

Article

Industry Network Structure Determines Regional Economic Resilience: An Empirical Study Using Stress Testing

Nan Qiao and Chengjun Ji *

School of Business Administration, Liaoning Technical University, Huludao 125105, China;
471710057@stu.lntu.edu.cn

* Correspondence: jichengjun@lntu.edu.cn

Abstract: We evaluate the network robustness of industrial capabilities across China's provincial administrative regions, focusing on their resilience in the wake of the 2008 economic crisis. By adopting a novel network science methodology within the context of economic geography, we leverage co-classification data from the China Statistical Yearbook to conduct stress tests on regional industrial resilience. The findings indicate a considerable variability in robustness among provincial industry networks. Through regression analysis, it is evident that regions with more robust industrial network structures exhibit greater resilience in employment rates in response to both random and targeted disruptions. Notably, regions characterized by high employment levels coupled with weak industrial foundations are identified as particularly vulnerable, facing significant challenges in sustaining economic resilience. This study highlights the imperative for further in-depth research into the relationship between the structural dynamics of regional economic networks and their resilience to economic shocks, emphasizing the critical role of robust industrial infrastructures in enhancing regional economic stability.

Keywords: industrial network; network structure; economic resilience; network science



Citation: Qiao, N.; Ji, C. Industry Network Structure Determines Regional Economic Resilience: An Empirical Study Using Stress Testing. *Sustainability* **2024**, *16*, 5686. <https://doi.org/10.3390/su16135686>

Academic Editor: Stephan Weiler

Received: 29 May 2024

Revised: 22 June 2024

Accepted: 25 June 2024

Published: 3 July 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Economic development in China showcases significant disparities across its regions, with major structural challenges including the concentration of resources and talent in larger cities. This centralization exacerbates the economic struggles of smaller, less developed cities [1]. Globally, this pattern of uneven development is not unique to China; the 2019 report of the Organization for Economic Co-operation and Development (OCED) [2] on regional productivity underlines similar structural issues. It highlights a stark productivity gap, where the least productive region in some countries is less than half as productive as the most productive one. Moreover, about a third of the countries within the OECD are highly dependent on just one region for their economic growth, which underscores the depth of regional economic imbalances. These imbalances are further complicated by the increasing economic and trade connections between regions, which, while enhancing efficiency through interdependence, also increase vulnerability to catastrophic events. Such interconnectivity can lead to rapid and widespread economic disruptions if a key region suffers a downturn or disaster. The dual nature of these connections necessitates strategies that not only capitalize on the benefits of regional interdependence but also mitigate the risks associated with it, ensuring a more balanced and resilient economic growth model. This complex dynamic between regional interdependence and vulnerability highlights the need for robust economic policies that address structural imbalances and enhance economic resilience across all regions.

To meet these challenges, policymakers and academics are increasingly emphasizing regional economic resilience, the ability of a regional economy to absorb, withstand, and recover from economic shocks while sustaining long-term development [3–5]. This focus

reflects a growing awareness of the need to enhance regional economic structures to better cope with external disturbances, such as financial crises, industry shifts, or technological changes [6], which can have profound and lasting impacts on economic growth and exacerbate existing regional imbalances [7]. Recent scholarly work highlights that regional economic resilience is not merely about weathering crises but also involves a dynamic capacity to adapt to changing external conditions, including shifts in industry demand, technological advancements, and policy changes [8–10]. These adaptations are critical for regions to maintain competitive advantages and secure economic stability and growth over time. However, the capacity of a region to achieve such resilience is significantly shaped by its available resources and its historical economic structures [11,12]. Regions endowed with diverse and rich resources and robust economic infrastructures are better positioned to respond to and recover from disruptions. Conversely, regions with limited resources or those dependent on single industries may find it challenging to adapt to new economic conditions and recover from economic shocks. This understanding calls for targeted policy interventions that not only address immediate economic challenges but also strategically enhance the foundational economic capacities of regions to support their long-term resilience and growth. Such policies must consider the unique economic profiles and needs of each region to effectively foster an environment conducive to sustainable development and resilience.

Despite extensive research, the factors contributing to the varied economic resilience observed across regions are not fully understood [6,13,14]. A crucial element in this puzzle is the local economic structure, which profoundly influences a region's vulnerability to economic shocks and its capacity for recovery. Economically, regions function as networks of interdependent industries [15]. In this framework, industries are represented as nodes, and the links between them indicate the economic correlations and interdependencies that exist. This network perspective is instrumental in explaining the operational dynamics of regional economies, how they regulate development, and their methods of responding to external shocks. Network science, therefore, provides critical insights into understanding regional economic resilience by revealing the intricacies of these interconnections. However, despite the potential of network science, more empirical evidence is necessary to fully comprehend how these economic networks react under the stress of economic crises. The recent advancements in stress testing methods offer powerful tools for examining these network sensitivities. These methods allow for a more detailed analysis of how different industry nodes within a regional economy are likely to respond to shocks, thus offering valuable insights for policymakers aiming to bolster economic resilience. This approach underscores the need for continued innovation in research methodologies to better predict and mitigate the impacts of economic disturbances on regional economies [16].

In summary, the main research content of this paper is the relationship between regional industrial structure and economic resilience. Thus, we explore the robustness of regional industrial network structures by integrating network science with stress testing techniques, aiming to link industrial network robustness to regional economic resilience through regression analysis. Specifically, we develop a provincial-level industrial network using input–output tables from China's provincial regions and other pertinent data. The robustness of these networks is assessed by strategically removing nodes (either randomly or targetedly) until significant fragmentation is observed. This simulates the impact of severe external shocks on regional economic development, thus providing a practical measure of each province's network robustness. The stress tests are instrumental in identifying the vulnerability of these networks to disruptions. We then employ regression analysis to delve into the impact of the 2008 global economic crisis, specifically examining the relationship between industrial network robustness and regional economic resilience, as reflected in employment rates. This analysis is crucial for understanding how well regions can withstand and recover from economic disturbances, providing valuable insights that could help policymakers enhance economic stability and resilience across various provinces.

Our research findings from the 2008 economic crisis indicate significant variability in the robustness of industrial networks across China's provincial-level regions. Regions endowed with more robust industrial network structures exhibited greater resilience, particularly noticeable through less volatile employment rate fluctuations. These observations were consistent under various stress test conditions, including both random and targeted elimination strategies, which simulate the loss of frequently combined industrial capabilities. Importantly, this correlation between industrial robustness and economic resilience remained significant even when accounting for established metrics of regional economic structure, such as related and unrelated variety. These results underscore the critical role that well-integrated industrial networks play in buffering regional economies against external shocks.

This paper advances the field of regional economic resilience by investigating the connection between resilience and regional industrial network structures through a novel network scientific measurement method applied within economic geography. Conceptually, this method is rooted in the adaptive capacity framework, highlighting the critical role of local base structure in understanding and enhancing regional resilience. By merging advanced resilience techniques and network robustness research, this study fills a gap in our understanding of how network structures impact regional economic resilience [15]. Furthermore, it aligns with broader trends in economic geography that utilize network analysis to delve into regional diversification [17–19] and the complexities of urban economic structures and resilience [20]. This integrated approach not only sheds light on theoretical aspects but also offers practical insights for policymakers and planners aiming to fortify regional economies against disruptions.

The upcoming section offers a comprehensive summary of empirical studies that focus on regional resilience and network-based economic research methods, connecting these areas to the concept of network robustness. This is followed by an in-depth presentation of the dataset utilized in this study, alongside a detailed description of the newly adopted methodology for measuring industrial network robustness. Additionally, the specifications of the econometric model employed are thoroughly explained. The results of the study are meticulously analyzed in the penultimate section. Finally, the concluding section provides a detailed discussion of the findings, highlighting their implications and identifying potential avenues for further research. This structure ensures a systematic exploration of the themes and robust analysis, paving the way for a deeper understanding of network structures in economic resilience.

2. Literature Review

2.1. Regional Economic Resilience

Despite the burgeoning body of literature on regional resilience, as extensively discussed in the 'Handbook on Regional Economic Resilience' [21], the theoretical framework guiding this concept continues to evolve [22]. Current interpretations of regional resilience are primarily derived from interdisciplinary perspectives [23], emphasizing two distinct approaches. The first approach, rooted in economics, evaluates regional resilience by examining how swiftly a regional economy can return to its pre-shock state in terms of metrics like employment and income. This perspective views resilience primarily as the capacity of a region to rebound after an impact. The second approach, influenced by ecological theories, posits that regions demonstrating greater resilience can withstand more severe shocks before transitioning to a new state of equilibrium [6,23]. This ecological view considers resilience as the ability of a region to maintain its core economic structures and performance levels during periods of shock. However, both these perspectives have limitations as they tend to overlook the long-term aspects of resilience. True resilience involves not only the capacity for immediate recovery but also the ability of a region to adapt and reconfigure its economic structures in response to ongoing or future shocks. This more comprehensive understanding of resilience incorporates the dynamics of adaptation and long-term sustainability, suggesting that a region's resilience should be measured not

just by its ability to recover but also by its capability to evolve and thrive in the face of new challenges [7,23,24].

Recent developments in the literature on regional resilience have marked a significant shift from traditional balance-based approaches to a more dynamic, evolutionary perspective. This new approach draws heavily on principles from evolutionary economics and economic geography (EEG), placing a strong emphasis on the interactions between local economic factors. These interactions dictate whether economic systems are inherently adaptive or remain rigid, shaping the resilience of regions over time [5,6]. Under this evolutionary framework, regions are analyzed through the lens of their historical economic activities [5,23], which inherently influence and define the range of economic structures they can potentially adopt [5,18]. This method not only considers the short-term capabilities of regions to respond effectively to immediate economic shocks but also their long-term ability to evolve and establish new growth trajectories [5,14,25]. From this perspective, a resilient region is distinguished by its proactive capacity to modify and adapt its economic structure. This adaptability is crucial both in anticipation of potential economic disturbances and in response to them. It underscores the importance of flexibility in economic planning and policy-making, aiming to cultivate an environment where regions are not just reactive to changes but are prepared to innovate and transform their economic landscapes as needed. This evolutionary approach to regional resilience offers a more comprehensive understanding of how regions can sustain growth and stability in the face of continuous economic change.

Martin [6] outlines four interrelated dimensions of regional economic resilience that encapsulate the dynamic ways regions respond to shocks: Resistance, Recovery, Repositioning, and Renewal. Resistance is defined as a region's sensitivity to shocks, indicating how strongly an area is affected initially. Recovery refers to the speed and extent to which a region recovers from these shocks, including how quickly it can restore its economic stability. Repositioning involves the degree of structural changes a region undergoes in response to shocks, which affects economic outcomes such as employment, output, and income. Lastly, Renewal assesses the extent to which a region can return to its pre-shock growth path or trajectory. Much of the existing research on regional resilience has been centered on responses to sudden crises, such as natural disasters or the 2008 financial crisis [26–28], and the local economic impacts of major events like factory closures [29]. These studies highlight the importance of both adaptation (making changes within a predetermined path) and adaptability (the capacity to create new growth paths) [13,26]. The challenge, however, lies in how regions can leverage their existing industry bases effectively while maintaining the flexibility required for adaptability [5]. This involves balancing the use of established skills and industries with the need to innovate and embrace new economic opportunities. Thus, fostering regional economic resilience is not only about recovery but also about enabling regions to evolve and transform in the face of adversity, using both their existing strengths and new capabilities to navigate and thrive in a changing economic landscape.

