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Global Industrial Chain Resilience Research: Theory and Measurement

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Abstract: Global industrial chain resilience refers to the capability of industrial chains, on a global scale, to maintain or restore their normal operations and value-creating ability in the face of various risks and uncertainties. This resilience is crucial for addressing crises, promoting economic growth, and upholding national security. However, there is currently a lack of unified standards and methods for measuring and enhancing global industrial chain resilience. This study constructs a global industrial chain production model in a multi-country and multi-stage open economy context. It utilizes data from the 1990–2021 Eora MRIO (Multi-Regional Input–Output) dataset to analyze the formation, measurement, and influencing factors of global industrial chain resilience. The research findings indicate that since 2010, the disparity in industrial chain resilience between different countries has gradually widened. Manufacturing plays a pivotal role in maintaining industrial chain stability. Additionally, factors such as input costs and technological levels have been found to positively impact the enhancement of global industrial chain resilience. Therefore, this study provides theoretical and empirical support for exploring and improving global industrial chain resilience, offering valuable guidance for policymakers and entrepreneurs.

Keywords: global industrial chain; resilience; measurement; influencing factors

1. Introduction

The global industrial chain constitutes a complex network that encompasses diverse regions, cultures, and organizational entities engaged in production, distribution, and consumption activities [1,2]. This intricate structure plays a crucial role in driving economic growth, promoting trade liberalization, and fostering global integration. However, it is also exposed to various risks and uncertainties, including natural disasters, geopolitical conflicts, trade protectionism, and the COVID-19 pandemic [3–5]. These factors can lead to disruptions or failures within the global industrial chain, resulting in significant economic losses and societal impacts. Consequently, the assessment and enhancement of global industrial chain resilience—defined as its ability to maintain or restore normal operations and value creation in the face of disturbances—have emerged as critical concerns for governments, businesses, and scholars worldwide.

With the objective of exploring the theme "Global Industrial Chain Resilience Research: Theory and Measurement", this paper addresses the following key questions: What are the nature and characteristics of global industrial chain resilience? What is the theoretical foundation and framework underpinning global industrial chain resilience? How can the resilience level of global industrial chains be effectively measured and evaluated? To achieve this, we leverage multi-country, multi-stage open economy contexts, utilizing Eora MRIO (Multi-Region Input–Output table) data from 1990 to 2021. We combine social network theory with the PageRank algorithm to iteratively model the global industrial chain network, constructing a comprehensive resilience index that captures its multidimensional traits. The primary innovations and contributions of this paper are as follows: (1) This

study extends the specialized production stage in a multi-stage general equilibrium model to derive a country's participation probability within the global industrial chain under the circumstances of multiple references and referenced situations in a multi-country and multi-production stage context. This approach examines the resilience of chains from the perspective of interdependence among countries, regions, and sectors globally. (2) Leveraging Eora MRIO data, the conceptualization of the global industrial chain is transformed into a complex network, departing from the existing depiction of a "snake-like" production division path. Within this framework, the study employs social network theory and the PageRank algorithm to comprehensively analyze the formation, measurement, and influencing factors of global industrial chain resilience from various angles. (3) The introduction of a comprehensive resilience index further enhances the study's scope. Rooted in the derivation of a multi-country and multi-stage general equilibrium model and the intricate network setting, this holistic resilience metric captures the characteristics of the global industrial chain's complex system. It reflects attributes across national, sectoral, and regional levels, providing a novel tool to assess and compare the resilience of the global industrial chain.

The subsequent sections of this paper are organized as follows: Section 2 provides a literature review. Section 3 outlines the theoretical model underlying the formation of global industrial chain resilience. Section 4 introduces the data and relevant variables employed in our study. The measurement results and analysis of influencing factors are covered in Section 5. Lastly, Section 6 presents the conclusions and policy recommendations.

2. Literature Review

In the backdrop of a highly interconnected global economy, the resilience of global industrial chains has emerged as a focal point of attention. Resilience in this context refers to the ability of industrial chains to maintain or restore their normal operations in the face of uncertainties and disruptions [6–8].

Presently, global industrial chains confront significant risks and challenges, underscoring the need for in-depth exploration of the theory and measurement of global industrial chain resilience in order to provide more effective strategies for mitigation. Scholars have engaged in extensive discussions within the realm of industrial chain resilience, exploring diverse concepts and theories. Dynamic capability theory offers a multidimensional and multilayered perspective for understanding industrial chain resilience, emphasizing the collaborative interactions among various segments and participants [9–11]. Meanwhile, the complex systems theory directs attention towards the systemic and nonlinear attributes of industrial chain resilience, aiding in comprehending the interdependencies and influences within supply chains [12–14].

In the measurement of industrial chain resilience, researchers have employed a variety of indicators and methods to comprehensively capture its multidimensional nature. Core capabilities, performance metrics, and topological indices have been applied for evaluating industrial chain resilience across different levels [15–18]. Furthermore, mathematical models, simulation techniques, and statistical approaches have provided a diverse array of methodologies for studying this topic [19–21].

To enhance industrial chain resilience, scholars have proposed an array of strategies and measures. These strategies encompass cost optimization, the establishment of multi-supplier collaborations, and heightened visibility, as well as flexible utilization of digital technologies and resource allocation [22–25]. However, existing strategies may require refined design approaches [26] to suit the diverse nature of industrial chains and potential disruptions.

While substantial progress has been made in the domain of global industrial chain resilience research, challenges persist. The diversity of conceptual approaches necessitates clearer definitions and unified frameworks to facilitate the integration of theory and practice. Additionally, limitations in measurement methods may hinder an accurate reflection of the multidimensional facets of industrial chain resilience, urging continual refinement and

expansion. Given the challenges confronted by global industrial chains in an increasingly complex environment, delving into the theory and measurement of global industrial chain resilience holds paramount importance.

3. Theoretical Model

Given the critical importance of global industrial chain resilience and its impact on economic development, this paper conducts a thorough analysis of the complex challenges faced by industrial chain resilience. In this regard, it draws inspiration from the research approach of Antràs and Gortari (2020) [27] , as well as from the work of Caliendo and Parro (2015) [28]. It aims to delve into the intricate process of resilience formation within global industrial chains and examine the underlying factors that shape it. It establishes a multi-country, multi-stage production model under the framework of an open economy. In an open economic environment with N countries, each country participates in the production process based on its unique technological capabilities and factor endowments. To represent countries, we use $i, n, m, k \in \{1, 2, \cdots, N\}$, while $j \in \{1, 2, \cdots, J\}$ represents different production stages along the industrial chain. The final product is denoted as $\omega \in [0, 1]$. Hence, during the production process, the production of a product is decomposed into a series of independent production stages. Each stage is undertaken by countries with a comparative advantage and involves the production of intermediate goods for global trade.

