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Complex Network-Based Global Value Chain Accounting System

From the Perspective of Econophysics

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Preface

Since the reform and opening-up, China has been actively participating in the international economic cooperation. With its abundant labor forces, huge market potential and positive opening-up policies, China as a latecomer has been quickly integrated into the world economic system and made its vital part in the vertical specialization in world trade. Under the context of global economic integration, the world political and economic order is undergoing tremendous changes and adjustments, leading to both new opportunities and challenges for competition and cooperation between economies. It is thus the academia's most urgent task to re-examine China's role and status in the global economic system, identify the strategic positioning and development path and devise practical political measures in accordance with China's national conditions, thus achieving the goals of a broader international market and stronger competitive advantages.

As is known to all, globalization is a product of declining costs for communication and transport; distance is now of the least concern. In this irresistible trend, the **industrial value chains (IVCs)** in various countries are interlinked, forming the **global value chain (GVC)**, which is a complex network system. This system embodies the characteristics of mega-complex systems, such as distinct levels, multiple attributes and interdependencies. The traditional economic research methods are thus unable to effectively deal with such large-scale and multi-dimensional data structures. In this book, we try to analyze the economic complexity of GVC, which involves the utilization of ICIO data and network techniques to predict and explain the economic trajectories of economies and their industrial sectors. Therefore, there are a lot of key issues to be discussed.

This book incorporates six parts, which are *Background* (Part I), *Topological Structure* (Part II), *Markov Process* (Part III), *Competition and Collaboration* (Part IV), *Evolutionary Mechanism* (Part V) and *Causal Inference* (Part VI). The specific issues and co-authoring information in the thirteen chapters are listed in the following table.

List of co-authors

Part	Chapter	Content	Co-authors
I	1	What are the Fundamental Issues in This Book	Lizhi Xing, Jun Guan, Simeng Yin
II	2	How to Recognize the Trade Roles of Industrial Sectors	Lizhi Xing, Xianlei Dong, Wen Chen, Shuo Zhang
	3	How to Probe the Industrial Linkages Reasonably and Effectively	Lizhi Xing, Xianlei Dong, Xiaoyu Xu, Yu Han, Xufeng Li, Shuo Zhang
	4	How to Find the Vital Industrial Sectors and IO Relations	Lizhi Xing, Xianlei Dong, Xiaoyong Qiao, Yafei Li, Yu Han, Xufeng Li, Shuo Zhang
III	5	How to Measure the Global Impact of Industrial Sector	Lizhi Xing, Xianlei Dong, Qing Ye, Jun Guan
	6	Measure the Impact of Final Demands on the Global Production System	Lizhi Xing, Xianlei Dong, Shan Wu, Jun Guan
	7	What are the Industrially Economic Impacts of Trump Administration's Trade Policy toward China	Lizhi Xing, Xianlei Dong, Yuwan Duan, Dawei Wang, Chunxiu Liu
IV	8	How to Quantify the Competitive Strength and Weakness of Economies	Lizhi Xing, Xianlei Dong, Dawei Wang, Chuke Jiang
	9	How to Quantify the Collaborative Opportunity and Threat of Economies	Lizhi Xing, Dawei Wang, Yu Han, Chunxiu Liu, Chuke Jiang
V	10	How to Extract the Backbone of Global Value Chain	Lizhi Xing, Yu Han
	11	How to Identify the Worldwide Industrial Transfer Patterns	Lizhi Xing, Yu Han
	12	How to Depict the Nested Structure of Production System	Lizhi Xing, Jiaqi Ren, Xianlei Dong, Shuo Zhang
VI	13	Why to Connect the Structural Feature and Economic Status	Lizhi Xing, Xi Ai, Dawei Wang, Jiaqi Ren

To complete this study, we build a set of analytical frameworks of the **global value chain accounting system** with the convergence of the international economic accounting, complex network theory and statistical physics. We name it the **global industrial value chain network**, which is used to trace the transfer of intermediate goods in the form of value stream among countries/regions and industrial sectors.

By observing its evolution, we can figure out an optimal way to allocate the global production resources and improve the economies' international competitiveness. In sum, we hope to provide a novel **econophysics** perspective for economists who master the knowledge of **physical statistics** and **world economics**.

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All the relevant data of this book can be found on my ResearchGate webpage:

https://www.researchgate.net/publication/355058759_Complex_Network-Based_Global_Value_Chain_Accounting_System_From_the_Viewpoint_of_Econophysics.

Also, readers can contact me directly via e-mail: itwasa@163.com or koken@bjut.edu.cn.

Beijing, China Lizhi Xing

Contents

Part I
Background

Chapter 1
Fundamental Issues in This Book

1.1 Concept of Econophysics

Econophysics as a term was first mentioned in 1995 [1], when H. Eugene Stanley, et al. named it according to the interdisciplinary background. Econophysics can roughly be defined as a discipline that uses quantitative approaches to produce ideas, models, conceptual and computational methods of statistical physics applied to socio-economic phenomena [2]. There are two factors that the physicists in the fields of sociology and economics have great interests in. One is the Golden Age of condensed matter physics thanks to the success of the modern theory of phase transitions based on the renormalization group techniques [3]. The other is the growing computerization of society that paves the way for new perspectives by offering massive data or observations. From then on, physicists have continuously re-examined economic issues from the perspective of physical laws. They emphasized empirical research on economic data and incorporated cutting-edge theories and methods of statistical physics into economics.

A century ago, Alfred Marshall pointed out in his book Principles of Economics that economics also bears scientific nature just as natural sciences both in research objectives and in research methods. Economics differs from other social sciences due to its uniform and clear conception, as well as strong analyzability. In combination with mathematics, economists developed their unique "hypothesis-inference-conclusion" model analysis framework. But in many cases, a lot of assumptions in this self-consistent methodology don't conform with hard facts, such as rational-economic man and efficient market in the fundamental theories of economics. Whereas, physicists have consistently insisted that theory and assumptions should be based on facts, and the original theories and hypotheses must be corrected only if any inconsistent experimental phenomena are found. In their eyes, the economic system is the complex system comprising of a special group of units with complex interactions in the medium number (however far less than the Avogadro number), and these units stand for people who can make rational decisions but have natural weaknesses, that is, greed and fear.

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1.2 Purpose of Book

With trade barriers being removed and driven by the scientific and technological revolution, the world economic integration based on the ***Global Value Chain (GVC)*** has gradually formed. In the meanwhile, what economists called the "Leontief Paradox" arises, under the circumstances that the Heckscher-Ohlin model can no longer explain why the division of labor and economic trade between countries keep growing and become unprecedentedly complicated [4]. They attempted to illustrate this tendency with various economic theories, such as ***Labor Proficiency*** [5, 6], ***Human Capital*** [7, 8], ***Technology Gap*** [9], ***Product Cycle*** [10], ***Demand Preference Similarity*** [11], and ***Intra-Industry Trade*** [12], all of which explain important issues such as contemporary international division of labor, value-added trade, and industrial structure upgrading from diverse angles.

As an emerging yet important research area, GVC accounting is mainly represented by teams of Timmer, Koopman, and Wang, who have made important breakthroughs in economic theories and statistical techniques, and contributed to studies on both national level and sectoral level. The important quantitative results they obtained have enriched the original GVC research and cemented a theoretical basis for both the upcoming analysis and the formulation of relevant policies. They've also enabled the theoretical expansion to other GVC-related fields. Among all the achievements in the GVC studies, a set of preliminary accounting systems has been formed around value-added exports, which contains a series of indicators reflecting industrial sectors' competitiveness and the participation degree on the GVC.

The global economic system, however, is a complex nonlinear emergence system, and the multiple emergences as its essential feature cannot be simply obtained by the linear addition of individualities. That is to say, the whole picture will be shadowed if only the individuals are analyzed. We should focus on the interrelationship and influence mechanism between individuals and the whole under the perspective of systems science. All complex systems have their unique topological structures, and their functions often depend on the characteristics of the microstructures. In other words, the prerequisite of understanding the internal operating mechanism of an economic system is to gauge the structural complexity of the entire system. Fortunately, the constantly developing complex network technology facilitates the understanding of the complexity of economic systems. Modeling the global economic system based on complex network theory and analyzing the topological characteristics and evolutionary mechanism has, therefore, become an important research topic from now on.