Regional resilience is a multifaceted concept, deeply intertwined with the structure, performance, and functionality of economic systems [30]. Performance within this framework is gauged by a region's ability to maintain or achieve satisfactory metrics in key areas such as employment, output, income, and innovation [6,31,32]. Persistent spatial differences highlight the varying degrees of resilience across regions, prompting an investigation into the factors that contribute to a region's adaptability. Research into regional resilience is increasingly focusing on several critical determinants. These include the composition and complexity of industrial structures, the dynamics of local labor markets, the robustness of financial systems, the efficacy of governance mechanisms, and the capacity for strategic decision-making. Each of these elements plays a crucial role in shaping a region's ability to withstand and adapt to economic shocks [14]. This article utilizes network science tools to specifically explore how industrial structures impact regional resilience. By analyzing these structures, we aim to deepen our understanding of how interconnectedness and network characteristics influence a region's economic stability. This approach provides valuable

insights into the pathways through which regions can enhance their resilience in the face of diverse economic challenges.

2.2. Correlation and Ability

The structure of a region's industrial base plays a pivotal role in defining its economic resilience. A diversified industrial structure helps to mitigate risks by spreading them across various sectors, buffering against demand and supply fluctuations and minimizing the impacts of disturbances on specific industries [27]. For example, during the 2008 financial crisis, European regions with a significant presence of medium- and high-tech industries were better able to maintain their economic stability [33] and keep unemployment rates relatively low [33]. This resilience stems from their capacity to resist economic shocks due to their diversified economic base. Diversification allows regions the flexibility to seize new market opportunities and creatively restructure their capacities in the face of economic challenges [14]. This adaptability is crucial for enhancing a region's potential for recovery and long-term growth [5]. Conversely, regions that specialize in a limited number of core activities often face greater vulnerability to economic shocks, particularly if these industries do not align with current technological advancements or market demands [24]. However, there is a notable challenge: industries that rely on complex knowledge and could potentially forge new growth paths are often concentrated in larger urban areas [24]. This concentration restricts the options available to more remote areas, limiting their ability to tap into these innovative industries. This geographical imbalance in industrial complexity underscores the need for strategic policies that foster industry spread and encourage the development of high-tech sectors across a wider array of regions, enabling broader access to the benefits of diversified economic structures and enhancing regional resilience against economic shocks.

Advancements in EEG have expanded our understanding of local economic structures, highlighting the need to move beyond the basic dichotomy of diversity versus specialization [34,35]. This refined approach involves identifying and harnessing correlations among economic activities that may not be immediately apparent. Specifically, EEG emphasizes the importance of achieving an optimal level of cognitive proximity and interactive learning among industries, even if they are not closely related by traditional standards [5]. Such correlations allow industries within a region to share and combine capabilities effectively during the production process [36], thereby enhancing the region's overall productive capacity [37]. These capabilities are underpinned by critical resources such as property rights, base structure, labor, and capital, which collectively facilitate sustained economic activity within the region [38]. Additionally, the availability of local industry forms the foundation for localized capabilities that support a region's competitive advantage [39]. This brings into focus the concept of 'related variety', which is pivotal in allowing regions to strike a balance between adaptability and resilience. By leveraging and recombining learning opportunities across different but related industries, regions can forge new growth paths [5], thereby enhancing their economic robustness and adaptability. This approach not only strengthens a region's immediate economic base but also prepares it for future challenges by fostering an environment conducive to innovation and dynamic growth.

While local industries connected through similar capabilities and input–output relationships play a crucial role in fostering long-term economic success [5] through related diversity [19,27], these connections also introduce a significant challenge. The very networks that promote economic integration and growth can also accelerate the spread of economic crises within regions. This related diversity, while capable of rapidly boosting employment and fostering economic integration, may also lead to increased vulnerability to economic fluctuations [14]. Studies examining the average relevance of industries in regions like the UK and EU [40] have found that both related and unrelated industrial specializations can sometimes have negligible or even negative impacts on employment growth [28]. This highlights a complex tension: industry correlation can simultaneously support growth opportunities and enhance a region's exposure to economic downturns.

Consequently, the role of industry correlation in shaping regional resilience is ambiguous, serving as a double-edged sword that can either underpin a region's economic stability or undermine it by magnifying the effects of adverse economic conditions [14,41].

2.3. Networks and Robustness

The intricate tension between the advantages and vulnerabilities of interconnected local economies suggests the need for a more nuanced view of economic structures as networks. Within this framework, the regional economy is conceptualized as a network of specialized production units. These units are not standalone entities but are interconnected through tightly integrated industry relations, shared skills, and tacit knowledge, all essential for creating value [42]. The field of EEG has significantly benefited from incorporating network science [43], which has introduced innovative insights and methodologies for analyzing clusters [44], knowledge networks [45], and innovation performance [46]. These advancements have underscored the critical role of location links [47] in driving regional economic growth and diversification [48]. Despite these contributions, the application of a network perspective in economic geography is still evolving and requires further refinement [49]. To fully understand regional economies as complex systems, there is a pressing need for deeper investigations into the structural and dynamic relationships within regional networks. This involves examining how nodes (industries) are interconnected, the flow of information and resources across these connections, and how these networks respond to external shocks and internal developments. Such an exploration would enhance our understanding of regional resilience and adaptability, providing a more comprehensive basis for policy interventions aimed at fostering robust and sustainable economic growth.

Next, developing on recent studies that view regional economies as complex networks composed of nodes and links (where nodes represent industries and links depict the correlations between them), we delve into the mechanisms of division of labor and coordination within these networks. This network-based approach, drawing from insights offered by researchers such as Shutters et al. [50], conceptualizes the industrial space as a matrix where specific industries (nodes) are frequently combined (linked), as evidenced by input–output data reflecting economic activities [5,19,51]. This detailed representation not only highlights the integration of industry-specific capabilities to achieve particular outcomes [37] but also offers significant insights into the unique capabilities local to each region [15]. However, this network perspective, while providing a nuanced view of how industrial capabilities are integrated, may not completely encompass all regional capabilities, particularly those that are not easily codified within traditional industry parameters. Previous research has indicated that regions with a higher degree of shared industrial capabilities tend to exhibit greater resilience in production scenarios within US metropolitan areas [52] and foster employment growth in regions across the UK and EU [28]. By adopting this network approach, we gain a more granular understanding of the industrial structures that underpin regional economies. This is crucial for comprehensively understanding the dynamics of regional economic resilience, as it allows for a clearer assessment of how well regions can adapt to economic shifts and disruptions. This method not only highlights the interconnectedness of economic activities but also facilitates the identification of critical nodes and links that could be leveraged to enhance regional economic stability and growth.

Our goal is to deepen the understanding of system robustness through the application of network science principles. Robustness, in this context, is defined as the ability of a complex system to sustain its critical functions despite disruptions, such as the loss of nodes or links [15,53,54]. This resilience becomes particularly crucial when a network fragments into disconnected components [28,55], a process that often occurs abruptly rather than gradually [56]. In network theory, there is a recognized critical threshold: if node removal stays below this threshold, the network's giant component (comprising a significant proportion of all connected nodes) remains largely unaffected. However, crossing this threshold can precipitate the collapse of the network structure. When viewing a region as a complex system composed of interlinked elements [57], it is subjected to various disturbances, in-

cluding factory closures, technological shifts, economic recessions, and natural disasters. In the context of regional industrial spaces, these disturbances can disrupt the established models of industry coordination that have been historically and regionally developed. Such disruptions can transform a cohesive network of interlinked industrial capabilities into fragmented, unrelated clusters of industries. This fragmentation can severely weaken the local economic interdependence and performance, as the region loses the synergistic benefits derived from a well-integrated industrial network. Understanding and enhancing the robustness of these systems is essential to maintaining economic stability and fostering resilience against the multitude of disturbances that can affect regional economies.

Importantly, the robustness of a network's structure is significantly influenced by the method of node elimination [58], which can drastically alter the network's functionality [56,57]. In regional industrial spaces, random failures are a common phenomenon. These can occur due to various factors, such as the emergence of new industries, the obsolescence of old capabilities, or the exit of industries that are heavily reliant on specific, perhaps outdated, technologies [14]. These random failures can significantly impact industries that depend on these industrial capabilities, leading to a decline or even closure. Despite the loss of organizational structures, the industrial knowledge, encapsulated in skills and assets, may persist. However, without the framework of an industry to apply these capabilities, they may become dormant until new opportunities arise for their application. This ongoing flux in the economic landscape underscores that a region's model of coordinating industrial elements is not static but is continually reshaped by these disturbances. The region evolves through cycles of resistance to initial shocks, destruction from ongoing disruptions, and ultimately recovery and renewal as new opportunities are created and capitalized upon. This dynamic process highlights the importance of understanding and designing industrial networks that can adapt and reconfigure themselves to maintain regional economic resilience and robustness amid constant change.

Random failures within a network often highlight unknown interdependencies between nodes, which can significantly impact regional industrial landscapes. When a region loses access to one of its core industrial capabilities, it potentially jeopardizes other related capabilities that are frequently integrated with it. Such a disruption can precipitate cascading failures that ripple through the local economic and industrial sectors, affecting a wide array of entities and operations. Extensive research in various domains, including natural, social, and economic systems, has demonstrated that networks are inherently sensitive to these cascading effects [56,57,59,60]. Particularly, networks characterized by a few highly connected nodes or hubs, while the majority have fewer connections, exhibit a unique vulnerability-resilience paradox. While these networks may appear robust against random disruptions due to their sparse connectivity, they are acutely vulnerable to the failure of their hubs. The failure of a single hub can lead to significant disruptions throughout the network, underscoring the disproportionate impact of these critical nodes. Therefore, the economic resilience of a region is intrinsically linked to the robustness of its industrial network structure. Understanding and managing these critical interdependencies is essential to safeguard against cascading failures and ensure regional stability. This involves not only identifying key hubs within the network but also enhancing the resilience of these hubs and the overall network structure to sustain regional economic vitality amid potential disruptions.

To underpin our study, we establish three foundational assumptions that guide our analysis of the relationship between industrial network structure and regional economic resilience:

(i) **Regional Economic Reflection:** We assume that the regional economy is directly reflected by the employment rate. This assumption facilitates the construction of a measurement index for regional economic resilience, details of which are explored in the following section. By focusing on employment rates, we can gauge economic stability and growth, assuming that higher employment rates are indicative of a resilient economy.

