxyj/qwfb/ztbg/202602/P020260203541656034523.pdf>
- [26] Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., *et al.* (2018) Double/Debiased Machine Learning for Treatment and Structural Parameters. *The Econometrics Journal*, **21**, C1-C68.
<https://doi.org/10.1111/ectj.12097>
- [27] Zhang, T. and Li, J.C. (2023) Network Infrastructure, Inclusive Green Growth, and Regional Disparities: Causal Inference Based on Double Machine Learning. *Journal of Quantitative & Technological Economics*, **40**, 113-135. (In Chinese)
https://www.jqte.net/sljjssjy/ch/reader/view_ab-

[stract.aspx?file_no=20230406&flag=1&journal_id=sljjjsjyj](#)

- [28] Xu, H.D. and Wang, J.H. (2025) Artificial Intelligence and New Quality Productive Forces of Manufacturing Enterprises: Evidence Based on a Double Machine Learning Model. *Soft Science*, No. 5, 26-33. (In Chinese)
<http://dianda.cqvip.com/Qikan/Article/Detail?id=7201204729>
- [29] Wang, X.D., Zhou, S.T. and Shi, Y.T. (2025) The Employment Effects of Artificial Intelligence: Causal Inference Based on Double Machine Learning. *Journal of Business Economics*, No. 7, 32-49. (In Chinese)