The purpose of this book is to theoretically and empirically enrich the GVC accounting framework with statistical physics and complex network theory from the perspective of econophysics, thus adding up to the existing theories. Besides, we also aim at capturing the essences of network models such as topological complexity, hierarchy, transmissibility, interaction, causality, etc., and reflecting the objective interrelations among economies or between economies and economic systems on the GVC, so as to reveal the inherent evolution of the cross-regional and even global economic systems.

1.3 Literature Review

In the real world, there are so many scale-free networks, such as the Internet, World-Wide Web, Protein Interaction Networks, Research Collaboration Networks and Citation Networks, with scale invariance in their topological structure. But, as a sort of man-made network, does the ***International Trade Network (ITN)*** agree with this well-known scaling analysis and universal concepts of statistical physics? There is no doubt that it is the value stream in many forms that lead to the complexity and heterogeneity of ITNs. They are not supposed to be analyzed with general statistical physics tools, or without consideration of the importance of edge weight.

In this section, we explain the interaction among ***Industrial Complex Network (ICN), GVC*** and ***Input–Output (IO) Network.*** We believe IO network, especially the ***Inter-Country Input–Output (ICIO)/Multi-Regional Input–Output (MRIO) Network,*** as the synthesis of ICN and ITN, can help readers better understand the topological complexity and evolutionary mechanism of GVC.

1.3.1 Industrial Complex Network

The industrial complex network is a kind of social network, in which product sectors are intricately interrelated by the products and services provided and/or consumed simultaneously. These sectors are presented as nodes and their economic relations as edges, enabling the analyses of specific economic issues according to different backgrounds.

In the last two decades, a large number of theoretical and empirical studies on industrial economics were carried out based on a complex network in areas of industrial development, structure, association, organization, and policymaking. Chmiel, et al. established networks of companies and branches in Poland through bipartite graph theory [13]. Based on the same theory, Inoue, et al. investigated the spatial characteristics of a Japan's patent network [14]. Chang, et al. proved that the degree distribution of nodes in a projected sub-network follows the drift power-law in general cooperation as well as in competition networks [15]. Liu, et al. employed complex network to study the development of China's high-tech park and constructed the network of China's top 100 electronic and IT companies as the basic model [16]. Hou, et al. extended the research field from a monopoly market to a macro-reality market to build a competitive complex network model targeting logistics enterprises [17]. Li, et al. established a global nuclear power plant network based on priority queuing network model and reflected the evolution with its numerical characteristics [18]. Yao, et al. designed the directed weighted competitive pressure network, over which they made a simulation analysis on the rivalry spread effect [19]. The above-mentioned analyzes the mechanism of contagion in banking and financial networks [20]. After calculating economic distance matrices based on annual GDP of nine sectors from 1995 to 2010 in 31 Chinese provinces and autonomous regions, Hu, et al. built spatial economic networks through the threshold and minimal spanning tree [21].

As stated above, scholars have created various complex network models to describe inter-organization competition and collaboration and analyze diverse economic phenomena. But the early works are prone to use binary approaches, i.e., unweighted and undirected network models similar to the simple physical ones, with less to be known or much to be neglected on the mechanism of informational, material and capital flows between economic entities manifested in their dependencies. However, the literature on industrial complex networks grows rapidly, and an increasing number of scholars start to focus on the sophisticated topological structure of the economic system based on weighted and directed graph. In the meanwhile, more and more relevant studies incorporate economic issues, such as investment stocks [22], inter-bank connection [23], innovation [24], ownership [25], systemic risk [26], information flow [27], environmental capacity [28], etc.

1.3.2 Global Value Chain

The rise of GVC has naturally captured the attention of international trade economists who are eager to bridge the apparent gap between the new characteristics of the international organization of production and the standard methods used to collect, manipulate, and interpret international trade statistics. In particular, ingenious empirical methods have been proposed in a remarkable body of work to disentangle the value-added and intermediate inputs of international trade flows.

Among related studies, IO tables boast the feasibility in measuring both standard and vertical trades. With the availability and utilization of ICIO/MRIO database, it is possible to construct quantitative indicators to assess its impact on the GVC, because it better depicts the international source and use of intermediate goods than previous databases. As a result, distinctive approaches have been developed to measure sectors' function and status amid globalization. Important studies are as follows.

Hummels, et al., focusing on the use of imported inputs in producing export goods, proposed vertical specialization—the first empirical measure of participation in vertically specialized trade [29]. Antràs, et al. derived two distinct approaches to measure industrial upstreamness and proved their significant impacts on trade flows [30]. Fally made quantitative analyses on the average length of production chains, reflecting the number of stages required for production and the number of stages between production and final consumption [31]. Then, he and Hillberry extended the empirical research from across plants to across borders by employing the IDE-JETRO 4-dimensional IO tables [32]. Johnson and Noguera quantified cross-border production linkages with combined IO and bilateral trade data, and computed bilateral trades in value-added [33]. Koopman, et al. adjusted all previous measures of vertical specialization and value-added trade to analyze the back-and-forth trade of intermediates across multiple borders, and presented GVC position and participation indices to gauge the extent to which a national sector is involved in the global production chain. To empirically conduct gross export decomposition, they constructed a global ICIO mainly based on version 7 of the GTAP database [34]. Wang et al. decomposed total production activities with a new framework based on whether related value chains are for pure domestic demand, traditional international trade or simple and complex GVC activities and also introduced their unique but effective participation indices [35]. With the ICIO database updated, we can apply these research frameworks to generate a time series decomposition of gross trade flows into their value-added components.

1.3.3 Input–Output Network

From an empirical perspective, a handful of studies have characterized the structure of IO networks, which help understand the topological structure of inter-industry dependencies and their repercussions on industrial economics. For instance, Blöchl, et al. adopted STAN database at OECD to establish 37 countries' IO networks and derived two measures for weighted and directed network: random walk centrality to reveal the most immediately affected nodes by a shock based on Freeman's closeness centrality and counting betweenness to identify the most accumulatively affected nodes based on Newman' random walk betweenness [36]. Kagawa, et al. found industries with large CO_2 emissions through industrial relations based on IO table with an optimal combinatorial method, depicting environmentally important industrial clusters in Japanese automobile supply chain [37]. McNerney, et al. studied the structure of inter-industry relations using networks of capital flows between industries in 20 national economies, and found these networks vary according to a typical structure featuring a Weibull link weight distribution [38]. Martha, et al. investigated how economic shocks propagate and expand through the IO network which connects industrial sectors in developed economies [39].

With the development of IO databases, related studies progressively shifted the focus from independent national systems to multi-regional even global systems, most of which extracted data from the ICIO table. As a result, studies on the GVC turned to ICIO databases. However, basic ICIO databases could not distinguish imported intermediate from final goods in bilateral trade flows, and more importantly, did not consider that heterogeneity generally exits in economic endowment, geographical location, development stage, industrial structure and so forth at the domestic and regional levels. More and more scholars thus are paying attention to how global production is fragmented and extended internationally or domestically. To be specific, domestic linkages are measured via endogenously embedding a target country's domestic ***Inter-Region Input–Output (IRIO)*** tables into the ICIO tables, building up ***Regionally-Extended Inter-Country Input–Output (REXICIO)*** tables [40–42]. Surprisingly, this emerging framework precisely follows the concept of super-network in the field of econophysics.