(ii) **Causal Relationship:** We posit that there is a direct causal relationship between the structure of the industrial network and regional economic resilience. While this assumption

establishes a linkage between industrial structure and economic outcomes, the specifics of which network structures most effectively support resilience remain to be fully determined. This area of our research seeks to identify and quantify the attributes of industrial networks that correlate with strong economic resilience.

(iii) Network Structure Measurement: The structure of the industrial network is conceptualized through inter-industry linkages. By measuring these linkages, we are able to map and analyze the network, providing a structural framework for our investigation. This approach allows us to understand how industries interact within a region and how these interactions influence economic stability.

These assumptions are crucial for driving our investigation into how industrial network structures impact regional economic resilience. It is important to recognize that while these assumptions underpin a model that demonstrates robustness in subsequent chapters, they introduce inherent limitations to our conclusions. We encourage readers to consider these assumptions critically and adapt them based on their specific contexts, potentially exploring alternative hypotheses that could offer different insights.

3. Data and Methods

We will use the 2008 economic crisis as a test case to verify the relationship between industrial structure and economic resilience at the provincial level in China. China's regional input–output tables, calculated at producer prices, serve as a vital tool for analyzing the interconnections and proportional balances between various industrial sectors within the regions. These tables facilitate a comprehensive examination of regional industrial networks and can be categorized either dynamically or statically, depending on the focus—be it by region or by specific sector. Although the granularity of the input–output data may be somewhat coarse, they still provide a sufficient level of accuracy for studying the complex industrial structures of provincial-level regions across China. Additionally, the 2008 economic crisis has been chosen as a case study for this analysis due to its wide-reaching and deep impact on the global economy. This period provides a robust framework for analyzing a complete cycle of economic resilience, from the initial shock to eventual recovery. This analysis is particularly poignant when contrasted with the ongoing global economic recovery from the COVID-19 pandemic, which, unlike the 2008 crisis, has not yet stabilized to pre-pandemic economic levels. Moreover, the current recovery is further complicated by additional global instabilities, such as geopolitical tensions and conflicts, which add layers of complexity to understanding and measuring economic resilience in today's interconnected global landscape.

3.1. Dependent Variables

Changes in employment rates are frequently used to assess regional economic resilience [28], serving as a measure of a regional capacity to endure external shocks. However, while this metric provides valuable insight, it represents only one facet of resilience. The employment rate alone does not reveal the deeper, underlying causes or the specific sources of regional resilience. Boschma et al. [23] pointed out that the industrial structure and institutional level are the main determinants of regional resilience, and the ideal economic output level is an important indicator of resilience measurement. A resilient industrial structure makes a resilient region. Therefore, in the empirical analysis, the change in employment rate is related to the robustness of the industrial network. The dependent variable is defined as follows:

$$EMPRATE\ CHANGE_i = \left(\frac{EMP_{i,2012}}{POP_{i,2012}} \right) / \left(\frac{EMP_{i,2006}}{POP_{i,2006}} \right) \quad (1)$$

where $EMPRATE\ CHANGE_i$ specifically tracks changes in the regional employment rate (the proportion of the employed population, EMP_i / POP_i) over the period from 2006 to 2012. This timeframe is strategically chosen to reflect the economic landscape before and after the pivotal economic crisis. The year 2006 is used as the baseline because it is the last

year before the onset of the crisis, providing crucial insight into the network structure and economic conditions just prior to the downturn. The endpoint of 2012 is selected because it marks a return to pre-crisis levels of economic development. The significance of starting with 2006, rather than 2007, lies in understanding the network's initial configuration and its role in the region's resilience during the initial resistance phase of the economic crisis, highlighting how pre-crisis conditions influence recovery trajectories [20].

3.2. Independent Variable: Network Robustness

To measure the robustness of industrial networks, we first need to develop a regional industrial network. In the industrial network, each node represents an industry, the size of the node is proportional to the output value, and the connection weight is calculated based on the input–output table. The specific calculation process is as follows:

Before calculating the weight, we first understand the structure of the input–output table. The simplified input–output table is shown in Table 1.

Table 1. The general structure of the simplified input–output table.

Input		Output			
		Intermediate Input			End Use
		Sector 1	Sector 2	Sector 3	
Intermediate input	Sector 1	d_{11}	d_{12}	d_{13}	Y_1
	Sector 2	d_{21}	d_{22}	d_{23}	Y_2
	Sector 3	d_{31}	d_{32}	d_{33}	Y_3
Value added		V_1	V_2	V_3	

In Table 1, d_{ij} represents the intermediate input value from sector i to sector j and it is also the intermediate usage from sector j to sector i . V_i and Y_i are the added value and end use of sector i . Since the amount of input must be equal to the amount of use, the sum of the intermediate input and the added value of each sector is equal to the sum of the intermediate use and the final use of the sector. According to the nature of input and output, the following set of equations are obtained:

$$d_{11} + d_{21} + d_{31} + V_1 = d_{11} + d_{12} + d_{13} + Y_1 \quad (2)$$

$$d_{12} + d_{22} + d_{32} + V_2 = d_{21} + d_{22} + d_{23} + Y_2 \quad (3)$$

$$d_{13} + d_{23} + d_{33} + V_3 = d_{31} + d_{32} + d_{33} + Y_3 \quad (4)$$

$$V_1 + V_2 + V_3 = Y_1 + Y_2 + Y_3 \quad (5)$$

The network is constructed by the consumption coefficient, and the matrix G that characterizes the relationship between industrial sectors is obtained as follows:

$$G = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix} = \begin{bmatrix} \frac{d_{11}}{d_{11}+d_{21}+d_{31}+V_1} & \frac{d_{12}}{d_{12}+d_{22}+d_{32}+V_2} & \frac{d_{13}}{d_{13}+d_{23}+d_{33}+V_3} \\ \frac{d_{21}}{d_{11}+d_{21}+d_{31}+V_1} & \frac{d_{22}}{d_{12}+d_{22}+d_{32}+V_2} & \frac{d_{23}}{d_{13}+d_{23}+d_{33}+V_3} \\ \frac{d_{31}}{d_{11}+d_{21}+d_{31}+V_1} & \frac{d_{32}}{d_{12}+d_{22}+d_{32}+V_2} & \frac{d_{33}}{d_{13}+d_{23}+d_{33}+V_3} \end{bmatrix} \quad (6)$$

For the demand side, we obtain the form of matrix G that characterizes the relationship between industrial sectors in the following:

$$G = \begin{bmatrix} \delta_{11} & \delta_{12} & \delta_{13} \\ \delta_{21} & \delta_{22} & \delta_{23} \\ \delta_{31} & \delta_{32} & \delta_{33} \end{bmatrix} = \begin{bmatrix} \frac{d_{11}}{d_{11}+d_{21}+d_{31}+Y_1} & \frac{d_{12}}{d_{12}+d_{22}+d_{32}+Y_2} & \frac{d_{13}}{d_{13}+d_{23}+d_{33}+Y_3} \\ \frac{d_{21}}{d_{11}+d_{21}+d_{31}+Y_1} & \frac{d_{22}}{d_{12}+d_{22}+d_{32}+Y_2} & \frac{d_{23}}{d_{13}+d_{23}+d_{33}+Y_3} \\ \frac{d_{31}}{d_{11}+d_{21}+d_{31}+Y_1} & \frac{d_{32}}{d_{12}+d_{22}+d_{32}+Y_2} & \frac{d_{33}}{d_{13}+d_{23}+d_{33}+Y_3} \end{bmatrix} \quad (7)$$

We chose $\sigma_{ij} + \delta_{ij}$ as the weight between nodes, which considers both the production process of regional economy and the consumption process.

Because the preparation of China's base year input–output table depends on a special input–output survey, it takes a lot of manpower, material resources and time, which leads to a long time interval between the base year input–output tables. The time interval for compiling the baseline table is 5 years.

To make up for the time lag of the input–output table, based on the research of Dong et al. [61], we calculated the industrial structure rationalization index [62], the industrial structure upgrading index [63], and the industrial agglomeration index [5]. The data are derived from the 'China Statistical Yearbook', the 'China Regional Economic Statistical Yearbook', the 'China Urban Statistical Yearbook' and the statistical yearbooks of some provinces and cities. The time span is from 2006 to 2012.

The input–output table data of 28 sectors from 2006 to 2012 are obtained. The sectors are divided into industry 1 of the primary industry, agriculture, forestry, animal husbandry and fishery and industry 2 to industry 23 of the secondary industry: coal, oil and gas mining, metal mining and dressing, non-metallic mining and dressing, food and tobacco, textiles, clothing, shoes and hats, wood furniture, printing and sports, petroleum coking products, chemical products, non-metallic mineral products, metal smelting and rolling, metal products, general special equipment, transportation equipment, electrical machinery, communication computers, instruments and meters, other manufactured goods, power, gas, and water, and the construction industry. The third division includes 24 to industry 28: transportation, warehousing and postal services, commerce, residents and public services, administration, and business, and financial industry.

Through the above methods, regional industrial networks can be developed. After observing the developed industries, it is found that the links between most industries are extremely weak, and the contribution of weak links to economic resilience is low. Therefore, we did not analyze weak inter-industry links. For this reason, the industrial network is simplified, and the specific simplification process is as follows: when the connection weight between nodes is less than 15% of the average weight, the connection is deleted. The deleted network can more easily evaluate the robustness of the industrial network.

Each network form represents a regional industrial structure, and different industrial structures correspond to different regional economic resilience. Therefore, it is necessary to analyze the regional industrial network structure first. Therefore, two parameters are introduced to evaluate the industrial structure.

Ω denotes the maximum amount of node removal that a regional industrial network can withstand. When the regional economy is affected by external shocks, the number of industries decreases accordingly. When the number of reduced industries (nodes) exceeds Ω , the industrial network will be divided into several disconnected components. Of course, when external shocks only destroy a few nodes, we think it is acceptable, so how to determine the threshold becomes a problem that must be solved. To solve this problem, we chose the MolloyReed criterion [64] to determine the threshold of this connectivity:

$$\langle k^2 \rangle / \langle k \rangle > 2 \quad (8)$$

$$\langle k \rangle^2 = \sqrt{\frac{\sum_{i=1}^N k_i}{N}} \quad (9)$$

$$\langle k \rangle = \frac{1}{N} \sum_{i=1}^N k_i \quad (10)$$

where $\langle k \rangle^2$ denotes the average square of the degree of nodes in the network, $\langle k \rangle$ denotes the average degree of nodes in the network, k_i represents the degree of nodes i , and N is the total number of nodes in the network.

Assuming that the number of nodes in the network is proportionally reduced, the range of Ω is $[\varepsilon, 1]$, where ε represents the minimum possible value greater than 0, and Ω will never reach 1, because no system can survive after eliminating all nodes. According to the above definition, it can be seen that areas with high Ω can better withstand economic shocks than areas with low Ω .