3.1. Consumer Preferences

To determine consumer preferences, we draw upon the research conducted by Melitz (2003) [29]. We assume that consumers in country i contribute L_i units of labor without elasticity to produce intermediate or final products. As a result, they receive wage compensation of w_i units, which they utilize for consuming final products and derive utility from them. We represent consumer preferences using a CES utility function, as follows:

$$U_i = \left[\int_0^1 \left(C_i^F(\omega) \right)^{(\sigma-1)/\sigma} d\omega \right]^{\sigma/(\sigma-1)} \tag{1}$$

In Equation (1), $C_i^F(\omega)$ represents the consumer's consumption of the final product, and σ represents the substitution elasticity coefficient of the final product ω when utility is constant.

3.2. Production and Technology

During the global division of labor within the industrial chain, the final product ω undergoes multiple stages of production. Each country selects its position in the production process based on its technological level and factor endowments, contributing to the production of each final product. To depict the technological characteristics of countries within the industrial chain, we define $z_i^j(\omega)$ as the technological level, $V_i^j(\omega)$ as the domestic value added, and $M_i^j(\omega)$ as the foreign value added. Considering the participation of each country in the production stages, the production function is represented by the Cobb–Douglas production function:

$$f_i^j(\omega) = z_i^j(\omega) \left(V_i^j(\omega) \right)^{\gamma^j} \left(M_i^{j-1}(\omega) \right)^{1-\gamma^j} \tag{2}$$

In Equation (2), $f_i^j(\omega)$ represents the output level of a country in different production stages. The technology level $z_i^j(\omega)$ is assumed to follow the Fréchet extreme value distribution [30]. $M_i^{j-1}(\omega)$ denotes the utilization of intermediate products from stage $j-1$ during stage j, which represents the domestic value added. The parameter γ^j represents the share of domestic value added produced by a country, while $(1 - \gamma^j)$ represents the share of accumulated value added from intermediate products in the previous production stage.

Under the specified open economic conditions, the domestic value added $V_i^j(\omega)$ is composed of two components: composite intermediate inputs and labor input. Hence, the expression for domestic value added can be formulated as

$$V_i^j(\omega) = \left(x_i^j(\omega)\right)^{1-\alpha_i} \left(L_i^j(\omega)\right)^{\alpha_i} \tag{3}$$

By substituting Equation (3) into Equation (2), we can derive the production function for a specific stage. In this formulation, α_i represents the output elasticity of labor input in domestic value added, while $1 - \alpha_i$ represents the output elasticity of composite intermediate inputs in domestic value added. The composite intermediate inputs $x_i^j(\omega)$ are produced by utilizing the final composite products Q_i, where a portion of Q_i is allocated for composite intermediate inputs and the remaining portion is used for final consumption. Thus, we can formulate an equation to determine Q_i:

$$Q_i = \left[\int_0^1 \left(f_i^J(\omega)\right)^{(\rho-1)/\rho} d\omega\right]^{\rho/(\rho-1)} \tag{4}$$

We make the assumption that the distribution of technology levels in country i follows a Fréchet extreme value distribution. The distribution function is denoted as $F_i(Z) = e^{-A_i z^{-\theta}}$, where $A_i > 0$ represents the parameter associated with the technology level of country i, and θ represents heterogeneity of goods in production.

We further assume that the market operates under perfect competition. Within the framework of general equilibrium conditions, we solve for the profit maximization function of a country given a wage rate W_i and a CES price index. Consequently, the factor input cost associated with not including intermediate products from country i in each production stage can be expressed as

$$c_i = \left(\frac{P_i}{1-\alpha_i}\right)^{1-\alpha_i} \left(\frac{w_i}{\alpha_i}\right)^{\alpha_i} \tag{5}$$

3.3. Global Industrial Chain Production

In the model proposed by Eaton and Kortum (2002) [31], the decision-making process for countries' procurement of intermediate goods is relatively straightforward, as they only need to choose the product with the lowest price in the global market. However, in the multi-country, multi-stage production model under open economic conditions, the selection of intermediate products in the global market is more complex and goes beyond simply seeking the lowest price. The division of labor in production becomes intricate, characterized by intricate network relationships. Baldwin and Venables (2013) argue that a country's participation in global competition does not solely involve exporting a single product [32]. Instead, a country's involvement in the industrial chain includes both supplying intermediate products to other countries and importing intermediate products from other countries. Furthermore, the country's position in the production process can vary. Therefore, the division of labor exhibits a "snake-type" path, which is characterized by multiple production stages. The specification of this path is as follows:

$$l_k = \{l_k(1), l_k(2), \cdots, l_k(J)\} \tag{6}$$

In the context of the global division of labor system, the final product undergoes a series of specialized production stages and is eventually consumed by consumers in different countries represented by k. We use the symbol k to denote the destination country where the final product is sold and to specify the globally integrated production path. This path can be traced back from country k in a unique pattern. In Equation (6), let l_k represent a specific production path with j stages for a given value of $k \in \{1, 2, \ldots, N\}$. The element $l_k(1)$ in this set represents the country participating in the first stage of production for that particular production chain.

In each production stage, country $l_k(j)$ needs to buy upstream products from the previous stage at the lowest global prices. Hence, each country at stages $j \in \{2, 3, \ldots, J\}$ faces a decision on purchasing products with the minimum prices from their respective upstream stages. However, since the production technology level of each upstream country follows a Fréchet extreme value distribution, downstream countries cannot fully observe the technology levels when making purchasing decisions for upstream products. This complexity adds difficulty to the pricing issues.

To address the complexity of purchasing upstream products, we assume that a country at a certain production stage j cannot directly observe the lowest price of upstream products from stage $(j-1)$ before making a purchase decision. Instead, it can only predict the lowest price of the upstream product based on the global distribution of productivity.

Furthermore, we introduce the concept of iceberg trade costs to determine the minimum price for purchasing products in stage j. Let τ_{in} denote the trade costs when country i engages in trade with country n. We assume that the trade cost for the domestic trade of intermediate goods is $\tau_{in} = 1$. This implies that to compensate for the loss due to inter-country trade costs, country i needs to transport $\tau_{in} \geq 1$ units of goods to country n when transporting one unit of intermediate product. To ensure no arbitrage in inter-country trade, we impose the triangular inequality of trade: $\tau_{im}\tau_{mn} \geq \tau_{in}$. For this reason, the price formula for intermediate products in which a country participates in the stages of the industrial chain can be derived based on general equilibrium conditions:

$$p_{l(j)}^j = \frac{c_{(j)}^{j-1} \left(p_{l(j-1)}^{j-1} \tau_{l(j-1)(j)}^j \right)^{1-\gamma^j}}{z_{l(j)}^j} \tag{7}$$