Some relevant studies are as follows. Zhu, et al. proposed that industry-level GVC is indeed not chain-like but features tree topology, hence they computed the global value trees for all the industries available in WIOD [43]. In consideration of inter-country trade, Cerina, et al. argued production systems within economies tend to connect on a global scale. They viewed the world IO system as an interdependent network where the nodes are the individual industries in different economies and the edges are the monetary goods flowing between industries, thereby analyzing the properties of global, regional, and local networks and documenting its evolution over time [44]. In other words, international trade has been increasingly ordered and organized in the form of GVC where production stages vary in different countries. Thus, on the one hand, Zhu, et al. introduced network-based measure of node similarity to compare the GVC between any pair of countries, considering all the direct and indirect relations between national sector pairs [45]. On the other hand, Cerina, et al. constructed a model for three countries with national and multinational (multi-plant) firms, in which oligopolistic firms in each country export their goods to other countries, they also investigated the effects of two countries' trade liberalization on a third country [46]. Amador and Cabral examined data on the bilateral foreign value added in exports from the WIOD for the period 1995–2011 and, in each period, the GVC is represented as a directed network of nodes (countries) and edges (value-added flows). They found that GVC is characterized by centralized and asymmetric networks, and exposes a few large economies acting as hubs to the propagation of idiosyncratic shocks [47]. On this basis, Amador, et al. presented GVC as weighted networks of foreign value added in exports, which allows for the identification of the specific roles of countries and for the quantification of their relative importance over time [48]. Contreras, et al. investigated how economic shocks propagate and expand through the IO network connecting industrial sectors in developed economies [39]. Ando measured the importance of industrial sectors under the impact of the United States' gross outputs in the global IO model [49]. Tsekeris described a structural IO analysis of the inter-industry linkages and main activity clusters of the Greek economy, and employed suitable network metrics to measure the centrality and influence of each sector-agent on the other ones, and the possibilities for clustering of related (groups of) activities [50]. Grazzini and Spelta used the cost effect index to testify the robustness of the global IO network and the interdependency of intermediate inputs in production [51]. Araújo and Faustino provided a foolproof IO network-based framework to reflect the inter-industry proximity through bipartite graph projection and then evaluate the impact of the sovereign debt crisis and the implementation of the economic and financial adjustment program in Portugal [52]. He, et al. analyzed the rules of embodied resources consumption in the area's industries through the IO networks among the regional industries of Beijing-Tianjin-Hebei area in China, identified the core community structures, and studied the characteristics of industrial homogeneity through regional comparison [53]. Tsekeris employed network-based measures and tools, such as density, hierarchy, centralization, and modularity, to identify main drives of structural change [54]. Soyyigit, et al. applied weighted HITS algorithm for the ICIO data as a centrality measure to determine the real prominence of countries in trade networks, and empirically studied the trade in fossil fuel and olive oil [55, 56].

Network-based GVC studies also started to blend with the mainstream world economics. For instance, Xiao applied various network analyzing tools to the new GVC accounting system proposed by Koopman et al. and Wang et al., in which gross exports can be decomposed into value-added terms through various routes along GVC [57].

In addition, ***Environmentally Extended Multiregional Input–Output (EEMRIO)*** tables have emerged as the key framework to provide a comprehensive description of the global economy and analyze its effects on the environmental and social issues [58], including greenhouse gas emissions [59–62], mercury emissions [63–65], resource scarcity [66], forestry resources [67] and health impacts [68–70]. That will be the next stage of our research.

1.4 Data Structure

Beyond all questions, IO table as a quantitative technique of economic analysis presents the dependencies between different branches of national or regional economies in detail. This book adopts ICIO data to present the operating mechanism of a global economic system and thus is necessary to review the superiority and availability of IO data.

1.4.1 Advantage of IO Table

As a technique, the IO model quantifies interdependency in interconnected economic systems. In 1951, Wassily Leontief first introduced the IO model [71], which won him Nobel Prize in Economics in 1973. The model can be used to study the effect of consumption shocks on the interdependent economic system [72]. IO analysis examines quantitative relations between the output levels of an economy's various sectors and serves as a practical tool for national accounting and planning. Neoclassical economics focuses on the pure theory of the price mechanism, equilibrating supply and demand in free-market economies [73].

IO table's property of being in the form of a checkboard reflects the movements of products or services within the whole economic system from both production consumption and distributive utilization, which are the formation and distribution of values respectively. The dual identities of each sector as the producer and consumer at the same time, demand it not only to produce and distribute inputs for the other sectors but also to consume inputs from other sectors to accomplish its fabrication. This echoes with the inner identity proposed by Karl Marx.

Industrial sectors in IO table could be regarded as nodes while the inter-industry value stream enriches weighted and directed edges in the construction of network model. In consideration of both availability and authority, IO table is the priority-first data format that establishes the mathematics model. For instance, it shows flows of final and intermediate goods and services defined according to industry outputs. Also, it is provided as a matrix, which can be directly or with minor modification adopted as a complex network's adjacency matrix, establishing weighted and directed networks.

1.4.2 Available ICIO Database

This book utilizes ICIO data not only for its ability of reshowing flows of intermediate products, final goods, and services but also for possible comparison on the same basis, thanks to which the theoretical and empirical analyses on the GVC become possible. Let us consider a world economy with m countries $(u, v = 1, 2, \ldots, m)$, n sectors within each country, and totally $N = m \times n$ sectors $(i, j = 1, 2, \ldots, N)$, as shown in Table 1.1.

In the ICIO table, Z^{uv} is a $n \times n$ matrix of intermediate inputs that are produced in country u and used in country v, Y^{uv} is a $n \times 1$ vector giving final products produced in country u and consumed in country v, X^u is also a $n \times 1$ vector giving gross outputs in country u, and VA^u denotes a $n \times 1$ vector of direct value-added in country u [74]. To depict the transmission of value stream on the GVC, we take the region of inter-country inter-industry use and supply as the modeling data source, i.e., the Z^{uv} matrix, in which row vectors record the allocation of outputs and column vectors the composition of demand.

There are seven main ICIO databases available for now: ***World Input–Output Database (WIOD)*** [75]***, OECD-WTO Database on Trade in Value-Added (TiVA), Eora Multi-Region Input–Output Table Database (MRIOV199.82,*** and the simplified version with 26-sector harmonized classification is named ***Eora26)*** [76]***, Global Trade Analysis Program (GTAP), Asian International Input–Output Table (AIIOT), Asian Development Bank Multi-Regional Input–Output Tables (ADB-MRIO)*** and ***Externality Data and Input–Output Tools for Policy Analysis (EXIOPOL).*** However, only four of them cover both continuous period and wide range as shown in Table 1.2.

Two of them, WIOD and OECD-TiVA, provide more granular sectoral information and are more rooted in official statistics, and are widely used to exploit the analytical richness of trade-focused empirical analysis. Although Eora-MRIO covers 189 economies, the sectoral data provided are highly aggregated. This does not have too much impact on the topologically structural analysis of GVC, because we need to further aggregate the sectoral data according to special rules sometimes, the purpose of which is to facilitate the methodological study. ADB-MRIO, as an extension to

Table 1.1 The layout of ICIO table

	Output		Intermediate use				Final demand				Total output
Input	Country		Country A	Country B		ROW	Country A	Country B	$\cdots$	ROW	
		Sector	$A_1, \cdots, A_n$	$B_1, \cdots, B_n$	$\cdots$	$R_1, \cdots, R_n$	$A_1, \cdots, A_n$	$B_1, \cdots, B_n$	$\cdots$	$R_1, \cdots, R_n$	
Intermediate inputs	Country A	$A_1, \cdots, A_n$	Z^{AA}	Z^{AB}	$\cdots$	Z^{AR}	Y^{AA}	Y^{AB}	$\cdots$	Y^{AR}	X^A
	Country B	$B_1, \cdots, B_n$	Z^{BA}	Z^{BB}	$\cdots$	Z^{BR}	Y^{BA}	Y^{BB}	$\cdots$	Y^{BR}	X^B
	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	ROW	$R_1, \cdots, R_n$	Z^{RA}	Z^{RB}	$\cdots$	Z^{RR}	Y^{RA}	Y^{RB}	$\cdots$	Y^{RR}	X^R
	Value-Added		VA^A	VA^B	$\cdots$	VA^R					
	Total Input		X^A	X^B	$\cdots$	X^R					

Notes

$$Z^{uv} = \begin{pmatrix} Z_{u_1 v_1} & \cdots & Z_{u_1 v_n} \\ \vdots & \ddots & \vdots \\ Z_{u_n v_1} & \cdots & Z_{u_n v_n} \end{pmatrix};$$

Total Input $X^A = VA^A + Z^{AA} + Z^{BA} + \ldots + Z^{RA}$;

Total Output $X^A =$
$Z^{AA} + Z^{AB} + \ldots + Z^{AR} + Y^{AA} + Y^{AB} + \ldots + Y^{AR}$

Table 1.2 The basic information of each ICIO database

Database	Version	Time span	Country/region	Industrial sector	Abbr.
WIOD	2016 release	2000–2014	44	56	WIOD2016
	2013 release	1995–2011	41	35	WIOD2013
OECD-TiVA	2021 release	Unknow	Unknow	Unknow	TiVA2021
	2018 release	2005–2015	65	36	TiVA2018
	2016 release	1995–2011	64	34	TiVA2016
	2015 release	1995, 2000, 2005, 2008–2011	62	34	TiVA2015
Eora-MRIO	V199.82	1990–2015	189	26	Eora26
ADB-MRIO	Updated to 2019	2000, 2007–2019	63	35	ADB2019

Notes In addition to sovereign states, the Rest of World (ROW) is taken as an independent economic entity in WIOD, OECD-TiVA and ADB-MRIO, most of which belong to the developing countries; In TiVA2018, for "intermediates", "value added" and "output", data for Mexico and China are split into MX1, MX2 and CN1, CN2, respectively

WIOD (having the same sectoral classification as WIOD2013), facilitates the production and analysis of GVC-related statistics for more Asian economies and becomes a rich source of economic information for research and policymaking.