The parameters λ are introduced, $\lambda \in [0, 1]$, which mainly reflect the method of eliminating nodes, and can take into account the degree of nodes in the process of removing nodes. If the industry with the highest centrality is removed, the parameter λ is equal to 1, and $\lambda = 0$ represents the random removal of nodes (industries). A value between the two, that is, for example, $\lambda = 0.5$, means that both the removal of the highest central node and the random removal of the node are considered. Therefore, $\Omega^{\lambda=1}$ and $\Omega^{\lambda=0}$ define the two extremes of network robustness. Note that the purpose of this is not to establish a clear impact propagation model but to measure the ability of a region to resist external shocks.

Figure 1 illustrates the measurement method of industrial network robustness in Liaoning province. Figure 1a is the complete network without removing any nodes. Figure 1b shows the results after randomly removing 40% of the nodes from the network. When nodes are randomly removed from the network, the average degree is proportional to the number of nodes removed. In Figure 1c, the result after removing 40% of the nodes is represented. Different from Figure 1b, the method of preferentially removing the highest central node is used. It can be observed that in the case of the random removal of 40% of nodes, nodes with higher degrees still exist, and industries are still interconnected. Using degree-based targeted removal of nodes, the network will be divided into several disconnected industrial sub-networks.

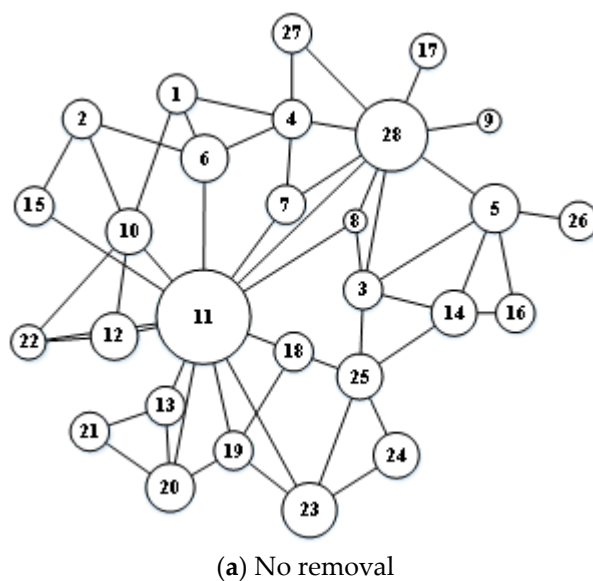


Figure 1. Cont.

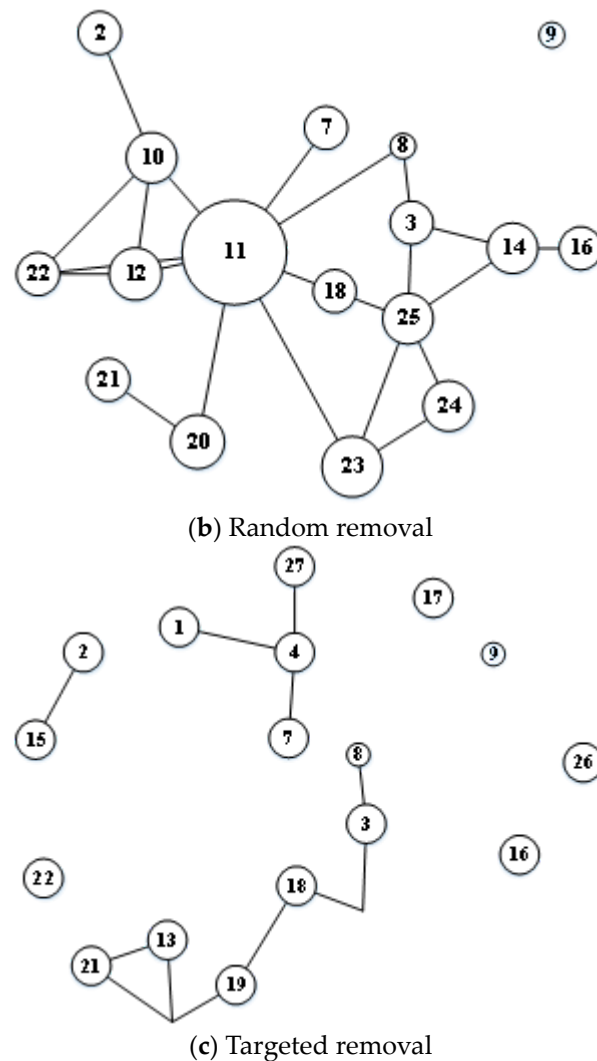


Figure 1. Removal of industries from Liaoning industry network (40%). The industry number is displayed in the circle.

3.3. Control Variables

To avoid interference from other variables related to regional economic resilience, some variables need to be controlled to ensure the quality of research. The first thing to be controlled is the average agglomeration coefficient. The local clustering coefficient of a node reflects the possibility that it is also interconnected with adjacent nodes. The degree of agglomeration of the entire network can be represented by the average clustering coefficient, which represents the average value of the local clustering coefficient of all nodes. In the context of regional industrial networks, the higher the average clustering level, the closer the connection between the regional economy and the core industry. The clustering coefficient C_i represents the degree of interconnection between a given node and adjacent nodes:

$$C_i = \frac{2L}{k_i(k_i - 1)} \quad (11)$$

where k_i represents the degree of the node i , that is, the number of adjacent edges the node; L represents the actual number of links of the node k_i . If there is no connection between the neighbors of the industry i , $C_i = 0$. When all adjacent nodes of i are connected, $C_i = 1$. Since the clustering coefficient is very sensitive to the size of the network [55], the results

obtained using the ER random graph (C_{ER}) are used to normalize the observed average clustering coefficient. The final control variables are as follows:

$$C' = \frac{\langle C \rangle}{C_{ER}} \quad (12)$$

where $\langle C \rangle$ represents the average clustering coefficient.

In addition, the variables that need to be controlled are the overall characteristics of economic and social development. The variables that need to be controlled specifically include the level of employment rate ($EMPRATE$), the population base (POP), and the gross value added (GVA). The the employment rate level is controlled because, when the employment rate level is high, it is more difficult to increase the employment rate; the population size is controlled because with the increase in population, the quantity and quality of economic development will increase disproportionately; the main reason for the final control of the value added is that controlling value added can better control economic activity, which is critical to economic resilience.

4. Econometric Model

To investigate the relationship between regional economic resilience and the robustness of industrial networks in relation to employment rates, we utilize a linear regression econometric model. This model is specifically designed to explore how variations in industrial network structures and their disruptions correlate with regional employment rates, thereby providing insights into economic resilience. The model incorporates two primary variables: economic resilience, as indicated by employment rates, and industrial network structure, which is characterized by Ω and λ . To enhance the robustness of our analysis, the model also includes two sets of control variables. These are intended to account for external influences that could potentially affect the outcomes, ensuring that the relationship under study is not confounded by extraneous factors. Furthermore, we rigorously address potential measurement errors within the data to ensure the accuracy and reliability of the model's results. By doing so, we aim to provide a clear and precise understanding of how industrial network robustness impacts regional economic resilience, specifically through changes in employment rates. The proposed model is as follows:

$$EMPRATE\ CHANGE_i = \alpha + \gamma_1 \Omega_i^\lambda + \beta_1 [\mathbb{Z}_i] + \beta_2 [A_i] + e_i \quad (13)$$

where $EMPRATE\ CHANGE_i$ represents the change in the employment rate in region i from 2006 to 2012, which reflects the change in economic resilience. Ω_i^λ reflects the relationship between industrial network robustness and economic resilience, in which two parameters are obtained by the removal method described in Section 3.2; $\mathbb{Z}_i$ is a set of control variables, which describes the structure of a regional industrial network. Specifically, it is the normalized average clustering coefficient C' ; A_i represents the set of economic and social control variables: employment rate ($EMPRATE$), gross value added (GVA) and population size (POP). e_i is the normal distribution error term of the base year 2006. Compared with the classical regression econometric model, the proposed model's outstanding advantage is that its independent variables can reflect the impact of external interference on the industrial network structure, which is very important for measuring the relationship between the industrial network structure and economic resilience. In addition, this model can well capture the relationship between industrial network structure and regional economic resilience and quantify the interference of various unfavorable factors.

Although the data used are collected by the National Bureau of Statistics of China, the conclusions are not necessarily suitable for all situations in China and can only be used as a decision-making reference. The economic development in all parts of China has various characteristics. In order to overcome these potential deviations, regression analysis is carried out at the provincial level.

5. Results

5.1. Provincial Industrial Network Robustness

Firstly, eight provincial-level administrative regions are selected as samples to study the robustness of industrial networks to evaluate their spatial heterogeneity. The selected provincial administrative regions are either economically more developed provinces or the central provinces of the region. The results are shown in Figure 2. The first significant feature of these industrial networks can be found in Figure 2. When the random method is used to eliminate the nodes ($\lambda = 0$), the robustness of the industrial network is stronger. When the nodes with higher centrality ($\lambda = 1$) are preferentially removed, the industrial network becomes very fragile. That is, even if the regional economy is subjected to a major random shock, the industrial network will not be decomposed into many disconnected nodes. However, when the highest node in the network is preferentially removed, that is, the industry at the core of the industrial network is preferentially disturbed (impacted), the maximum percentage of removal that the industrial network can tolerate will be greatly reduced. For example, the random removal of nearly 90% of the industrial nodes can make the Shanghai industrial network split into a disconnected state, and when the highest node in the network is preferentially removed, the removal of 37% of the nodes can reach the same state. Therefore, the core industry in the regional economy directly determines the level of regional economic development, and the core can often drive the development of other local industries.

Secondly, it can be seen from Figure 2 that there are also great differences in the robustness of regional industrial networks in different provinces. For example, Beijing can withstand 36% of the highest-degree nodes being removed before its industry is split, while Liaoning's industrial network can only withstand 15% of the highest-degree nodes being removed.

The industrial network robustness areas of 31 provincial-level administrative regions are shown in Figure 3. It can be seen from Figure 3 that most of the robust industrial networks are located in the core area of China's economy, i.e., the southeast coastal area. Of course, there are some other regions that are also very robust, such as Beijing. Of course, there are exceptions. For example, Fujian Province is located in the southeast coastal area, but its industrial agglomeration degree is high, so its industrial network robustness is poor. In addition, according to the calculation results, some traditional industrial regions, such as Shandong and Liaoning, have high vulnerability of industrial networks. Finally, although the industrial networks of Shanghai, Beijing, Jiangsu, Guangdong and other provinces have strong robustness, it is found that most provinces in the northern and western regions are more vulnerable to economic shocks. This is similar to the result of another related study [65]. China's regional economic development still has the problem of imbalance.