Consequently, if country i provides intermediate products to downstream industries, its cost cannot exceed the price of importing such intermediate products from other countries:

$$i = \arg\min_{l(j)} \left[\frac{\left(c_{l(j)} \right)^\gamma \left(p_{l(j-1)}^j \tau_{l(j-1)l(j)} \right)^{1-j}}{z_{l(j)}} \right] \tag{8}$$

as the price $p_{l(j)}^j$ of country i participating in the global industrial chain is related to the price $p_{l(j-1)}^{j-1}$ of the upstream stage in the industrial chain. There will be a continuous iterative process, using the iterative expectation solution rule. By iterating the expectations of pricing strategies for upstream and downstream participating countries, we can obtain the expected procurement decision of downstream countries on upstream. The specific calculation formula is as follows:

$$\varepsilon_i^j[s] = E_j\left[\left(p_{l(j)}^j \tau_{i(j)i} \right)^s \right] \tag{9}$$

By continuously iterating from Equation (7) to Equation (9), we can derive the following results:

$$\varepsilon_i^j[s] = E_j\left[\frac{\left(c_{l(j)} \right)^{\gamma's} \varepsilon_{l(j-1)}^{j-1} \left[(1-\gamma^j)s \right] \left(\tau_{l(j-1)(j)} \right)^s}{\left(z_{l(j)}^j \right)^s} \right] \tag{10}$$

Let $s = 1 - \gamma^{j+1}$. Using the iterative rule of Equation (9) in Equation (8), we can obtain the condition for country i to provide intermediate products downstream:

$$i = \arg\min_{l(j)} \left[\frac{c_{l(j)}^{\gamma^j \left(1-\gamma^{j+1}\right)} \varepsilon_{l(j-1)}^{j-1} \left[\left(1-\gamma^j\right)\left(1-\gamma^{j+1}\right)\right]\left(\tau_{l(j-1)l(j)}\right)^{1-\gamma^{j+1}}}{\left(z_{l(j)}^j\right)^{1-\gamma^{j+1}}} \right] \quad (11)$$

During the continuous iteration process, an increase in the foreign value-added share of $1 - \gamma^{j+1}$ results in higher trade costs and greater production technology requirements for downstream countries as the production stage increases. To capture the variations in trade costs across different stages of production, we define $\beta^j = \prod_{j'=j+1}^{N}\left(1-\gamma^{j'}\right)$. As there are more downstream production stages and a higher share of national value additions, β^j approaches 1, indicating that β^j is an increasing function of production stage j.

Based on the Fréchet distribution function, $F_i\left(\left(z_l^j\right)^{\beta^j}\right) = e^{A_i^{-\beta^j}z^{-\theta}}$ can be defined. Based on $F_i\left(\left(z_l^j\right)^{\beta^j}\right)$, the probability that country i provides intermediate goods from production stage j to production stage $j+1$ in the industrial chain is expressed as

$$\Pr(l(j) = i) = \Pr\left[\left(\frac{c_i}{z_i^j(\omega)}\right)^{j\beta^j} \varepsilon_i^{j-1}\left[\left(1-\gamma^{j+1}\right)\left(1-\gamma^j\right)\right]\left(\tau_{l(j-1)i}\right)^{1-\gamma^{j+1}}\right.$$
$$\left. \leq \left(\frac{c_n}{z_n^j(\omega)}\right)^{\gamma^j\beta^j} \varepsilon_n^{j-1}\left[\left(1-\gamma^{j+1}\right)\left(1-\gamma^j\right)\right]\left(\tau_{l(j-1)n}\right)^{1-\gamma^{j+1}}\right] \quad (12)$$

Based on Equation (12) and employing the processing methodology introduced by Eaton and Kortum (2002) [31], we utilize the properties of the Fréchet distribution function to determine the probability of a country becoming the jth production stage and supplying intermediate goods to the $j+1$th stage country:

$$\Pr(l(j) = i) = \frac{A_i\left(\left(c_i^j\right)^{\gamma^j}\tau_{l(j-1)i}\right)^{-\theta\beta^i} \varepsilon_i^{j-1}\left[\left(1-\gamma^{j+1}\right)\left(1-\gamma^j\right)\right]^{-\theta\beta^{j+1}}}{\sum_{n\in N} A_n\left((c_n)^{\gamma^j}\tau_{l(j-1)n}\right)^{-\theta\beta^j} \varepsilon_n^{j-1}\left[\left(1-\gamma^{j+1}\right)\left(1-\gamma^j\right)\right]^{-\theta\beta^{j+1}}} \quad (13)$$

Equation (13) highlights that the probability of country i supplying intermediate goods to production stage $j+1$ is primarily influenced by two key factors: technology level and factor utilization costs [1]. When country i possesses a superior technology level compared to other countries, the proportion of intermediate products procured by country $j+1$ from country i tends to approach 1. In addition, under other fixed conditions, countries with lower wage costs or higher levels of openness enjoy a competitive advantage in participation [2].

Based on the aforementioned analysis, it can be inferred that within the global industrial division system, the production of final goods is not solely determined by the purchasing decisions of downstream countries. It also depends on the technological distribution and pricing strategies of upstream countries. Consequently, a specific "snake-type" division pathway for the production of final goods emerges with distinct probabilities:

$$\pi_{l_i} = \frac{\prod_{j=1}^{N-1} A_{l(j)}\left(\left(c_{l(j)}\right)^{r^i}\tau_{l(j)l(j+1)}\right)^{-\theta\beta^j} \cdot A_{l(N)}\left(\left(c_{l(N)}\right)^{\gamma^j}\tau_{l(N)i}\right)^{-\theta\beta^j}}{\sum_{l'\in N}\prod_{j=1}^{N-1} A_{l'(j)}\left(\left(c_{l'(j)}\right)^{r^i}\tau_{l'(j)l'(j+1)}\right)^{-\theta\beta^j} \cdot A_{l'(N)}\left(\left(c_{l'(N)}\right)^{r^i}\tau_{l'(N)i}\right)^{-\theta\beta^j}} \quad (14)$$

Based on the analysis above, it is evident that the participation of countries in different stages of the division of labor is primarily influenced by their technological levels and factor cost efficiencies. Additionally, this participation is closely related to the domestic value-added share and labor output elasticity of each country. While π_{l_i} can represent the probability of country i participating in a specific production stage, it is important to recognize that multiple countries interconnected within a complex network are encompassed.The resilience refers to its ability to recover from shocks within this intricate environment. Thus, it becomes essential to integrate the participation probability π_{l_i} of country i in a specific production stage with the network to better comprehend and assess the level of resilience.

3.4. Network and Resilience

According to the previous assumption of one country participating in each production stage, there is a one-to-one correspondence between the production stages and the countries involved. Specifically, if country i is at production stage j denoted as $i = l_k(j)$, then it follows that $j = l_k^{-1}(i)$. However, it is evident that the single production pathway relationship cannot fully capture the hierarchical, complex, and systemic nature, nor can it adequately explain the inherent resilience in complex external environments. As a result, building upon the theoretical model derivation in the previous sections, we propose the concept of global industrial networks.