1.4.3 Hierarchy of Economies

The ICIO database comprises three different types of data, namely ***World Input–Output Table (WIOT)***, ***Regional Input–Output Table (RIOT)*** and ***National Input–Output Table (NIOT)***, all of which boast value-type IO data. Based on them, we can construct GVC, ***Regional Value Chain (RVC)***, and ***National Value Chain (NVC)*** networks accordingly. Their heat maps are as shown in Fig. 1.1.

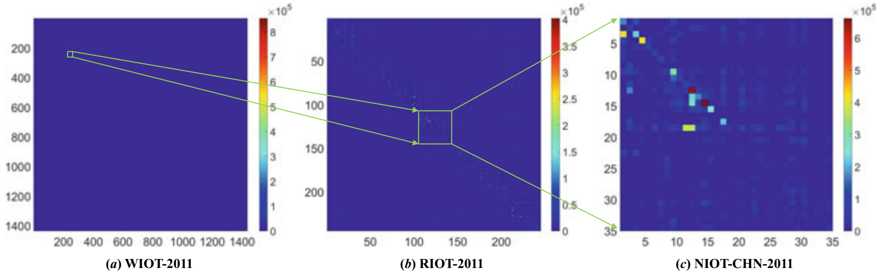


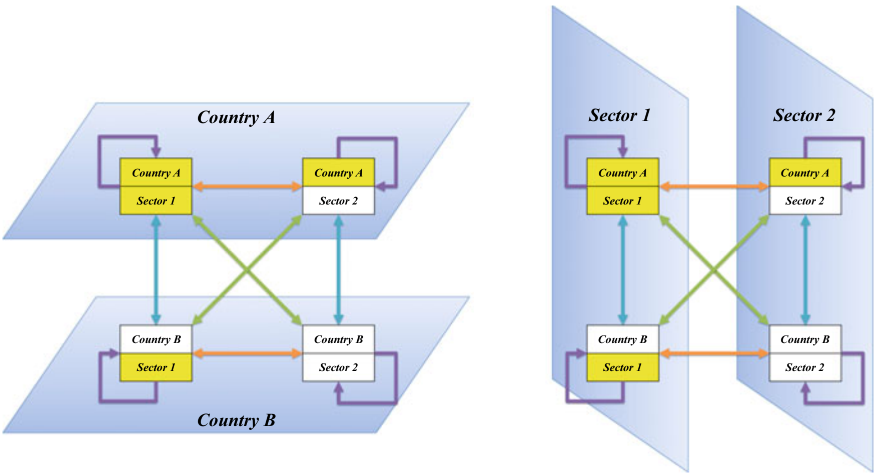
Fig. 1.1 Heat maps of three types of matrices in WIOD2013

For the sake of clarity, the difference among matrix elements can be reflected nowhere else except in WIOT and RIOT. They both compile single-country IO tables and detailed bilateral trade statistics; their elements around the diagonal are more significant than other segments, which means domestic trade will outstrip international trade for the most part. RIOT, in essence, is the abridged edition of WIOT.

We find that it is a common modeling method to build a multi-layer network according to the country or sector as the basis for division. Nevertheless, we believe there is no need to ascertain whether a sector on the GVC belongs to a given country or industry, unless carrying out the international trade policy simulation. Only in that situation, edges within and across layers will react differently to the changing economic environment.

A two-country two-sector case can be analyzed from a multi-layer perspective. One is to construct a multi-layer network in which the nodes are the industrial sectors, the layers are the countries, and links can be established from certain intermediate goods' provider to consumer within and across countries as shown in Fig. 1.2a. In another way, the only difference is that the layers are the industrial sectors as shown in Fig. 1.2b, and many ***World Trade Network (WTN)*** analyses are based on such setting [77]. Anyway, these two sorts of transformation of ICIO network are distinct from the general country-product bipartite networks since the economic agents contain both country and sector identities.

Furthermore, hypergraph-based network modeling is also a considerable method. For instance, multiple regional trade agreement, multinational industrial cluster, even division of communities based on different criteria can be used to constitute the hyperedge. This will be the focus of our next research (Table 1.3).



(*a*) Layer is Country **(*b*) Layer is Sector**

Fig. 1.2 Transforming a monopartite ICIO network into two multi-layer (bipartite) networks

Table 1.3 Economic organizations in mainstream ICIO databases

Economic organization	WIOD2016	TiVA2018	EORA26	ADB2019
European Union (EU)	28/27: Austria (AUT), Belgium (BEL), Bulgaria (BGR), Cyprus (CYP), Czech (CZE), Germany (DEU), Denmark (DNK), Spain (ESP), Estonia (EST), Finland (FIN), France (FRA), England (GBR), Hellenic (GRC), Croatia (HRV), Hungary (HUN), Ireland (IRL), Italy (ITA), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), Malta (MLT), Netherlands (NLD), Poland (POL), Portugal (PRT), Romania (ROU), Slovak (SVK), Slovenia (SVN), Sweden (SWE)	28/27: Austria (AUT), Belgium (BEL), Czech Republic (CZE), Denmark (DNK), Estonia (EST), Finland (FIN), France (FRA), Germany (DEU), Greece (GRC), Hungary (HUN), Ireland (IRL), Italy (ITA), Latvia (LVA), Lithuania (LTU), Luxembourg (LUX), Netherlands (NLD), Poland (POL), Portugal (PRT), Slovak Republic (SVK), Slovenia (SVN), Spain (ESP), Sweden (SWE), United Kingdom (GBR), Bulgaria (BGR), Croatia (HRV), Cyprus (CYP), Malta (MLT), Romania (ROU)	28/27: Austria (AUT), Belgium (BEL), Bulgaria (BGR), Croatia (HRV), Cyprus (CYP), Czech Republic (CZE), Denmark (DNK), Estonia (EST), Finland (FIN), France (FRA), Germany (DEU), Greece (GRC), Hungary (HUN), Ireland (IRL), Italy (ITA), Latvia (LVA), Lithuania (LTU), Luxembourg (LUX), Malta (MLT), Netherlands (NLD), Poland (POL), Portugal (PRT), Romania (ROU), Slovakia (SVK), Slovenia (SVN), Spain (ESP), Sweden (SWE), United Kingdom (GBR)	28/27: Austria (AUT), Belgium (BEL), Bulgaria (BGR), Cyprus (CYP), Czech Republic (CZE), Germany (GER), Denmark (DEN), Spain (SPA), Estonia (EST), Finland (FIN), France (FRA), United Kingdom (UKG), Greece (GRC), Croatia (HRV), Hungary (HUN), Ireland (IRE), Italy (ITA), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), Malta (MLT), Netherlands (NET), Poland (POL), Portugal (POR), Romania (ROM), Slovak Republic (SVK), Slovenia (SVN), Sweden (SWE)
Asia–Pacific Economic Cooperation (APEC)	10/21: Australia (AUS), Canada (CAN), China (CHN), Indonesia (IDN), Japan (JPN), Korea (KOR), Mexico (MEX), Russia (RUS), Chinese Taipei (TWN), America (USA)	20/21: Australia (AUS), Canada (CAN), Chile (CHL), Japan (JPN), Korea (KOR), Mexico (MEX), New Zealand (NZL), United States (USA), Brunei Darussalam (BRN), China (People's Republic of) (CHN), Indonesia (IDN), Hong Kong, China (HKG), Malaysia (MYS), Peru (PER), Philippines (PHL), Russian Federation (RUS), Singapore (SGP), Chinese Taipei (TWN), Thailand (THA), Viet Nam (VNM)	21/21: Australia (AUS), Brunei (BRN), Canada (CAN), Chile (CHL), China (CHN), Hong Kong (HKG), Indonesia (IDN), Japan (JPN), Malaysia (MYS), Mexico (MEX), New Zealand (NZL), Papua New Guinea (PNG), Peru (PER), Philippines (PHL), South Korea (KOR), Russia (RUS), Singapore (SGP), Taiwan (TWN), Thailand (THA), United States (USA), Viet Nam (VNM)	17/21: Australia (AUS), Canada (CAN), People's Republic of China (PRC), Indonesia (INO), Japan (JPN), Republic of Korea (KOR), Mexico (MEX), Russia (RUS), Taipei, China (TAP), United States (USA), Malaysia (MAL), Philippines (PHI), Thailand (THA), Viet Nam (VIE), Brunei Darussalam (BRU), Singapore (SIN), Hong Kong, China (HKG)