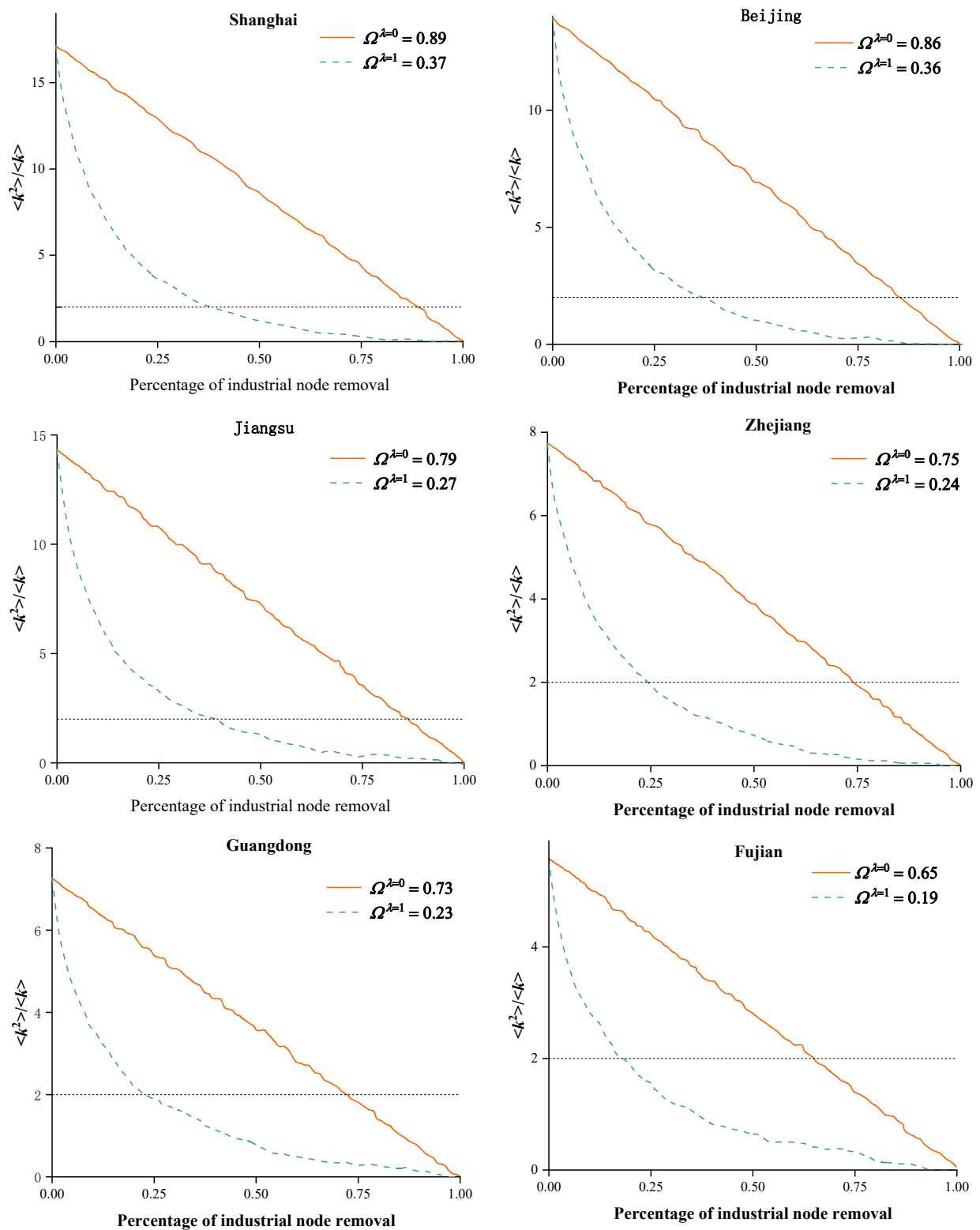


Figure 2. Cont.

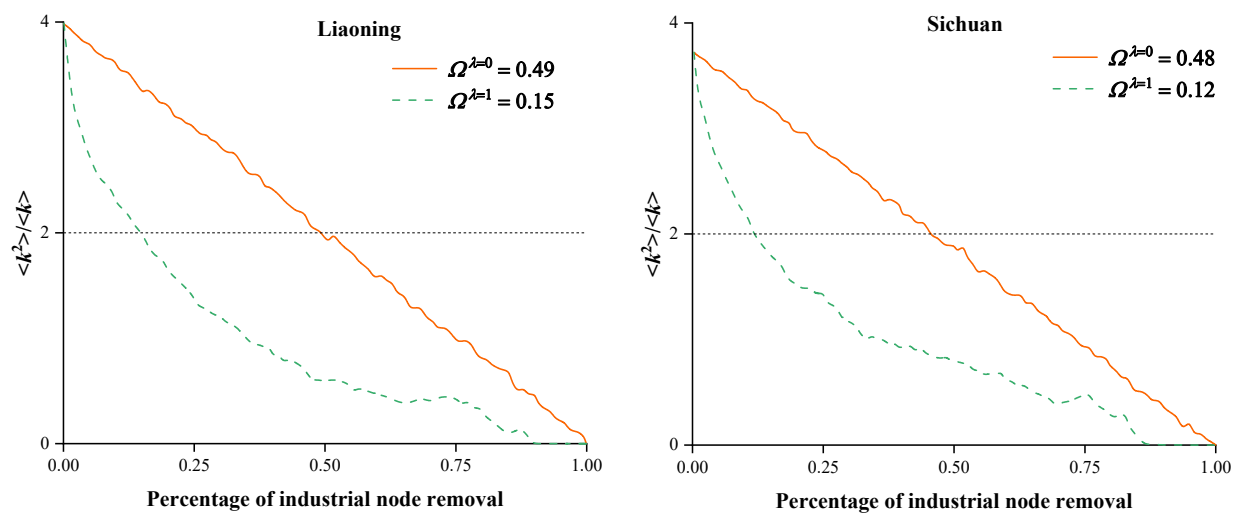


Figure 2. Removal curves for selected regions. The black dash lines represents the acceptable threshold of this connectivity is shown in Equation (8).

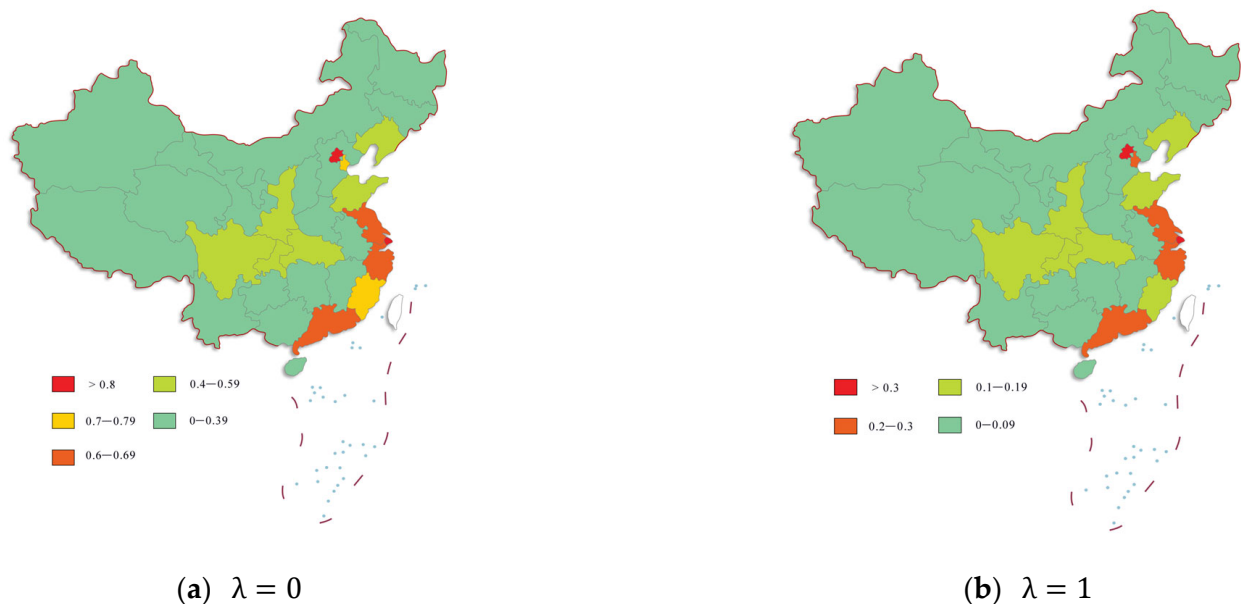


Figure 3. Robustness map of China's provincial industrial network.

5.2. The Role of Industrial Network Robustness in the 2008 Economic Crisis

Next, taking the 2008 economic crisis as an example, the relationship between the robustness of the regional industrial network and the change in employment rate is tested. The employment rate is linked to the robustness of the industrial network, and the robustness of the industrial network is used as a potential influencing factor of economic resilience. Table 2 shows the results obtained by using the least squares method (OLS) to verify the above. In Table 2, the dependent variable alternates between the employment rate in the whole industry of the regional economy (odd series) and the employment rate in the industry (even series).

Table 2. Regression results for the 2006–2012 period.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	All Industries	Single Industry	All Industries	Single Industry	All Industries	Single Industry
$\Omega^{\lambda=0}$			0.0559 (−0.0380)	0.0984 *** (−0.0360)		
$\Omega^{\lambda=1}$					0.1769 ** (−0.0759)	0.2719 * (−0.0789)
C'	−0.0033 *** (−0.0010)	−0.0033 *** (−0.0020)	−0.0716 ** (−0.0340)	−0.0365 (−0.0480)	−0.0811 ** (−0.0340)	−0.0532 (−0.0519)
log(GVA)	−0.0582 (−0.0280)	−0.0671 (−0.0405)	−0.0515 (−0.0290)	−0.0621 (−0.0425)	−0.0480 (−0.0290)	−0.0575 (−0.0436)
log(POP)	0.0158 (−0.0498)	−0.0138 (−0.0342)	0.0490 (−0.0581)	−0.0189 (−0.0363)	0.0504 (−0.0570)	−0.0222 (−0.0363)
log(EMPRATE)	0.0017 (−0.0395)	0.0059 (−0.0166)	−0.0335 (−0.0478)	0.0064 (−0.0177)	−0.0384 (−0.0447)	0.0048 (−0.0177)
Constant	1.3249 *** (−0.1333)	1.4998 *** (−0.1748)	1.2898 *** (−1529)	1.4988 *** (−0.1900)	1.2808 *** (−0.1518)	1.4895 *** (−0.1922)
Clustered SE	Yes ***	Yes	Yes	Yes	Yes	Yes
Mean VIF	3.60	3.60	3.47	3.47	3.20	3.20
R^2	0.184	0.158	0.200	0.183	0.207	0.187
Adj. R^2	0.166	0.140	0.177	0.159	0.184	0.163
Observations	272	272	272	272	272	272

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Columns (i) and (ii) are used as the control group, and only the influence of control variables is considered. In the analysis results of economic and social development conditions, it can be found that the gross value added level (log(GVA)) has a significant negative coefficient. Although log(GVA) is negative in each column, the economic meaning of the negative number is different. For the average agglomeration coefficient (C') of the regional industrial network, it is found that the C' is significantly negatively correlated with economic resilience, indicating that the regions with denser industrial integration in the region are more vulnerable to economic shocks.