In global industrial networks, a country's decision to purchase intermediate products during production stage j is represented by a decision set $D_{jn} = (j, n)$, indicating that the country purchases intermediate goods from another country in that production stage. The collective purchasing decision sets of multiple countries' paths can be represented as λ_i

$$\lambda_{l'} = \left\{ D_{l'|D_{(n|j=j')}} = (j', n), j' \in \{1, 2, \cdots, J\}, n \in \{1, 2, \cdots, N\} \right\} \tag{15}$$

Assuming that there is one country participating in each stage of the division of labor, we can construct a network set consisting of N^J industrial chains, denoted as $\lambda_i = \{\lambda_1, \lambda_2, \cdots, \lambda_{N^J}\}$, where i represents the country that consumes the final product. In this network set, each network represents a specific combination of countries involved in the production process, with the final product being consumed by country i. The number of networks in the set is determined by the number of countries that consume the final product.

With the concept of global industrial chain networks, we can define multiple reference and multiple referred relationships within the network. In a directed global industrial chain network, if intermediate products from country $l_{k_0}(j)$ flow to the next production stage process while also pointing towards $l_K(j+1)$, where $K \in \{k_1, k_2, \cdots, k_n\}$, it can be said that country $l_{k_0}(j)$ has multiple reference relationships in the global division of labor process. This can be expressed mathematically as

$$l_{k_0}(j) \bowtie \{l_{k_1}(j+1), l_{k_2}(j+1), \cdots, l_{k_n}(j+1)\} \tag{16}$$

The symbol $\bowtie$ is introduced as a directed multi-reference relationship symbol, representing the reference relationship where a single node country in the directed network points to a set of multiple node countries. By utilizing Equation (16), we can calculate the probability of multi-reference relationships within the directed network under the division of labor conditions:

$$\pi\big(i \mid \{l(j) \mid l_{k_1}(j+1), l_{k_2}(j+1), \cdots, l_{k_*}(j+1)\}\big) = \{\pi(i \mid l(j)), \\ \pi(i \mid l_{k_1}(j+1)), \pi(i \mid l_{k_2}(j+1)), \cdots, \pi(i \mid l_{k_*}(j+1))\} \tag{17}$$

If intermediate products flow from country $l_K(j-1)$ to country $l_{k_0}(j)$ in the next production stage, where $K \in \{k_1, k_2, \cdots, k_n\}$, it implies multiple references to country $l_{k_0}(j)$ in the jth production stage. Mathematically, this can be expressed as

$$l_{k_0}(j) \bowtie \left\{ l_{k_1}(j-1), l_{k_2}(j-1), \cdots, l_{k_0}(j-1) \right\} \tag{18}$$

Utilizing Equation (18), we can calculate the probability of directed referential relationships:

$$
\begin{aligned}
&\pi\big(\big(\{l(j) \mid l_{k_1}(j-1), l_{k_2}(j-1), \cdots, l_{k_n}(j-1)\} \mid i\big)\big) = \\
&\big\{\pi\big(i \mid l_{k_1}(j-1)\big), \pi\big(i \mid l_{k_2}(j-1)\big), \cdots, \pi\big(i \mid l_{k_*}(j-1)\big) \mid \pi\big(i \mid l(j)\big)\big\}
\end{aligned}
\tag{19}
$$

Considering that, in reality, we can mathematically represent the complex network relationship of country i in the global industrial chain network using Equations (16) and (18),

$$\left\{ l_{k_1}(j-1), l_{k_2}(j-1), \cdots, l_{k_*}(j-1) \right\} \bowtie l_{k_0}(j) \bowtie \left\{ l_{k_2}(j+1), l_{k_2}(j+1), \cdots, l_{k_n}(j+1) \right\} \tag{20}$$

The expression of participation probability in a directed network with multiple references and multiple referred relationships is complex and cannot be easily presented in a concise form as shown in Equation (20). In an industrial chain network, the presence of multiple references and multiple referred relationships results in a large number of probability relationships, which grows exponentially with the number of stages in the division of labor. Therefore, the participation probability π_{l_i} calculated using Equation (14) only reflects the participation rate of local countries, and to measure resilience accurately, it is necessary to calculate the participation rates of various countries from a global perspective. Hence, this paper further utilizes the PageRank algorithm to calculate the global participation probability of each country in the industrial chain, considering the cases of multiple references and multiple referred relationships within the network. The participation probability is computed in a complex network environment, which reflects a country's ability to withstand adverse external shocks within a complex system. Thus, the calculated participation probability, denoted as π_{PR}, serves as an indicator of a country's resilience. The calculation method for a country's resilience in the global Industry chain is further demonstrated in Section 4.

This chapter constructs a multi-country, multi-stage global industrial chain production model, analyzes the status and role of each country in the global industrial chain, evaluates the resilience of the global industrial chain, and explores the factors that affect its resilience, such as domestic value added, trade openness, labor elasticity, and human capital. The comprehensive explanation of these factors helps to reveal the formation mechanism and influencing factors of global industrial chain resilience, and provides a basis for the subsequent chapters of the study.

4. Data Source and Variable Construction

4.1. Data Source

Eora MRIO (Multi-Region Input–Output table) covers 189 countries and includes 26 industry classifications. Each year's input–output tables comprise the intermediate demand matrix, final demand matrix, and value-added matrix. A summarized representation of these matrices can be seen in Table 1. Other studies in international research have utilized the Organization for Economic Co-operation and Development database (OECD), Inter-Country Input–Output (ICIO) tables or the World Input–Output Database (WIOD). But they cover fewer countries and have a relatively shorter time span. By leveraging the Eora MRIO, we can overcome these limitations and measure the resilience of multiple countries in the global industrial chain over an extended period. In addition to assessing country resilience, the dataset also facilitates the computation of participation rates, iceberg trade costs matrices, and domestic value-added shares.

Table 1. Simplified schematic diagram of an input–output table [3].

		Input Use & Value Use			Final Use			Total Use
		Country 1	$\cdots$	Country J	Country l	$\cdots$	Country J	
Output supplied	Country 1	H_{11}	$\cdots$	H_{1J}	F_{11}	$\cdots$	F_{1J}	Y_1
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
	Country J	H_{J1}	$\cdots$	H_{JJ}	F_{J1}	$\cdots$	F_{JJ}	Y_J
	Value added	$W_1 L_1$	$\cdots$	$W_J L_J$				
	Gross output	Y_1	$\cdots$	Y_J				

The human capital index, labor elasticity, total factor productivity, and gross domestic product (GDP) are derived from the data of PWT9.1 for the period 1990–2019. The descriptive statistics of these variables are presented in Table 2. It is evident that there is a notable difference in resilience at both the national and industry levels. Specifically, at the national level, the difference in resilience between the maximum and minimum values is 0.33, and at the industry level, the difference is 0.35. It highlights the heterogeneity in resilience among entities within the global economy, emphasizing the importance of understanding and assessing the factors that contribute to resilience in order to enhance the overall stability and adaptability of countries and industries in the face of challenges.

Table 2. Descriptive statistics of variables.