(continued)

Table 1.3 (continued)

Economic organization	WIOD2016	TiVA2018	EORA26	ADB2019
Countries that have signed cooperation agreements with China on Belt and Road Initiative (BRI-Related Country)	22/141: Austria (AUT), Bulgaria (BGR), Cyprus (CYP), Czech (CZE), Estonia (EST), Hellenic (GRC), Croatia (HRV), Hungary (HUN), Indonesia (IDN), Italy (ITA), Korea (KOR), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), Malta (MLT), Poland (POL), Portugal (PRT), Romania (ROU), Russia (RUS), Slovak (SVK), Slovenia (SVN), Turkey (TUR)	38/141: Austria (AUT), Chile (CHL), Czech Republic (CZE), Estonia (EST), Greece (GRC), Hungary (HUN), Italy (ITA), Korea (KOR), Latvia (LVA), Lithuania (LTU), Luxembourg (LUX), New Zealand (NZL), Poland (POL), Portugal (PRT), Slovak Republic (SVK), Slovenia (SVN), Turkey (TUR), Brunei Darussalam (BRN), Bulgaria (BGR), Cambodia (KHM), Costa Rica (CRI), Croatia (HRV), Cyprus 2 (CYP), Indonesia (IDN), Kazakhstan (KAZ), Malaysia (MYS), Malta (MLT), Morocco (MAR), Peru (PER), Philippines (PHL), Romania (ROU), Russian Federation (RUS), Saudi Arabia (SAU), Singapore (SGP), South Africa (ZAF), Thailand (THA), Tunisia (TUN), Viet Nam (VNM)	129/141: Afghanistan (AFG), Albania (ALB), Algeria (DZA), Angola (AGO), Antigua (ATG), Armenia (ARM), Austria (AUT), Azerbaijan (AZE), Bahrain (BHR), Bangladesh (BGD), Barbados (BRB), Belarus (BLR), Benin (BEN), Bolivia (BOL), Bosnia and Herzegovina (BIH), Botswana (BWA), Brunei (BRN), Bulgaria (BGR), Burundi (BDI), Cambodia (KHM), Cameroon (CMR), Cape Verde (CPV), Chad (TCD), Chile (CHL), Congo (COG), Costa Rica (CRI), Croatia (HRV), Cuba (CUB), Cyprus (CYP), Czech Republic (CZE), Cote dIvoire (CIV), DR Congo (COD), Djibouti (DJI), Dominican Republic (DOM), Ecuador (ECU), Egypt (EGY), El Salvador (SLV), Estonia (EST), Ethiopia (ETH), Fiji (FJI), Gabon (GAB), Gambia (GMB), Georgia (GEO), Ghana (GHA), Greece (GRC), Guinea (GIN), Guyana (GUY), Hungary (HUN), Indonesia (IDN), Iran (IRN), Iraq (IRQ), Italy (ITA), Jamaica (JAM), Kazakhstan (KAZ), Kenya (KEN), Kuwait (KWT), Kyrgyzstan (KGZ), Laos (LAO), Latvia (LVA), Lebanon (LBN), Lesotho (LSO), Liberia (LBR), Libya (LBY), Lithuania (LTU), Luxembourg (LUX), Madagascar (MDG),	39/141: Austria (AUT), Bulgaria (BGR), Cyprus (CYP), Czech Republic (CZE), Estonia (EST), Greece (GRC), Croatia (HRV), Hungary (HUN), Indonesia (INO), Italy (ITA), Republic of Korea (KOR), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), Malta (MLT), Poland (POL), Portugal (POR), Romania (ROM), Russia (RUS), Slovak Republic (SVK), Slovenia (SVN), Turkey (TUR), Bangladesh (BAN), Malaysia (MAL), Philippines (PHI), Thailand (THA), Viet Nam (VIE), Kazakhstan (KAZ), Mongolia (MON), Sri Lanka (SRI), Pakistan (PAK), Fiji (FIJ), Lao People's Democratic Republic (LAO), Brunei Darussalam (BRU), Kyrgyz Republic (KGZ), Cambodia (CAM), Maldives (MLD), Nepal (NEP), Singapore (SIN)

(continued)

Table 1.3 (continued)

Economic organization	WIOD2016	TiVA2018	EORA26	ADB2019
			Malaysia (MYS), Maldives (MDV), Mali (MLI), Malta (MLT), Mauritania (MRT), Mongolia (MNG), Montenegro (MNE), Morocco (MAR), Mozambique (MOZ), Myanmar (MMR), Namibia (NAM), Nepal (NPL), New Zealand (NZL), Niger (NER), Nigeria (NGA), Oman (OMN), Pakistan (PAK), Panama (PAN), Papua New Guinea (PNG), Peru (PER), Philippines (PHL), Poland (POL), Portugal (PRT), Qatar (QAT), South Korea (KOR), Moldova (MDA), Romania (ROU), Russia (RUS), Rwanda (RWA), Samoa (WSM), Saudi Arabia (SAU), Senegal (SEN), Serbia (SRB), Seychelles (SYC), Sierra Leone (SLE), Singapore (SGP), Slovakia (SVK), Slovenia (SVN), Somalia (SOM), South Africa (ZAF), South Sudan (SDS), Sri Lanka (LKA), Sudan (SUD), Suriname (SUR), Tajikistan (TJK), Thailand (THA), TFYR Macedonia (MKD), Togo (TGO), Trinidad and Tobago (TTO), Tunisia (TUN), Turkey (TUR), Uganda (UGA), Ukraine (UKR), UAE (ARE), Tanzania (TZA), Uruguay (URY), Uzbekistan (UZB), Vanuatu (VUT), Venezuela (VEN), Viet Nam (VNM), Yemen (YEM), Zambia (ZMB), Zimbabwe (ZWE)	

(continued)

Table 1.3 (continued)

Economic organization	WIOD2016	TiVA2018	EORA26	ADB2019
Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP)	4/11: Australia (AUS), Canada (CAN), Japan (JPN), Mexico (MEX)	11/11: Australia (AUS), Canada (CAN), Chile (CHL), Japan (JPN), Mexico (MEX), New Zealand (NZL), Brunei Darussalam (BRN), Malaysia (MYS), Peru (PER), Singapore (SGP), Viet Nam (VNM)	11/11: Australia (AUS), Brunei (BRN), Canada (CAN), Chile (CHL), Japan (JPN), Malaysia (MYS), Mexico (MEX), New Zealand (NZL), Peru (PER), Singapore (SGP), Viet Nam (VNM)	8/11: Australia (AUS), Canada (CAN), Japan (JPN), Mexico (MEX), Malaysia (MAL), Viet Nam (VIE), Brunei Darussalam (BRU), Singapore (SIN)
Association of Southeast Asian Nations (ASEAN)	1/10: Indonesia (IDN)	8/10: Brunei Darussalam (BRN), Cambodia (KHM), Indonesia (IDN), Malaysia (MYS), Philippines (PHL), Singapore (SGP), Thailand (THA), Viet Nam (VNM)	10/10: Brunei (BRN), Cambodia (KHM), Indonesia (IDN), Laos (LAO), Malaysia (MYS), Myanmar (MMR), Philippines (PHL), Singapore (SGP), Thailand (THA), Viet Nam (VNM)	9/10: Brunei Darussalam (BRU), Cambodia (CAM), Indonesia (INO), Lao People's Democratic Republic (LAO), Malaysia (MAL), Philippines (PHI), Singapore (SIN), Thailand (THA), Viet Nam (VIE)
Regional Comprehensive Economic Partnership (RCEP)	6/16: Australia (AUS), China (CHN), Indonesia (IDN), India (IND), Japan (JPN), Korea (KOR)	14/16: Australia (AUS), Japan (JPN), Korea (KOR), New Zealand (NZL), Brunei Darussalam (BRN), Cambodia (KHM), China (People's Republic of) (CHN), India (IND), Indonesia (IDN), Malaysia (MYS), Philippines (PHL), Singapore (SGP), Thailand (THA), Viet Nam (VNM)	16/16: Australia (AUS), Brunei (BRN), Cambodia (KHM), China (CHN), India (IND), Indonesia (IDN), Japan (JPN), Laos (LAO), Malaysia (MYS), Myanmar (MMR), New Zealand (NZL), Philippines (PHL), South Korea (KOR), Singapore (SGP), Thailand (THA), Viet Nam (VNM)	14/16: Australia (AUS), People's Republic of China (PRC), Indonesia (INO), India (IND), Japan (JPN), Republic of Korea (KOR), Malaysia (MAL), Philippines (PHI), Thailand (THA), Viet Nam (VIE), Lao People's Democratic Republic (LAO), Brunei Darussalam (BRU), Cambodia (CAM), Singapore (SIN)
North American Free Trade Agreement (NAFTA)	3/3: Canada (CAN), Mexico (MEX), America (USA)	3/3: Canada (CAN), Mexico (MEX), United States (USA)	3/3: Canada (CAN), Mexico (MEX), United States (USA)	3/3: Canada (CAN), Mexico (MEX), United States (USA)
BRICS	4/5: Brazil (BRA), Russia (RUS), India (IND), China (CHN)	5/5: Brazil (BRA), Russian Federation (RUS), India (IND), China (People's Republic of) (CHN), South Africa (ZAF)	5/5: Brazil (BRA), Russia (RUS), India (IND), China (CHN), South Africa (ZAF)	4/5: Brazil (BRA), Russia (RUS), India (IND), People's Republic of China (PRC)