In Columns (iii) and (iv), the network robustness measure (Ω) is introduced. The parameter $\lambda = 0$ is set to indicate that the economic interference of the industry in the region is random. The results of the network robustness measure (Ω) are all positive, especially when only employment in the industry is considered (Column iv), and the results are particularly significant. The positive results show that China has strong resilience in the face of the 2008 economic crisis and can withstand the impact of the economic crisis on the industry in the region. Columns (v) and (vi) test the network robustness of $\lambda = 0$, reflecting the situation that the industry with the highest-degree industrial network in a region is preferentially affected by external shocks. It can be found from the results that network robustness and resilience are positively correlated and significant. To verify the influence of the parameter λ on the network robustness regression coefficient, different λ values are used, and the network regression coefficient obtained is shown in Figure 4. From Figure 4, it can be found that there is a positive correlation between network robustness and employment rate changes. This shows that the regional industrial network structure strongly determines regional economic resilience.

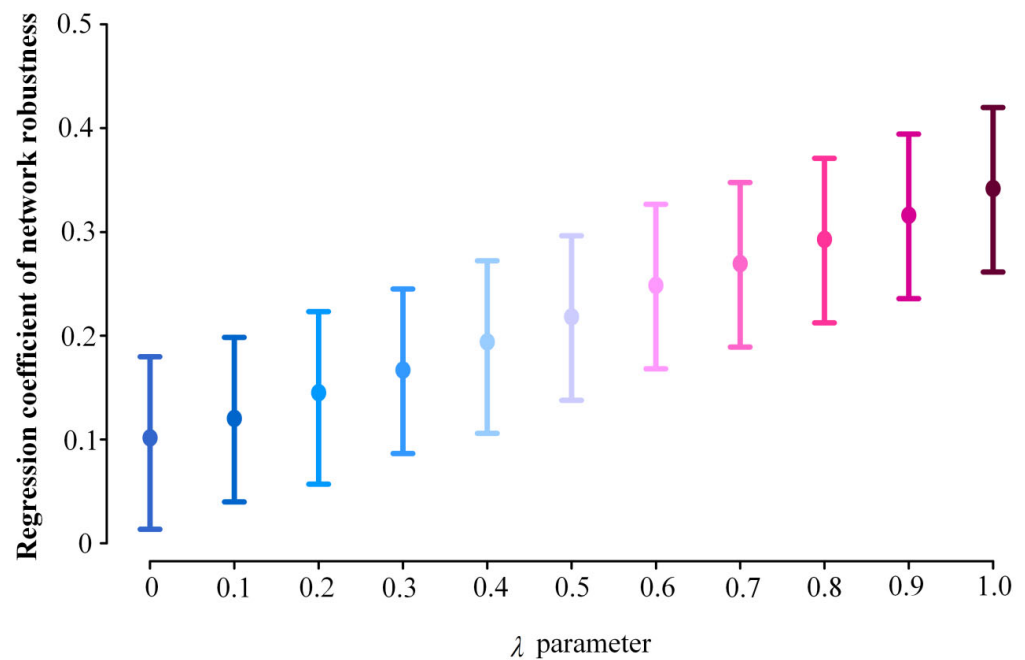


Figure 4. The regression coefficients of industrial network robustness under different λ .

Finally, in order to compare COVID-19 with the 2008 economic crisis, we used the same method to analyze the relationship between the robustness of the regional industrial network and the change in employment rate from 2020 to 2022. The results are shown in Table 3. The change in employment rate is selected as the ratio of 2019 to 2023 (Equation (14)):

$$EMPRATE\ CHANGE_i = \left(\frac{EMP_{i,2023}}{POP_{i,2023}} \right) / \left(\frac{EMP_{i,2019}}{POP_{i,2019}} \right) \quad (14)$$

Table 3. Regression results for the 2020–2023 period.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	All Industries	Single Industry	All Industries	Single Industry	All Industries	Single Industry
$\Omega^{\lambda=0}$			0.0813 (0.046)	0.1136 ** (0.052)		
$\Omega^{\lambda=1}$					0.1186 *** (0.082)	0.3099 ** (0.093)
C'	−0.0053 *** (0.002)	−0.0046 ** (0.004)	−0.0682 *** (0.041)	−0.0316 (0.053)	−0.0933 ** (0.045)	−0.0532 (0.063)
$\log(\text{GVA})$	−0.0682 ** (0.033)	−0.0760 (0.045)	−0.0511 * (0.031)	−0.0574 (0.032)	−0.0424 (0.031)	−0.0755 (0.053)
$\log(\text{POP})$	0.0269 (0.063)	0.0122 (0.045)	−0.0268 (0.065)	0.023 (0.049)	−0.0264 (0.063)	−0.0362 (0.027)
$\log(\text{EMPRATE})$	−0.0153 (0.078)	0.0134 (0.054)	0.0548 (0.069)	−0.0047 (0.023)	0.0393 (0.065)	0.0125 (0.032)
Constant	1.2146 *** (0.132)	1.4474 *** (0.156)	1.1670 ** (0.131)	1.4614 *** (0.169)	1.1736 *** (0.142)	1.3393 *** (0.183)
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Mean VIF	3.26	3.20	3.34	3.71	3.61	3.52
R^2	0.197	0.205	0.199	0.206	0.202	0.206
Adj. R^2	0.182	0.194	0.176	0.189	0.189	0.183
Observations	272	272	272	272	272	272

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Overall, during the COVID-19 epidemic, the relationship between the robustness of regional industrial networks and changes in employment rates is basically the same as that of the 2008 economic crisis, but there are also differences. It can be found from Table 3 that when $\lambda = 1$, the coefficient of all industries is significantly smaller than that of a single industry, which is significantly different from that during the 2008 economic crisis. This shows that the impact of regional industrial network structure on economic resilience, the whole industry is significantly weaker than a single industry. This shows that China's industrial structure is becoming more and more reasonable, although C' is still less than 0. Then in a single industry, this effect is still obvious, which shows that in a single industry, the impact of industrial structure on economic resilience is still obvious, and it is necessary to further improve the industrial structure within a single industry. In addition, in the context of the COVID-19 epidemic, although the population ($\log(\text{POP})$) and employment rate ($\log(\text{EMPTE})$) also showed negative numbers, the corresponding economic implications were different. This shows that the control variables have a certain impact on the measurement results. To solve this problem, a more accurate measurement model or a more microscopic perspective is needed for analysis.

5.3. Robustness Check

To check the robustness of the research conclusions, a series of tests were carried out. Firstly, due to the high correlation between population and industrial added value, the economic and social control variables and industrial network robustness introduced in a step-by-step manner are tested. The results are shown in Tables 3 and 4. From Tables 4 and 5, it can be found that the nodes with the highest degree of random elimination and priority elimination have a positive correlation with regional economic resilience, which confirms the research conclusions of this paper. Secondly, to comprehensively evaluate the impact of different sample periods on the study's findings, various intervals are meticulously analyzed using the proposed regression model. The period from 2008 to 2012, with 2008 designated as the base year for monitoring changes in employment rates, is specifically detailed in Table 6. The choice of this interval is strategic, as 2008 marks the onset of the global economic crisis, a pivotal event that had substantial impacts on the economy. Analyzing this specific timeframe enables a concentrated examination of the peak damage and its implications for the relationship between industrial network structure and regional economic resilience. The results from this period, as captured in Table 6, align closely with the initial conclusions drawn from the research, showing only minor discrepancies that do not significantly alter the overall understanding. Additionally, the analysis is extended through to 2015 to include periods during which the global economy had not only recovered but, in some regions, even surpassed pre-crisis economic levels. This extended timeline is chosen to delve deeper into the long-term effects of the crisis on the dynamics between industrial network structure and economic resilience. Appropriate adjustments are made to the model's remaining parameters to accommodate this broader timeframe, and the findings from this extended analysis are systematically presented in Table 7, offering insights into the enduring impacts of the crisis on regional economies. From Table 7, it can be found that the conclusions of this paper are also applicable to the sample data from 2008 to 2015. From the above results, it can be concluded that the research conclusions have strong robustness.

Table 4. Regression results for 2006 to 2012 (All Sectors).

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
$\Omega(\lambda=0)$					0.0799 *** (−0.03)	0.1489 *** (−0.024)	0.1089 *** (−0.019)	0.1501 ** (−0.062)				
$\Omega(\lambda=1)$									0.2069 *** (−0.049)	0.3150 *** (−0.059)	0.2849 *** (−0.052)	0.2929 ** (−0.139)
$\log(GVA)$		−0.005 (−0.002)		0.0119 (−0.06)		−0.0269 *** (−0.004)		−0.0188 (−0.01)		−0.0190 ** (−0.004)		−0.0030 (−0.046)
$\log(POP)$			−0.0169 ** (−0.005)	−0.0299 *** (−0.01)			−0.0280 *** (−0.005)	−0.0101 (−0.019)			−0.0271 *** (−0.004)	−0.2440 (−0.030)
$\log(EMP RATE)$	0.0079 (0.028)	0.0229 (−0.029)	0.0129 (−0.029)	−0.0130 (0.040)	−0.0432 (−0.029)	−0.0242 (0.029)	−0.0542 (−0.032)	−0.036 (−0.050)	−0.0322 (−0.029)	−0.0079 (−0.029)	−0.0376 (−0.029)	−0.0339 (−0.039)
Constant	1.0011 *** (0.019)	1.0723 *** (−0.059)	1.1189 *** (−0.051)	1.0676 *** (−0.07)	0.9246 *** (−0.02)	1.1712 *** (−0.061)	1.0916 *** (−0.50)	1.1732 *** (−0.0125)	0.9456 *** (−0.030)	1.1286 *** (−0.060)	1.1046 *** (−0.050)	1.1178 *** (−0.099)
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean VIF	-	1.09	1.01	2.86	1.21	1.7	1.3	3.13	1.21	1.4	1.2	2.41
R^2	0.002	0.005	0.03	0.041	0.062	0.132	0.122	0.129	0.049	0.091	0.111	0.135
Adj. R^2	0.002	0.002	0.01	0.031	0.051	0.121	0.111	0.112	0.039	0.07	0.089	0.129
Observations	272	272	272	272	272	272	272	272	272	272	272	272

Note: ** $p < 0.05$; *** $p < 0.01$.

Table 5. Regression results for 2006 to 2012 (Single Sectors).