Variable	N	Mean	SD	Min	Max
π-country	6048	0.010	0.010	0.000	0.330
π-industry	832	0.004	0.006	0.000	0.350
Ice_cost	6048	9.69	8.99	2.99	281.20
DVA_share	6048	0.61	4.64	−182.20	1.17
HC	4320	2.42	0.70	1.03	4.35
TFP	3450	0.65	0.24	0.070	1.53
Labor_share	4077	0.51	0.12	0.09	0.90
lnGDP	5070	11.08	2.02	5.30	16.84

4.2. Variable Construction

4.2.1. Global Industrial Chain Resilience

Global industrial chain resilience refers to a country's ability to adapt and recover quickly from external shocks and internal disruptions within the complex global system. Input–output tables provide valuable insights into the position and influence of countries in the division of labor, as well as the interdependencies between industries. They enable the analysis and evaluation of resilience at both the country and industry levels. Before conducting any calculations, it is crucial to construct a participation rate matrix that includes all countries worldwide. Some scholars, such as Antràs and Gortari (2020) [27], have used structural modeling techniques to estimate parameters for calculating participation rates. However, it is important to recognize that these methods rely on the assumptions of the theoretical model and that precise parameter estimation often requires numerical simulations that may not perfectly align with real-world conditions. To address this issue, we adopt the approach employed by Aslam et al. (2017) [33] and utilize data from the Eora MRIO. The participation rate of a country is measured by the share of value added in bilateral trade between that country and another. This method captures the contribution of a country's products or services to the value of production in another country, thereby

reflecting the level of participation between the two countries. The specific calculation formula for the participation rate is as follows:

$$\boldsymbol{TVA}_v = \begin{bmatrix} \hat{v}_1 & 0 & \cdots & 0 \\ 0 & \hat{v}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \hat{v}_N \end{bmatrix} \begin{bmatrix} \boldsymbol{B}_{11} & \boldsymbol{B}_{12} & \cdots & \boldsymbol{B}_{1N} \\ \boldsymbol{B}_{21} & \boldsymbol{B}_{22} & \cdots & \boldsymbol{B}_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{B}_{N1} & \boldsymbol{B}_{N2} & \cdots & \boldsymbol{B}_{NN} \end{bmatrix} \begin{bmatrix} e_1 & 0 & \cdots & 0 \\ 0 & e_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & e_N \end{bmatrix} \tag{21}$$

In Equation (21), where N is the total number of countries covered in the Eora MRIO (specifically, $N = 189$), it refers to the construction of the participation rate matrix between countries. The symbol $\hat{v}_N$ represents the value-added ratio, and the corresponding diagonal matrix is calculated by subtracting the sum of the direct consumption coefficients of each country from the identity matrix. The specific calculation formula is as follows. The matrix $\widehat{V}$ is defined as $I_{189 \times 189} - \text{diag}(\sum_s^{N=189} A_{s1}, \ldots, \sum_s^{N=189} A_{s189})$, where $s \in \{1, 2, \ldots, N\}$ and A_{sN} represents the direct consumption coefficient of country N. The matrix $\boldsymbol{B}_{NN}$ denotes the inverse matrix of the Leontief matrix. The value e_N represents the total export trade volume of country N. The matrix $\boldsymbol{TVA}_v$ obtained corresponds to π_{l_i} in the previous theoretical model, representing the probability of a country participating in the production stage of another country along the "snake-type" path.

The $\boldsymbol{TVA}_v$ matrix, as mentioned previously, does not fully capture the intricate multiple references and the division of labor paths from a global perspective. Consequently, to determine the participation probability of countries, we utilize the PageRank algorithm. This algorithm allows us to analyze the relationship between the local participation probability $\pi(l(j) = i)$ of countries in the chain and the overall structure. Through iterative traversal of the network, the algorithm converges to a stable state, enabling us to calculate the participation of each country and evaluate its resilience within the chain.

In summary, assuming that country i is participating in the division of labor in a networked manner, where $i \in \{1, 2, \ldots, N\}$, we define OD_i as the outdegree of country i, and π_i represents the resilience value of country i. The calculation formula is

$$\pi(l(j = i) \mid t + 1) = \frac{1 - q}{N} + q \sum_{i \equiv \{1, 2, \cdots, N\}} \frac{\pi(l(j = i) \mid t)}{OD_i} \tag{22}$$

In Equation (22), the maximum number of iterations is defined as 1000. Here, the variable N represents the total number of countries. To address the issue of isolated country nodes resulting in an outdegree of 0, we set the damping factor q to 0.85. This choice ensures that even if there are isolated nodes, the calculations can still be performed. Regarding the initial resilience value π at time $t = 0$, we select $\{\pi(l(j) = i) \mid i \in \{1, 2, \cdots, N\}, j \in \{1, 2, \cdots, J\}\}$ as the representation. When the π value for a particular country i is high, it indicates that the country has a greater level of involvement and centrality in the global industrial chain network. In such cases, we can consider that country i possesses higher resilience.

4.2.2. Cost of Iceberg Trading

Based on the previous analysis, we observe the presence of iceberg trade costs in international import and export trade. To calculate these costs, we refer to Head and Ries (2001) [34], who proposed a method for estimating bilateral trade costs between countries based on the share of final products in bilateral trade. We utilize Eora MRIO to compute the iceberg trade cost matrix. In this context, we define M_{in} as the quantity of intermediate products that country i inputs from country n, and F_{in} represents the amount of intermediate products used by country i from country n. The proportion of final products purchased by country i from country n is expressed as

$$\tau_{ni}^F = \frac{F_{ni}}{\sum_{n=1}^{I} F_{ni}}$$

We determine the bilateral iceberg trade cost between countries *i* and *n* as follows:

$$\tau_{in} = \left(\frac{\tau_{in}^F \tau_{ni}^F}{\tau_{ii}^F \tau_{nn}^F} \right)^{\frac{-1}{2\theta}}$$

where θ is a parameter associated with the elasticity of substitution. After obtaining the iceberg trade cost matrix τ_{in}, we calculate the average trade cost faced by country *i* by taking the row average of this matrix. We denote this average trade cost as τ_i.

4.2.3. Domestic Value Added Share

We already completed the calculation of the matrix of value-added ratios matrix $\boldsymbol{TVA_v}$. The diagonal elements of this matrix represent the proportion of a country's own value added to its total export trade. Therefore, we can extract the diagonal elements to obtain the domestic value-added ratio data for each country. These values provide insights into the extent to which a country's exports rely on its own domestic value added, as opposed to incorporating imported value added from other countries.

4.2.4. Human Capital Index

Using the education attainment data based on Barro and Lee (2013) [35] and the education return data calculated by Patrinos and Psacharopoulos (2004) [36], we compute the average human capital index of a country's population. This indicator is used to measure a country's human capital situation.

4.2.5. Labor Force Elasticity

We use the share of labor compensation in a country's gross domestic product to measure its labor elasticity.