Notes Latvia joined the Eurozone in 2014; The United Kingdom officially left the EU and EEA on 1st February 2020; At the end of 2021, there are 141 countries that have signed cooperation agreements with China on Belt and Road Initiative; Taiwan Province is an inalienable part of Chinese territory; Y stands for the number of subsistent countries or regions in the economic organization while X for the total amount in reality; Because of Brexit, we still put the United Kingdom in the EU, so the Y is only bigger than X for here

1.4.4 Classification of Industrial Sectors

Sometimes, it is necessary to use the aggregation of industrial sectors to facilitate the analysis and modeling in empirical analysis. For instance, industrial sectors in all ICIO databases can be divided into four sector categories as shown in Table 1.4, including ***Agriculture***, ***Mining***, ***Manufacturing***, and ***Services***.

We can also conduct a step-by-step aggregating. Just as ADB-MRIO did, the industrial sectors have been aggregated into thirteen categories (***ERDI Aggregation Level 1***) first, and then five categories (***ERDI Aggregation Level 2***), as shown in Table 1.5.

1.5 ICIO Network Model

ICIO data have proven itself to be a reliable source for analyzing economic globalization. Thanks to it, sectors all over the world can form a sophisticated GVC, bringing the advantages of simultaneous study on international and domestic economies in detail as a holistic network.

To establish an industrial complex network, a sector within a region is considered as a node and the inter-industry IO relation as a tie, and its weight represents the sale and purchase relations between producers and consumers. Thus, a graph $G = (V, E, W)$ containing n nodes is drawn to represent sectors within a nation or region and denote a node set V. Pairs of nodes are linked by ties to reflect their interdependencies, thereby forming an asymmetric edge set E. However, in valued graphs, a set E can be replaced by weight set W, which can be extracted from the region of inter-country and inter-industry use and supply in ICIO table.

Note that, typical IO or ICIO table includes three different areas, namely value-added, intermediate use, and final demand. It is possible that the whole global economic system can be abstracted to a ***Multi-Layer Network*** as shown in Fig. 1.3b, which includes three layers: the ***Value-Added Layer***, the ***Intermediate Use Layer***, and the ***Final Demand Layer***. The intermediate use layer can be further treated as a puzzle that is made of many single-layer networks out of a multi-layer network, in which the nodes are the countries/regions, the layers are the industrial sectors, and links can be established from sellers to buyers within and across industrial sectors [78, 79].

In this book, we study the topological complexity and evolutionary mechanism of global production system as an important component of GVC based on the intermediate use part of ICIO table. Then, we will incorporate the aspects of the input of labor and capital and the distribution of final products and services reflecting by the value-added part and the final demand part.

We name this single layer ICIO network model ***Global Industrial Value Chain Network (GIVCN)*** since its purpose is to reflect how economic shocks propagate and expand along the GVC, as well as to what extent the industrial impact generates

Table 1.4 Four-sector categories in mainstream ICIO databases

Category	WIOD2016	TiVA2018	EORA26	ADB2019
Agriculture (SC1)	1st–3rd sectors: crop and animal production; hunting and related service activities; forestry and logging; fishing and aquaculture	1st sector: agriculture, forestry and fishing	1st–2nd sectors: agriculture; fishing	1st sector: agriculture, hunting, forestry, and fishing
Mining (SC2)	4th sector: mining and quarrying	2nd–4th sectors: mining and extraction of energy producing products; mining and quarrying of non-energy producing products; mining support service activities	3rd sector: mining and quarrying	2nd sector: mining and quarrying
Manufacturing (SC3)	5th–27th sectors: manufacture of food products; beverages and tobacco products; manufacture of textiles; wearing apparel and leather products; manufacture of wood and of products of wood and cork; except furniture, manufacture of articles of straw and plaiting materials; manufacture of paper and paper products; printing and reproduction of recorded media; manufacture of coke and refined petroleum products; manufacture of chemicals and chemical products; manufacture of basic pharmaceutical products and pharmaceutical preparations; manufacture of rubber and plastic products; manufacture of other non-metallic mineral products; manufacture of basic metals; manufacture of fabricated metal products; except machinery and equipment; manufacture of computer; electronic and optical products; manufacture of electrical equipment; manufacture of machinery and equipment n.e.c.; manufacture of motor vehicles; trailers and semi-trailers; manufacture of other transport equipment; manufacture of furniture, other manufacturing; repair and installation of machinery and equipment; electricity; gas; steam and air conditioning supply; water collection; treatment and supply; sewerage, waste collection; treatment and disposal activities, materials recovery, remediation activities and other waste management services; construction	5th–22nd sectors: food products, beverages and tobacco; textiles, wearing apparel, leather and related products; wood and products of wood and cork; paper products and printing; coke and refined petroleum products; chemicals and pharmaceutical products; rubber and plastic products; other non-metallic mineral products; basic metals; fabricated metal products; computer, electronic and optical products; electrical equipment; machinery and equipment, nec; motor vehicles, trailers and semi-trailers; other transport equipment; other manufacturing; repair and installation of machinery and equipment; electricity, gas, water supply, sewerage, waste and remediation services; construction	4th–14th sectors: food and beverages; textiles and wearing apparel; wood and paper; petroleum, chemical and non-metallic mineral products; metal products; electrical and machinery; transport equipment; other manufacturing; recycling; electricity, gas and water; construction	3rd–18th sectors: food, beverages, and tobacco; textiles and textile products; leather, leather products, and footwear; wood and products of wood and cork; pulp, paper, paper products, printing, and publishing; coke, refined petroleum, and nuclear fuel; chemicals and chemical products; rubber and plastics; other nonmetallic minerals; basic metals and fabricated metal; machinery, nec; electrical and optical equipment; transport equipment; manufacturing, nec; recycling; electricity, gas, and water supply; construction

(continued)

Table 1.4 (continued)