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
$\Omega^{\lambda=0}$					0.1101 *** (−0.029)	0.2260 *** (−0.040)	0.701 *** (−0.029)	0.1599 ** (−0.060)				
$\Omega^{\lambda=1}$									0.2611 *** (−0.090)	0.4039 *** (−0.079)	0.4219 *** (−0.079)	0.3460 ** (−0.132)
$\log(GVA)$		−0.0089 (−0.003)		0.0401 (−0.06)		−0.0403 *** (−0.005)		−0.0209 (−0.031)		−0.0230 ** (−0.006)		−0.0295 (−0.032)
$\log(POP)$			−0.0401 ** (−0.008)	−0.0820 *** (−0.011)			−0.0601 *** (−0.008)	−0.0569 (−0.029)			−0.0530 *** (−0.008)	−0.0750 (−0.029)
$\log(EMP RATE)$	0.0899 (0.039)	0.1152 (−0.101)	0.1029 (−0.052)	−0.0201 (0.049)	−0.0230 (−0.049)	−0.0021 (0.099)	−0.0501 (−0.049)	−0.0752 (−0.049)	−0.0322 (−0.029)	−0.0752 (−0.049)	−0.0288 (−0.052)	−0.0070 (−0.090)
Constant	0.9972 *** (−0.052)	1.0653 *** (−0.023)	1.1324 *** (−0.046)	1.0132 *** (−0.063)	0.9563 *** (−0.021)	1.1856 *** (−0.059)	1.0145 *** (−0.456)	1.2120 *** (−0.0123)	0.9541 *** (−0.012)	1.1150 *** (−0.045)	1.1046 *** (−0.050)	1.1178 *** (−0.099)
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean VIF	-	1.09	1.01	2.86	1.21	1.7	1.3	3.13	1.21	1.4	1.2	2.41
R^2	0.013	0.021	0.065	0.077	0.045	0.123	0.105	0.165	0.045	0.069	0.165	0.146
Adj. R^2	0.008	0.007	0.032	0.045	0.03	0.089	0.099	0.154	0.028	0.036	0.092	0.136
Observations	272	272	272	272	272	272	272	272	272	272	272	272

Note: ** $p < 0.05$; *** $p < 0.01$.

Table 6. Regression results for the 2008 to 2012 period.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	All Industries	Single Industry	All Industries	Single Industry	All Industries	Single Industry
$\Omega^{\lambda=0}$			0.051 *** (−0.025)	0.0742 *** (−0.022)		
$\Omega^{\lambda=1}$					0.133 *** (−0.0518)	0.192 *** (−0.0473)
C'	−0.0774 ** (−0.0422)	−0.0425 (−0.0681)	−0.0662 ** (−0.0368)	−0.0255 (−0.0638)	−0.0758 * (−0.0389)	−0.0402 (−0.0638)
B'	0.5033 (−0.3618)	−0.0863 (−0.7891)	0.3788 (−0.3566)	0.2746 (−0.5874)	0.3672 (−0.3597)	−0.2827 (−0.6175)
$\log(GVA)$	−0.0265 (−0.0251)	0.0064 (−0.0460)	−0.0289 (−0.0251)	−0.0027 (−0.0460)	−0.0253 (−0.0293)	0.0079 (−0.0460)
$\log(POP)$	−0.0071 (−0.0187)	−0.0510 (−0.0394)	−0.0061 (−0.0581)	−0.0497 (−0.0394)	−0.0098 (−0.0187)	−0.0549 (−0.0394)
$\log(EMPRATE)$	−0.0323 (−0.0229)	−0.0197 (−0.0597)	−0.0346 (−0.0249)	−0.0233 (−0.0617)	−0.0402 (−0.0219)	0.0311 (−0.0617)
Constant	1.0898 *** (−0.1289)	1.0655 *** (−0.1801)	1.0928 *** (−0.1330)	1.0701 *** (−0.1832)	1.0848 *** (−0.1330)	1.0584 *** (−0.1852)
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.240	0.171	0.251	0.180	0.258	0.184
Adj. R^2	0.222	0.151	0.232	0.158	0.238	0.162
Observations	272	272	272	272	272	272

Note: * $p < 0.5$; ** $p < 0.05$; *** $p < 0.01$.

Table 7. Regression results for the 2008 to 2015 period.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	All Industries	Single Industry	All Industries	Single Industry	All Industries	Single Industry
$\Omega^{\lambda=0}$			0.0611 (−0.0381)	0.0946 (−0.0411)		
$\Omega^{\lambda=1}$					0.1415 (0.0761)	0.1804 (−0.0716)
C'	−0.0835 (−0.0353)	−0.0750 (−0.0614)	−0.0718 (−0.0298)	−0.0572 (−0.0549)	−0.0820 (−0.0325)	−0.0732 (−0.0586)
B'	0.5728 (−0.3930)	−0.0660 (−0.8346)	0.4454 (−0.3768)	0.2606 (−0.8579)	0.4519 (−0.3920)	−0.2209 (−0.8802)
$\log(GVA)$	−0.0435 (−0.0280)	0.0288 (−0.0504)	−0.0458 (−0.0289)	−0.0322 (−0.0504)	−0.0425 (−0.0280)	0.0275 (−0.0513)
$\log(POP)$	−0.0134 (−0.0250)	−0.0183 (−0.0499)	−0.0143 (−0.0250)	−0.0170 (−0.0379)	0.0110 (−0.0250)	−0.0214 (−0.0509)
$\log(EMPRATE)$	−0.0106 (−0.0388)	0.0951 (−0.0554)	−0.0133 (−0.0388)	−0.0912 (−0.0573)	−0.0183 (−0.0370)	0.0854 (−0.0739)
Constant	1.3502 (−0.1593)	1.2277 (−0.1857)	1.2125 (−0.1636)	1.2254 (−0.2163)	1.3448 (−0.1636)	1.2241 (−0.2195)
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.178	0.150	0.190	0.158	0.193	0.157
Adj. R^2	0.150	0.122	0.158	0.128	0.161	0.126
Observations	272	272	272	272	272	272

6. Conclusions

Industrial structure is considered to be the key determinant of the recovery from the economic crisis. Nevertheless, it is not clear which structure is more conducive to regional economic resilience, especially when the mechanism of regional industrial structure on economic resilience is not clear. To solve these problems, we used network science to develop a regional industrial network, which uses the stress test method to obtain the

robustness value of the industrial network. Finally, based on the robustness value, the impact of industrial structure on economic resilience is verified. Through the stress test of the industrial network of China's provincial-level administrative regions, it is found that there are great differences in the resilience of industrial networks among regions, but they all have a strong ability to resist the 2008 economic crisis, especially in the employment rate within the industry. This ability to resist an economic crisis is not only applicable to random interference but also to targeted interference, showing the strong resilience of China's economy.

We drew a series of structures, and as with any other paper, this study also has limitations, which should be paid attention to in future research.

This paper relies on the regional industrial network derived from the input-output table. The input-output table only reflects the economic activities at the macro level, not the more detailed economic activities. In addition, this paper focuses on the relationship between the industrial structure and economic resilience in China's more economically developed regions and central regional provinces, which cannot reflect all the situations in China. In summary, it is necessary to develop a more detailed industrial network to calculate a more accurate network robustness value. Secondly, this paper is limited to the study of the relationship between network robustness and economic resilience, but the mechanism of the two is not the focus of this paper. In addition, the evolution of regional economic resilience also emphasizes the renewal of economic structure and the ability to create new development paths. Therefore, further research can use dynamic methods to track the dynamic impact of local industrial structure on network robustness in crisis and the impact of local network structure on future diversified development models. In this way, people can distinguish network structures that are conducive to resilience, diversified development, or both.

Author Contributions: Conceptualization, N.Q. and C.J.; validation, N.Q. and C.J.; data curation, N.Q.; formal analysis, N.Q. and C.J.; writing-original draft preparation, N.Q.; writing-review and editing, N.Q. and C.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be available upon request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Tan, J.; Hu, X.; Hassink, R.; Ni, J. Industrial structure or agency: What affects regional economic resilience? Evidence from resource-based cities in China. *Cities* **2020**, *106*, 102906. [\[CrossRef\]](#)
2. OECD. *OECD Regional Outlook 2019: Leveraging Megatrends for Cities and Rural Areas*; OECD: Paris, France, 2019.
3. Hynes, W.; Trump, B.D.; Kirman, A.; Haldane, A.; Linkov, I. Systemic resilience in economics. *Nat. Phys.* **2022**, *18*, 381–384. [\[CrossRef\]](#)
4. Lemke, L.K.G.; Sakdapolrak, P.; Trippel, M. Unresolved issues in regional economic resilience: Conceptual ways forward. *Prog. Hum. Geogr.* **2023**, *47*, 699–717. [\[CrossRef\]](#)
5. Webber, D.J.; Healy, A.; Bristow, G. Regional growth paths and resilience: A European analysis. *Econ. Geogr.* **2018**, *94*, 355–375. [\[CrossRef\]](#)
6. Martin, R. Regional economic resilience, hysteresis and recessionary shocks. *J. Econ. Geogr.* **2012**, *12*, 1–32. [\[CrossRef\]](#)
7. Simmie, J.; Martin, R. The economic resilience of regions: Towards an evolutionary approach. *Camb. J. Reg. Econ. Soc.* **2010**, *3*, 27–43. [\[CrossRef\]](#)
8. Duan, W.; Madasi, J.D.; Khurshid, A.; Ma, D. Industrial structure conditions economic resilience. *Technol. Forecast. Soc. Chang.* **2022**, *183*, 121944. [\[CrossRef\]](#)
9. Lee, S.; Wang, S. Impacts of political fragmentation on inclusive economic resilience: Examining American metropolitan areas after the Great Recession. *Urban Stud.* **2023**, *60*, 26–45. [\[CrossRef\]](#)
10. Wang, P.; Li, H.; Huang, Z. Low-carbon economic resilience: The inequality embodied in inter-regional trade. *Cities* **2024**, *144*, 104646. [\[CrossRef\]](#)