4.2.6. Total Factor Productivity

We calculate the total factor productivity (TFP) related to welfare using purchasing power parity (PPP), and compare it with the United States (whose value is 1) as a benchmark. This indicator is used to measure a country's technological level.

5. Discussion

5.1. Spatial Analysis

The analysis of resilience measurements for the years 1990, 2000, 2010, and 2021 is conducted using Stata 17 software. The results obtained are utilized to generate a spatial evolution map illustrating the resilience of the global industrial chain as shown in Figure 1. Based on the distribution characteristics of resilience values across the mentioned years, we classify them into distinct categories. The resilience values are categorized as follows: 0.0050–0.0100 represents a relatively lower level of adaptability; 0.0100–0.0500 indicates a moderate level of robustness; and 0.0500–0.1100 denotes a higher level of resilience. The United States consistently demonstrates a high level of resilience, emphasizing its pivotal role in the division of labor within the global industrial chain. This can be attributed to the United States' exceptional competitiveness and its advantages in high-value sectors, such as technology, finance, and healthcare. These industries serve as key drivers for the United States' active engagement, allowing it to secure a competitive edge. European countries and Japan also exhibit notable strength in terms of resilience. These regions have diverse industrial structures and place a strong emphasis on innovation, which contributes to their sustained performance and resilience within the global industrial chain.

Additionally, Figure 1 illustrates a significant increase in the resilience of BRICS countries (China, India, Russia, and Brazil) from 1990 to 2021. This highlights their growing importance and ability to play pivotal roles in the industrial chain. Several factors contribute to this positive trend. First, BRICS countries benefit from abundant resources and a large labor force. China, in particular, possesses the world's largest labor market, while India

excels as a major exporter of IT services. Furthermore, these nations' governments have implemented effective policies and measures to attract foreign investment and promote economic development. Notable examples include China's "Belt and Road" Initiative and India's "Make in India" campaign, both aimed at supporting their economic expansion.

However, African and Central Asian countries have consistently displayed lower levels of resilience, facing challenges in recovering swiftly from external shocks within limited timeframes. This situation can be largely attributed to inherent limitations stemming from their relatively limited industrial diversification. These regions heavily rely on traditional raw materials and industries with low value-added sectors, while their presence in high-value-added and technology-intensive sectors remains notably deficient.
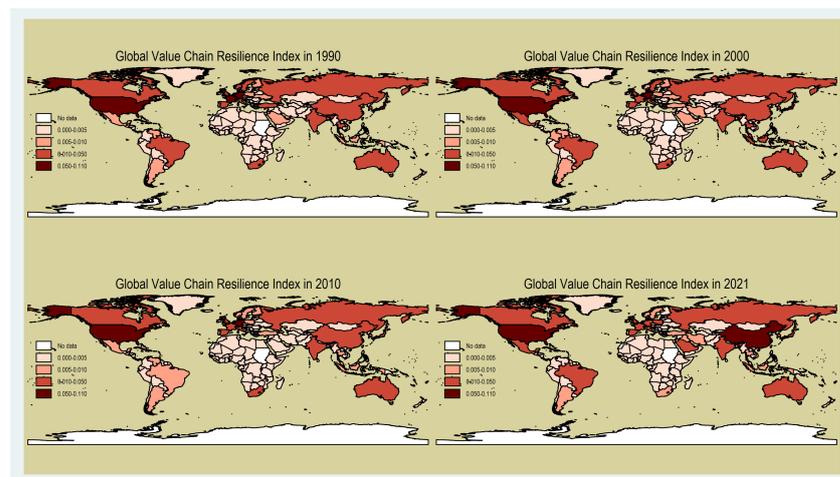
Figure 1. Temporal evolution of resilience spatial distribution (1990–2021).

5.2. Temporal Trend

To analyze the temporal changes in the resilience of global industrial chains at a global level, we employ kernel density estimation and plot the density for the years 1990, 2000, 2010, and 2021 (refer to Figure 2). The analysis reveals a distinct long-tail distribution pattern in the resilience of global industrial chain across the four years [4]. A noticeable leftward shift in the mean of the density distribution of resilience is observed after 2000, indicating a weakening of the overall resilience level. One plausible explanation for this phenomenon could be the adoption of trade protectionism policies by certain countries and regions in recent years. Measures such as tariffs and import restrictions have contributed to increased trade barriers and elevated risks, thereby reducing resilience. Furthermore, it is important to acknowledge the significant impact of major public health events. The outbreak of the COVID-19 pandemic in 2020 serves as a prominent example, leading to widespread disruptions, halted production activities, and a substantial decline in international trade. These consequences have had profound effects on the global economy and highlight its vulnerability in the face of such events.

The variance of the kernel density distribution indicates a noticeable decrease in the steepness of resilience in 2021 compared to 2010, suggesting a widening divergence in resilience levels among countries. The analysis reveals that countries that initially had lower levels of resilience have experienced further declines in this context. This phenomenon can be attributed to the dominant positions held by certain countries in global technology and innovation. These countries are able to effectively adapt to evolving market demands, optimize production efficiency, and enhance product quality. As a result, their capacity to withstand and recover from disruptions within the framework has been strengthened.
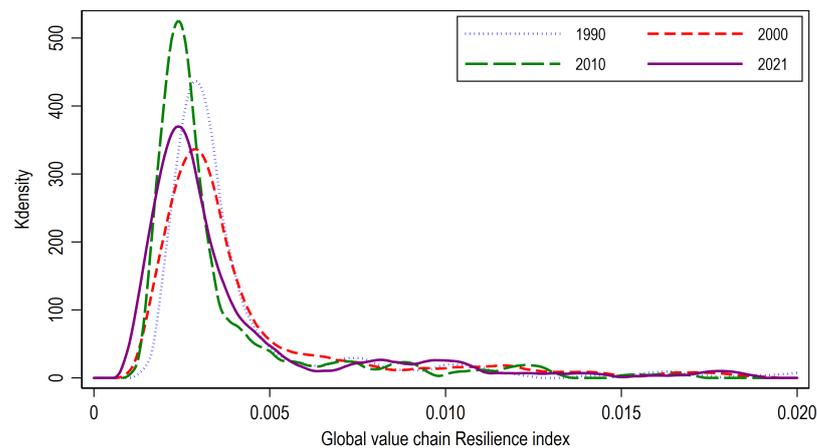
Figure 2. Kernel density distribution of resilience.