Category	WIOD2016	TiVA2018	EORA26	ADB2019
Services (SC4)	28th–56th sectors: wholesale and retail trade and repair of motor vehicles and motorcycles; wholesale trade; except of motor vehicles and motorcycles; retail trade; except of motor vehicles and motorcycles; land transport and transport via pipelines; water transport; air transport; warehousing and support activities for transportation; postal and courier activities; accommodation and food service activities; publishing activities; motion picture; video and television programme production; sound recording and music publishing activities, programming and broadcasting activities; telecommunications; computer programming; consultancy and related activities, information service activities; financial service activities; except insurance and pension funding; insurance; reinsurance and pension funding; except compulsory social security; activities auxiliary to financial services and insurance activities; real estate activities; legal and accounting activities, activities of head offices, management consultancy activities; architectural and engineering activities, technical testing and analysis; scientific research and development; advertising and market research; other professional; scientific and technical activities, veterinary activities; administrative and support service activities; public administration and defence, compulsory social security; education; human health and social work activities; other service activities; activities of households as employers, undifferentiated goods- and services-producing activities of households for own use; activities of extraterritorial organizations and bodies	23rd–36th sectors: wholesale and retail trade; repair of motor vehicles; transportation and storage; accommodation and food services; publishing, audiovisual and broadcasting activities; telecommunications; it and other information services; financial and insurance activities; real estate activities; other business sector services; public admin. And defence; compulsory social security; education; human health and social work; arts, entertainment, recreation and other service activities; private households with employed persons	15th–26th sectors: maintenance and repair; wholesale trade; retail trade; hotels and restraurants; transport; post and telecommunications; financial intermediation and business activities; public administration; education, health and other services; private households; others; re-export and re-import	19th–35th sectors: sale, maintenance, and repair of motor vehicles and motorcycles; retail sale of fuel; wholesale trade and commission trade, except of motor vehicles and motorcycles; retail trade, except of motor vehicles and motorcycles; repair of household goods; hotels and restaurants; inland transport; water transport; air transport; other supporting and auxiliary transport activities; activities of travel agencies; post and telecommunications; financial intermediation; real estate activities; renting of machinery and equipment; other business activities; public administration and defense; compulsory social security; education; health and social work; other community, social, and personal services; private households with employed persons

Table 1.5 Industrial sector aggregation used in ADB-MRIO

No.	Sectors at the level used by world input–output database	ERDI aggregation level 1 (13 sectors)	ERDI aggregation level 2 (5 sectors)
1	Agriculture, hunting, forestry, and fishing	Primary	Primary
2	Mining and quarrying	Primary	Primary
3	Food, beverages, and tobacco	Low tech	Low tech
4	Textiles and textile products	Low tech	Low tech
5	Leather, leather products, and footwear	Low tech	Low tech
6	Wood and products of wood and cork	Low tech	Low tech
7	Pulp, paper, paper products, printing, and publishing	Low tech	Low tech
8	Coke, refined petroleum, and nuclear fuel	High and medium tech	High and medium tech
9	Chemicals and chemical products	High and medium tech	High and medium tech
10	Rubber and plastics	Low tech	Low tech
11	Other nonmetallic minerals	High and medium tech	High and medium tech
12	Basic metals and fabricated metal	High and medium tech	High and medium tech
13	Machinery, nec	High and medium tech	High and medium tech
14	Electrical and optical equipment	High and medium tech	High and medium tech
15	Transport equipment	High and medium tech	High and medium tech
16	Manufacturing, nec; recycling	Low tech	Low tech
17	Electricity, gas, and water supply	Utilities	Low tech
18	Construction	Construction	Low tech
19	Sale, maintenance, and repair of motor vehicles and motorcycles; retail sale of fuel	Trade and repair services	Business services
20	Wholesale trade and commission trade, except of motor vehicles and motorcycles	Trade and repair services	Business services
21	Retail trade, except of motor vehicles and motorcycles; repair of household goods	Trade and repair services	Business services

(continued)

Table 1.5 (continued)

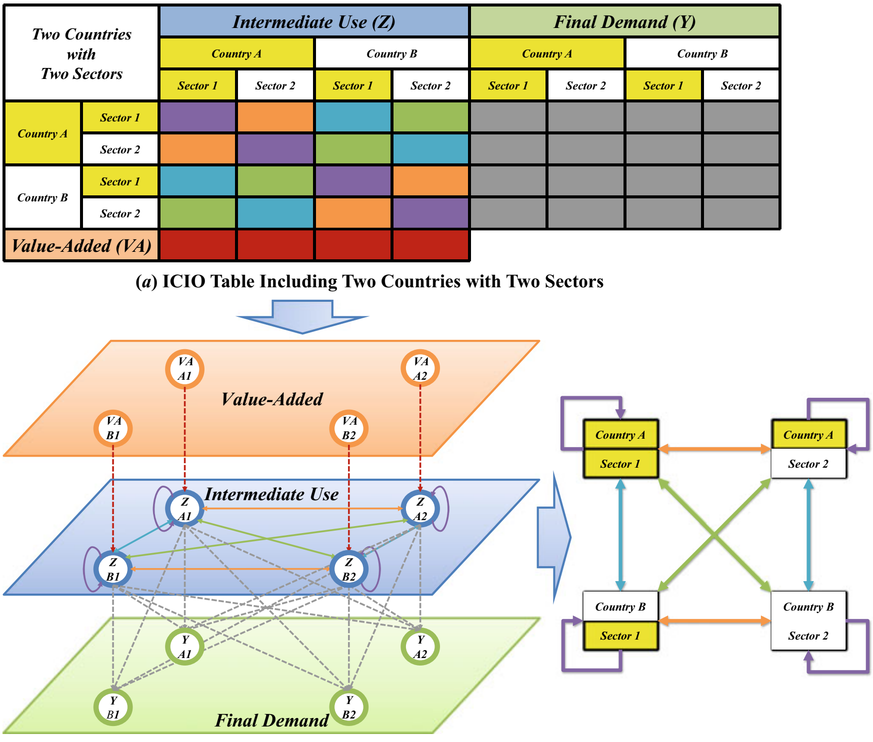
No.	Sectors at the level used by world input–output database	ERDI aggregation level 1 (13 sectors)	ERDI aggregation level 2 (5 sectors)
22	Hotels and restaurants	Tourism	Business services
23	Inland transport	Transport services	Business services
24	Water transport	Transport services	Business services
25	Air transport	Transport services	Business services
26	Other supporting and auxiliary transport activities; activities of travel agencies	Transport services	Business services
27	Post and telecommunications	ICT services	Business services
28	Financial intermediation	Finance and insurance services	Business services
29	Real estate activities	Property services	Business services
30	Renting of machinery and equipment; other business activities	Property services	Business services
31	Public administration and defense; compulsory social security	Public and welfare services	Public and welfare services
32	Education	Public and welfare services	Public and welfare services
33	Health and social work	Public and welfare services	Public and welfare services
34	Other community, social, and personal services	Public and welfare services	Public and welfare services
35	Private households with employed persons	Services provided by private households	Public and welfare services

on the national level. However, the density of such a directed and weighted network is very high, the number of edges, including self-loops, is almost equal to the square number of nodes, resulting in that many complex network techniques are not available to analyze the topological structure of GIVCN model. Indeed, that is perhaps the key feature which differentiates this book.

The topological structure of GIVCN-Eora26-2015 is shown in Fig. 1.4.

1.6 Summary

We propose the GIVCN model to reveal the mechanism of creation, distribution, transfer, and value-addition in the multi-layer economic system, and it owns the following properties:



(*b*) Tripartite Valued Graph Based on ICIO Table (*c*) Graph Form of Intermediate Use Part

Fig. 1.3 The relationship between ICIO table and GVC network

(1) It is a directed and weighted network, in which the nodes play the roles of upstream and downstream industrial sectors simultaneously on the GVC. The ties between paired nodes and weights on them represent the inter-industry IO relations in terms of both direction and quantity of value stream.

(2) The subgraphs made up of nodes within the same country have a high density of connections, indicating there are much more trade activities at home than abroad.

(3) The abundant existence of self-loops, even some of which carrying on very large weights, reflects that the inner consumption of intermediate goods produced by industrial sectors themselves is a common phenomenon.