11. Zhou, Q.; Qi, Z. Urban economic resilience and human capital: An exploration of heterogeneity and mechanism in the context of spatial population mobility. *Sustain. Cities Soc.* **2023**, *99*, 104983. [\[CrossRef\]](#)
12. Lee, Y.J.A.; Kim, J.; Jang, S.; Ash, K.; Yang, E. Tourism and economic resilience. *Ann. Tour. Res.* **2021**, *87*. [\[CrossRef\]](#)
13. Christopherson, S.; Michie, J.; Tyler, P. Regional resilience: Theoretical and empirical perspectives. *Camb. J. Reg. Econ. Soc.* **2010**, *3*, 3–10. [\[CrossRef\]](#)
14. Martin, R.; Sunley, P. Complexity thinking and evolutionary economic geography. *J. Econ. Geogr.* **2007**, *7*, 573–601. [\[CrossRef\]](#)
15. Balland, P.A.; Rigby, D.; Boschma, R. The technological resilience of US cities. *Camb. J. Reg. Econ. Soc.* **2015**, *8*, 167–184. [\[CrossRef\]](#)
16. Linkov, I.; Trump, B.; Trump, J.; Pescaroli, G.; Mavrodieva, A.; Panda, A. Stress-test the resilience of critical infrastructure. *Nature* **2022**, *603*, 578. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Neffke, F.; Henning, M.; Boschma, R. How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Econ. Geogr.* **2011**, *87*, 237–265. [\[CrossRef\]](#)
18. Rigby, D.L. Technological relatedness and knowledge space: Entry and exit of US cities from patent classes. *Reg. Stud.* **2015**, *49*, 1922–1937. [\[CrossRef\]](#)
19. Kogler, D.F.; Essletzbichler, J.; Rigby, D.L. The evolution of specialization in the EU15 knowledge space. *J. Econ. Geogr.* **2017**, *17*, 345–373. [\[CrossRef\]](#)
20. Moro, E.; Frank, M.R.; Pentland, A.; Rutherford, A.; Cebrian, M.; Rahwan, I. Universal resilience patterns in labor markets. *Nat. Commun.* **2021**, *12*, 1972. [\[CrossRef\]](#)
21. Bristow, G.; Healy, A. *Handbook of Regional Economic Resilience*; Edward Elgar: Cheltenham, UK, 2020.
22. Pendall, R.; Foster, K.A.; Cowell, M. Resilience and regions: Building understanding of the metaphor. *Camb. J. Reg. Econ. Soc.* **2010**, *3*, 71–84. [\[CrossRef\]](#)
23. Boschma, R.; Balland, P.A.; Kogler, D.F. Relatedness and technological change in cities: The rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Ind. Corp. Chang.* **2015**, *24*, 223–250. [\[CrossRef\]](#)
24. Kogler, D.F. Evolutionary economic geography—theoretical and empirical progress. *Reg. Stud.* **2015**, *49*, 705–711. [\[CrossRef\]](#)
25. Pike, A.; Dawley, S.; Tomaney, J. Resilience, adaptation and adaptability. *Camb. J. Reg. Econ. Soc.* **2010**, *3*, 59–70. [\[CrossRef\]](#)
26. Doran, J.; Fingleton, B. US metropolitan area resilience: Insights from dynamic spatial panel estimation. *Environ. Plan. A Econ. Space* **2018**, *50*, 111–132. [\[CrossRef\]](#)
27. Xiao, J.; Boschma, R.; Andersson, M. Resilience in the European Union: The effect of the 2008 crisis on the ability of regions in Europe to develop new industrial specializations. *Ind. Corp. Chang.* **2018**, *27*, 15–47. [\[CrossRef\]](#)
28. Cainelli, G.; Ganau, R.; Modica, M. Industrial relatedness and regional resilience in the European Union. *Pap. Reg. Sci.* **2019**, *98*, 755–779. [\[CrossRef\]](#)
29. Eriksson, R.H.; Hane-Weijman, E.; Henning, M. Sectoral and geographical mobility of workers after large establishment cutbacks or closures. *Environ. Plan. A Econ. Space* **2018**, *50*, 1071–1091. [\[CrossRef\]](#)
30. Bristow, G.; Healy, A. Regional resilience: An agency perspective. *Handb. Reg. Econ. Resil. Edw. Elgar Publ.* **2020**, 36–53.
31. Cappelli, R.; Montobbio, F.; Morrison, A. Unemployment resistance across EU regions: The role of technological and human capital. *J. Evol. Econ.* **2021**, *31*, 147–178. [\[CrossRef\]](#)
32. Brakman, S.; Garretsen, H.; van Marrewijk, C. Regional resilience across Europe: On urbanisation and the initial impact of the Great Recession. *Camb. J. Reg. Econ. Soc.* **2015**, *8*, 225–240. [\[CrossRef\]](#)
33. Balland, P.A.; Jara-Figueroa, C.; Petralia, S.G. Complex economic activities concentrate in large cities. *Nat. Hum. Behav.* **2020**, *4*, 248–254. [\[CrossRef\]](#) [\[PubMed\]](#)
34. Whittle, A.; Kogler, D.F. Related to what? Reviewing the literature on technological relatedness: Where we are now and where can we go? *Pap. Reg. Sci.* **2020**, *99*, 97–114. [\[CrossRef\]](#)
35. Hausmann, R.; Hidalgo, C.A. The network structure of economic output. *J. Econ. Growth* **2011**, *16*, 309–342. [\[CrossRef\]](#)
36. Neffke, F.; Hartog, M.; Boschma, R.; Henning, M. Agents of structural change: The role of firms and entrepreneurs in regional diversification. *Econ. Geogr.* **2018**, *94*, 23–48. [\[CrossRef\]](#)
37. Bustos, S.; Yıldırım, M.A. Production ability and economic growth. *Res. Policy* **2022**, *51*, 104153. [\[CrossRef\]](#)
38. Maskell, P.; Malmberg, A. Localised learning and industrial competitiveness. *Camb. J. Econ.* **1999**, *23*, 167–185. [\[CrossRef\]](#)
39. Frenken, K.; Van Oort, F.; Verburg, T. Related variety, unrelated variety and regional economic growth. *Reg. Stud.* **2007**, *41*, 685–697. [\[CrossRef\]](#)
40. Rocchetta, S.; Mina, A. Technological coherence and the adaptive resilience of regional economies. *Reg. Stud.* **2019**, *53*, 1421–1434. [\[CrossRef\]](#)
41. Boschma, R. Proximity and innovation: A critical assessment. *Reg. Stud.* **2005**, *39*, 61–74. [\[CrossRef\]](#)
42. Boschma, R.A.; Martin, R.L. (Eds.) *The Handbook of Evolutionary Economic Geography*; Edward Elgar Publishing: Northampton, MA, USA, 2010.
43. Ducruet, C.; Beauguitte, L. Spatial science and network science: Review and outcomes of a complex relationship. *Netw. Spat. Econ.* **2014**, *14*, 297–316. [\[CrossRef\]](#)
44. Broekel, T.; Balland, P.A.; Burger, M.; Van Oort, F. Modeling knowledge networks in economic geography: A discussion of four methods. *Ann. Reg. Sci.* **2014**, *53*, 423–452. [\[CrossRef\]](#)
45. Ter Wal, A.L.J.; Boschma, R.A. Applying social network analysis in economic geography: Framing some key analytic issues. *Ann. Reg. Sci.* **2009**, *43*, 739–756. [\[CrossRef\]](#)

46. Hermans, F. The contribution of statistical network models to the study of clusters and their evolution. *Pap. Reg. Sci.* **2021**, *100*, 379–404. [[CrossRef](#)]
47. Hoekman, J.; Frenken, K.; Van Oort, F. The geography of collaborative knowledge production in Europe. *Ann. Reg. Sci.* **2009**, *43*, 721–738. [[CrossRef](#)]
48. Hidalgo, C.A. Economic complexity theory and applications. *Nat. Rev. Phys.* **2021**, *3*, 92–113. [[CrossRef](#)]
49. Shutter, S.T.; Lobo, J.; Muneeppeerakul, R. Urban occupational structures as information networks: The effect on network density of increasing number of occupations. *PLoS ONE* **2018**, *13*, e0196915. [[CrossRef](#)] [[PubMed](#)]
50. Strumsky, D.; Lobo, J.; Van der Leeuw, S. Using patent technology codes to study technological change. *Econ. Innov. New Technol.* **2012**, *21*, 267–286. [[CrossRef](#)]
51. Kogler, D.F.; Rigby, D.L.; Tucker, I. Mapping knowledge space and technological relatedness in US cities. In *Global and Regional Dynamics in Knowledge Flows and Innovation*; Routledge: London, UK, 2015; pp. 58–75.
52. Rocchetta, S.; Mina, A.; Lee, C.; Kogler, D.F. Technological knowledge spaces and the resilience of European regions. *J. Econ. Geogr.* **2022**, *22*, 27–51. [[CrossRef](#)]
53. Albert, R.; Jeong, H.; Barabási, A.L. Error and attack tolerance of complex networks. *Nature* **2000**, *406*, 378–382. [[CrossRef](#)] [[PubMed](#)]
54. Solé, R.V.; Rosas-Casals, M.; Corominas-Murtra, B.; Valverde, S. Robustness of the European power grids under intentional attack. *Phys. Rev. E* **2008**, *77*, 026102. [[CrossRef](#)] [[PubMed](#)]
55. Barabási, A.L. *Network Science*; Cambridge University Press: Cambridge, UK, 2016.
56. Zitnik, M.; Sosič, R.; Feldman, M.W.; Leskovec, J. Evolution of resilience in protein interactomes across the tree of life. *Proc. Natl. Acad. Sci. USA* **2019**, *116*, 4426–4433. [[CrossRef](#)] [[PubMed](#)]
57. Cohen, R.; Havlin, S. Percolation in complex networks. In *Encyclopedia of Complexity and Systems Science*; Meyers, R.A., Ed.; Springer: New York, NY, USA, 2009; pp. 6495–6504.
58. Albert, R.; Barabási, A.L. Statistical mechanics of complex networks. *Rev. Mod. Phys.* **2002**, *74*, 47. [[CrossRef](#)]
59. Acemoglu, D.; Carvalho, V.M.; Ozdaglar, A.; Tahbaz-Salehi, A. The network origins of aggregate fluctuations. *Econometrica* **2012**, *80*, 1977–2016. [[CrossRef](#)]
60. Lengyel, B.; Bokányi, E.; Di Clemente, R.; Kertész, J.; González, M.C. The role of geography in the complex diffusion of innovations. *Sci. Rep.* **2020**, *10*, 15065. [[CrossRef](#)] [[PubMed](#)]
61. Dong, B.; Ma, X.; Zhang, Z.; Zhang, H.; Chen, R.; Song, Y.; Shen, M.; Xiang, R. Carbon emissions, the industrial structure and economic growth: Evidence from heterogeneous industries in China. *Environ. Pollut.* **2020**, *262*, 114322. [[CrossRef](#)] [[PubMed](#)]
62. Chen, J.; Xie, L. Industrial policy, structural transformation and economic growth: Evidence from China. *Front. Bus. Res. China* **2019**, *1*, 18. [[CrossRef](#)]
63. Zhao, Q.; Niu, M. Influence Analysis of FDI on China's Industrial Structure Optimization. *Procedia Comput. Sci.* **2013**, *17*, 1015–1022.
64. Molloy, M.; Reed, B. A critical point for random graphs with a given degree sequence. *Random Struct. Algorithms* **1995**, *6*, 2–3.
65. Xie, S.; Zhang, J.; Li, X.; Xia, X.; Chen, Z. The effect of agricultural insurance participation on rural households' economic resilience to natural disasters: Evidence from China. *J. Clean. Prod.* **2024**, *434*, 140123. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.