To analyze the resilience changes in selected countries or regions, the study focuses on 19 major countries or regions, including Australia, Brazil, Canada, China, Germany, Spain, France, the United Kingdom, Indonesia, India, Japan, South Korea, Mexico, Russia, Turkey, the United States, Hong Kong, Macau, and Taiwan. These countries and regions were chosen because, although they represent less than 1/10 of the total number of countries globally, they account for over 60% of the global population and over 70% of global GDP based on the PWT 9.1 data. Thus, studying the changes in resilience levels in these sample countries provides a strong representation of the overall trend. Figure 3 presents the temporal changes in resilience for the 19 countries and regions mentioned. From 1990 to 2021, their resilience exhibited distinct patterns. A noticeable decline in resilience occurred in 1996, followed by a significant improvement in 1999. This suggests that these countries experienced changes in resilience around the time of the 1998 financial crisis. Prior to the crisis, resilience weakened, indicating a decreased ability to withstand external shocks. However, after the crisis, countries demonstrated an enhanced capacity to swiftly recover and restore normal functioning, leading to an increase in resilience. It is worth noting that starting from 2015, the resilience levels of the United States and China diverged from those of other countries. The gap in resilience between these two nations and other countries gradually widened. By 2021, China's resilience level surpassed that of the United States, contributing significantly to its ability to maintain robust economic vitality even after the outbreak of the COVID-19 pandemic.
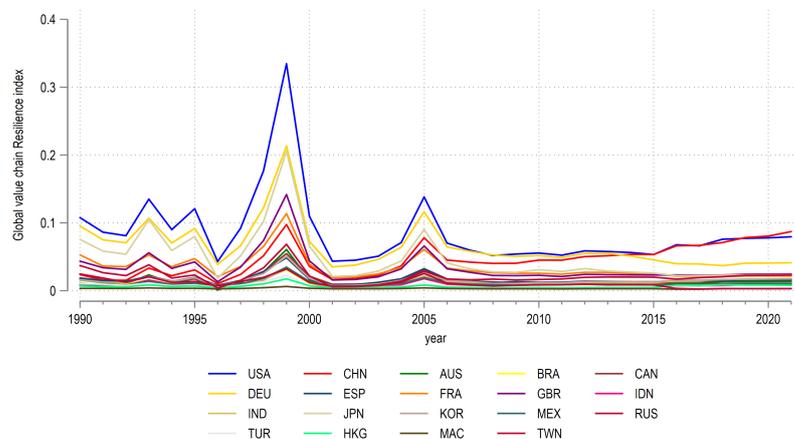

Figure 3. Temporal trends in global industrial chain resilience at the national level: 1990–2021.

We conduct a comprehensive examination of the temporal dynamics of resilience within global industrial chains at the industry level. To accomplish this, we utilize the Eora MRIO, which offers a classification of 26 industries. The time-varying trends of industry-specific resilience from 1990 to 2021 are presented in Figure 4. The analysis reveals a remarkable level of resilience in the manufacturing sector. This can be primarily attributed to the decentralized distribution of value chains within manufacturing, which effectively mitigates risks associated with excessive concentration of products or services. The persistent resilience of the manufacturing industry also highlights China's remarkable trajectory in terms of resilience. As a prominent manufacturing powerhouse, China has consistently demonstrated robust growth in its manufacturing sector. According to data released by the Ministry of Industry and Information Technology of China, in 2022, China's manufacturing value added accounted for nearly 30% of the global total, and the sector has maintained its position as the world's largest for 13 consecutive years. It is incontrovertible that upholding a formidable presence in the manufacturing sector serves as a paramount determinant of a nation's resilience amidst the intricacies. In contrast, the resilience levels of the postal and telecommunications services, public utility sectors, including electricity, gas, and water supply, as well as trade modes, such as re-exports and re-imports, exhibit a relatively diminished magnitude.
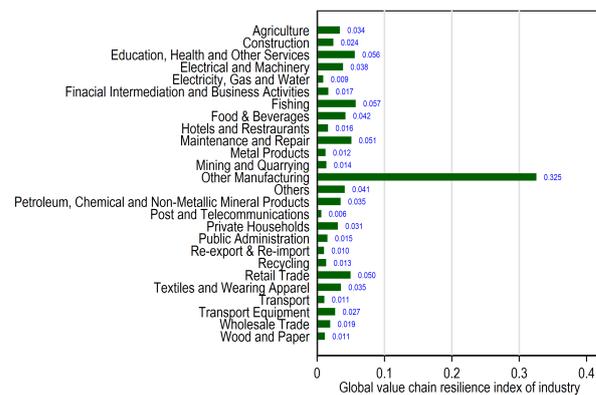

Figure 4. Temporal evolution of mean resilience across industries (1990–2021).

5.3. Impact Factors

To further understand the underlying factors that shape global industrial chain resilience, a detailed analysis of influencing factors is necessary. These factors go beyond the scope of the theoretical model and include variables such as domestic value addition, labor elasticity, and human capital. The third section of the scholarly work provides comprehensive explanations of each of these variables. Furthermore, by conducting the VIF test and observing that all VIF values are below the threshold of 10, it confirms that there is no significant multicollinearity among the selected variables related to industrial chain resilience. This finding supports the rationale behind considering these variables as independent factors influencing resilience.

Considering the inherent heterogeneity across countries in terms of the unobservable individual-specific effects and the time-varying unobserved time trends associated with the impact of different factors on resilience, we employ a fixed effects model to scrutinize the intricate interplay between a country's resilience and the myriad of influencing factors. The model is precisely formulated as follows:

$$\pi\_country\ y_{it} = Ice\_cost_{it-1} + DVA\_share_{it-1} + HC_{it-1} \\ + TFP_{it-1} + Labor\_share_{it-1} + \lambda_i + \delta_t + \varepsilon_{it} \tag{23}$$

In Equation (23), where *i* represents the country, *t* represents the year, $\pi\_country\ y_{it}$ represents the resilience level of a country in a given year, λ_i represents individual fixed

effects for each country, δ_t represents time fixed effects, and ε_{it} represents random error terms. To address the potential endogeneity issues arising from reverse causality between explanatory factors and resilience, all explanatory variables are lagged by one year. To account for heteroscedasticity, robust standard errors are used, clustered at the country-year level. This clustering approach considers potential heterogeneity and correlation within each country–year observation, resulting in more reliable test results.

Furthermore, to enhance the robustness of the estimates obtained from the fixed effects model, a centrality metric called degree is formulated. This metric serves as an indicator of localized resilience exhibited by countries. The construction of this centrality measure follows the methodology outlined by Wasserman and Faust (1994) [37] for devising centrality metrics within the realm of resilience analysis:

$$Degree_{it} = \sum_{j=1}^{n} y_{ij,t} \tag{24}$$

$Degree_{it}$ represents the centrality of country i in the network in year t. $y_{ij,t}$ denotes the extent to which country i participates in the production division of labor of country j in year t within the industrial chain. To facilitate comparison, we have normalized $Degree_{it}$.

The empirical findings of Equation (23) are presented in Table 3. The results indicate a significant inverse relationship between iceberg trade costs and both the macro-level and micro-level resilience of countries. These findings suggest that reduced transportation costs facilitate the seamless circulation of intermediate goods across international, enabling countries to effectively leverage production specialization and thereby enhance their resilience architecture. Furthermore, the negative coefficient of iceberg trade costs on the resilience highlights the advantages of countries expanding their trade openness and lowering tariff barriers. This fosters heightened levels of trade cooperation, fostering the seamless flow of advanced products and cutting-edge technologies network. Consequently, it empowers countries to enhance their technological capabilities, fortify their position, and strengthen their overall resilience.

The proportion of domestic value added has been found to have a significant positive impact on a country's resilience within local global industrial chains, indicating its importance in enhancing resilience at the local level. A higher proportion of domestic value added suggests that a country has a stronger capability for independent research and production, leading to higher value-added activities and greater resilience within its local industry chains. However, when examining resilience at the global level, the influence of the proportion of domestic value added is not as evident. This is because global production specialization is more complex, and a lower proportion of domestic value added does not necessarily indicate a weak position for a country.

Both human capital and total factor productivity have been found to have a significant positive impact on a country's resilience in global industrial chains, regardless of whether it is at the global or local level. This highlights the critical role of human capital and technological advancements in maintaining a country's core competitiveness within the global industrial chains. Consequently, investing in human capital development and fostering technological advancements are crucial strategies for countries to enhance their position and resilience within global industrial chains. These factors contribute to improved labor productivity, industrial competitiveness, and overall economic performance, enabling countries to adapt to external shocks and disruptions more effectively. Labor elasticity has been found to have a significant inverse impact on a country's resilience in global industrial chains, both at the local and global levels. At the local level, higher labor elasticity promotes an increase in resilience. This suggests that countries with high labor returns and a stable labor supply are better able to optimize their industrial structure and adapt to changing market conditions. A flexible labor market allows for the efficient allocation of labor resources, leading to increased productivity and competitiveness within local industrial chains. In contrast, at the global level, higher labor elasticity and a larger share of labor costs have a negative impact on a country's resilience. This indicates that

countries heavily reliant on low value-added industries, where labor costs are a significant proportion of production costs, face challenges in maintaining a competitive advantage in global industrial chains. Such industries often face intense global competition and are more susceptible to disruptions and shocks.

Table 3. Estimation results of resilience determinants.

	(1) π-Country	(2) Degree
L. Ice_cost	−0.0004 **	−0.0030 ***
	(0.0002)	(0.0011)
L. DVA_share	0.0005	0.0035 ***
	(0.0004)	(0.0013)
L. H C	0.0041 ***	0.0443 ***
	(0.0009)	(0.0064)
L. T F P	0.0045 ***	0.0364 ***
	(0.0009)	(0.0052)
L. Labor_share	−0.0042 **	0.0345 ***
	(0.0018)	(0.0102)
Constant	−0.0005	−0.0653 ***
	(0.0028)	(0.0201)
Country Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N	3450	3450
R^2	0.751	0.936

Note : Robust standard errors clustered at the country level are presented in parentheses. The significance levels ** and *** correspond to the 5%, and 1% levels.

6. Conclusions and Recommendation

6.1. Conclusions

By constructing a multi-country and multi-stage global industrial chain production model and utilizing Eora MRIO data from 1990 to 2021, this study analyzed the formation, measurement, and influencing factors of global industrial chain resilience. The research findings are as follows: Firstly, within the framework of the multi-country and multi-stage global industrial chain production model, the formation of a country's resilience is primarily determined by its technological proficiency and the cost of utilizing production factors. Secondly, concerning the spatial pattern of global industrial chain resilience, developed countries, such as the United States and those in Europe, have consistently maintained a high level of resilience, while the resilience of BRICS countries has notably improved. In contrast, countries in Africa and Central Asia have consistently exhibited lower levels of resilience. Furthermore, examining the temporal trends in global industrial chain resilience reveals that disparities between countries have gradually widened since 2010. China's position within the global industrial chain has significantly elevated, resulting in a substantial increase in resilience levels, surpassing that of the United States by 2021. Moreover, the manufacturing sector has maintained a higher level of resilience within the global industrial chain, whereas the resilience of the service sector has become comparatively weaker. Finally, empirical tests confirm that hidden trade costs and technological proficiency positively impact a country's resilience within the global industrial chain. Human capital also plays a significant role in enhancing a country's resilience, while domestic value-added ratios and labor elasticity only exhibit positive effects on the resilience of countries within domestic networks.

6.2. Recommendation

This section outlines the following policy recommendations, based on the aforementioned conclusions, with the aim of strengthening national resilience within the global industrial chain.

To start with, enhancing technological capabilities and overall factor productivity is of the utmost importance. These factors play a critical role in determining a country's resilience within the global industrial chain. In light of this, governments should increase

investments in research and development, encourage domestic enterprises to allocate more resources towards technological innovation, and facilitate collaboration between academia, industry, and research sectors to both advance and implement cutting-edge technologies. This concerted effort will not only enhance national production efficiency and product quality but also bolster the country's fundamental competitiveness in the global industrial chain, thereby fortifying its ability to withstand external shocks.

Moreover, promoting trade openness and fostering cooperation are vital components. Iceberg trade costs are mainly caused by high tariffs and non-tariff barriers, which restrict the cross-border flow of goods and services. To address this challenge, governments should undertake measures such as reducing trade barriers, streamlining trade procedures, and facilitating trade liberalization and regional integration. Concurrently, governments should also strengthen the development and negotiation of international trade regulations, cultivating an open and transparent external environment while ensuring equal participation rights for all nations in the global production division. This will empower countries to more actively and effectively engage in the global industrial chain and effectively respond to external changes.

Furthermore, nurturing the integration of manufacturing and service sectors holds significant value. Governments can realize this through initiatives like establishing industry alliances, promoting technological cooperation, and encouraging innovation partnerships, all of which contribute to the harmonious advancement of diverse industries along the supply chain. Additionally, governments should provide support to emerging industries and high-tech enterprises, while gradually phasing out obsolete production capacities and integrating traditional industrial structures. These efforts will facilitate the seamless convergence of manufacturing and service sectors, ultimately enhancing the efficiency and cohesion of the entire production chain.

In conclusion, with the acceleration of globalization, the global industrial chain is becoming increasingly intricate, dynamic, and diverse. This presents both heightened competition and cooperative opportunities for countries participating in the global industrial chain. Governments should tailor their policies using scientific evaluation metrics and adaptive interventions that align with their positions and developmental trajectories within the global industrial chain. Such an approach will effectively elevate the stability and flexibility of the global industrial chain.

Notes

1   Factor utilization costs encompass factors such as factor input costs and Iceberg trade costs.

2   Openness includes various Iceberg trade costs associated with international trade, such as transportation costs, tariff barriers, and cultural differences.

3   This table represents a simplified illustration of the Eora MRIO, which does not include the intra-industry input–output relationships within the table. For the specific structure and detailed industry classifications, please refer to the official website at http://worldmrio.com.

4   To highlight the significant portion of resilience distribution (referred to as head classes), values below 0.02 representing less frequent occurrences (tail classes) were excluded from the analysis.

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