The GIVCN model and its derived models are typical graphic models, which means their topological structures have already been clearly described based on real databases, and we thus do not carry out advanced analytical tools (i.e., network embedding and machine learning) in this book to decouple and forecast further. However, if we want to take more features of industrial sectors, countries/regions, or economic organizations into consideration, we must apply them to make related

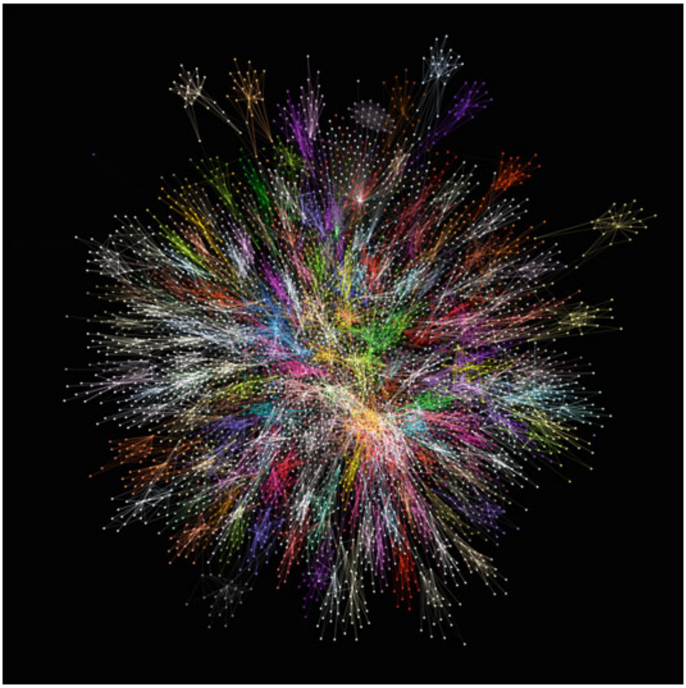


Fig. 1.4 GIVCN-Eora26-2015. *Notes* Based on the simplified Eora-MRIO (V199.82), we build GIVCN-Eora26 model in which all countries are included in a common 26-sector classification and the supply-use tables from the full Eora-MRIO have been converted to symmetric product-by-product IO tables using the Industry Technology Assumption. For the reason of visualization, we delete the weak industrial relevance based on our RFWA (details are in the Sect. 10.3.1)

empirical results more scientific and convincing. That is exactly what we are going to do in the next stage.

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Part II
Topological Structure

Chapter 2
Recognize the Trade Roles of Industrial Sectors

2.1 Introduction

Marsden defined Brokerage as a process, by which intermediary actors facilitate transactions between other actors [4]. That is to say, three actors exist in the most basic structural form of information transfer and one of them is the intermediary—the so-called broker. Many empirical and theoretical studies focus on brokerage and take it as an important theoretical concept [5–7], but limited efforts had been made in quantification until Could and Fernandez proposed a formal definition of the brokerage in concrete social systems [8] They found if a network can be divided into mutually exclusive subgroups, nodes acting as information brokers under different non-overlapping subgroups would bear five formally, analytically, and intuitively distinct brokerage types or roles and the commutation relation of information between nodes is probably heterogeneous simultaneously. Figure 2.1 illustrates different types of brokerage, in all of which B plays the role of a broker.

If all three actors belong to the same group as shown in Fig. 2.1a, the brokerage relation is completely internal to the group and broker *B* is denoted by Coordinator. If *A* and *C* belong to the same subgroup while *B* belongs to a different group, *B* as an outer is denoted by Consultant in Fig. 2.1b. If *B* with either of *A* or *C* belongs to the same group while *A* and *C* are in a different group, i.e., *B* brings information in Fig. 2.1c and spreads it out in Fig. 2.1d, the broker is denoted by Gatekeeper or Representative according to its specific function. As for the last role denoted by Liaison in Fig. 2.1e, *A*, *C* and *B* belong to non-overlapping subgroups respectively.

There are several factions about the measures of brokerage. Burt, Galaskiewicz, and Krohn defined brokers as actors sending and receiving resources from different parts of the network [9, 10]. They focused on the role of the transmitters in consideration of the topologically structural position. Another attempt to quantify brokerage is through betweenness-based measures, e.g., geodesics, which was proposed by Freeman [11]. If attention is just paid on the scope of a single intermediary, a package of formal approaches to brokerage based on statistical inference is available [8],

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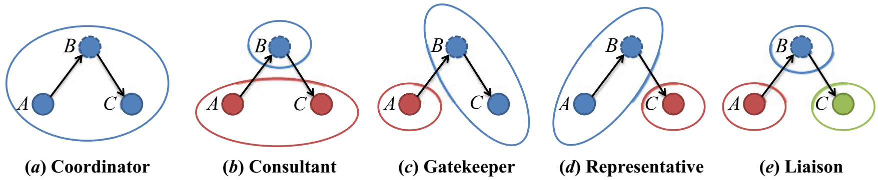


Fig. 2.1 Five types of brokerages in SNA

which is possible to be further extended to the level of the whole network, taking account of multiple relations.

We realize that any industrial sector may play different medium roles when it locates between its numerous upstream sectors and downstream ones. In order to solve this problem both qualitatively and quantitatively, we adopt the concept of brokerage to enumerate all kinds of possibility and develop the corresponding calculation formulas.

2.2 Definition

2.2.1 Trade Types on the GVC

While international trade has grown dramatically in the last half-century, the nature of trade has been through a dramatic change. One of the most important changes involves the increasing interconnectedness of production processes in a vertical trading chain that stretches across many countries, each of which specializing in particular stages of production. The main feature of vertical specialization is a country imports intermediate goods as inputs from another country, and then its inputs are translated with value-added into outputs that are exported to the third country. This production process includes numerous domestic and foreign trades about intermediate goods, and it ends until final goods arrive at the consumer market.

Trade can be classified into four types according to whether commerce and trade economy happens within the same country or not and whether the exchange of goods and services happens between different sectors or not. Then, classification in detail has also been made based on two dimensions shown in Fig. 2.2: ***Inter-Industry Trade***, ***Intra-Industry Trade***, ***Industrial Input–Output Trade***, and ***Industrial Self-Consumption Trade***.

International trade is one of the key factors in measuring any country's macroeconomic prosperity. As globalization advances, international trade becomes increasingly complex and is usually divided into inter-industry trade and intra-industry trade by academia. Although the wording is quite similar, these two terms convey different meanings.

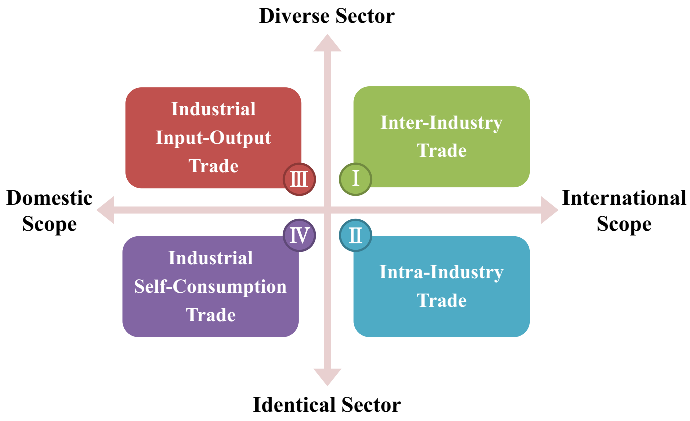


Fig. 2.2 Four trade types in quadrants

Inter-industry trade is to trade goods of different industries, i.e., ***Vertical Trade***. Countries engage in inter-industry trade according to their competitive advantages in different levels of economic development. In other words, inter-industry trade usually occurs between developed and developing countries.

Intra-industry trade, on the other hand, is to products of the same industry, i.e., ***Horizontal Trade*** or ***Two-Way Trade***. In the nature, this type of international trade increases the variety of goods that are from the same industry but different country and helps countries benefit from the economies with large scale and comparative advantages. Intra-industry trade usually happens within countries on a similar level of economic development.

Anyway, they both need inter-country participation, which is attributed to the fragmentation of production, e.g., outsourcing and offshoring, with the only difference lies in whether inter-industry cooperation is needed or not.

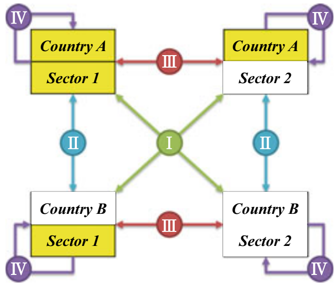
Domestic trade, also known as internal trade or home trade, is the exchange of goods within the boundary of a country. It is further divided into two types as previously mentioned, which are industrial IO trade and Industrial self-consumption trade. The former is based on the classic IO model that shows how the outputs from one sector may become inputs to another, while the latter only pays attention to the consumption within one sector and another. Added up, they constitute the whole IO table with the latter being the special form of the former—the only difference is whether the receiver and the provider of goods are the same or not.

For clearer comprehension, a two-country and two-sector case is used to illustrate the relation between trade classifications, as shown in Fig. 2.3, in both matrix and network forms. Trade types are distinguished by roman numbers and varied colors according to their definitions.

According to Fig. 2.3a, Type I represents IO relations between different countries' different sectors, which correspond to the green edges of the network in Fig. 2.3b. Type II refers to IO relations between different countries' identical sectors, which

Two Countries with Two Sectors		Country A		Country B	
		Sector 1	Sector 2	Sector 1	Sector 2
Country A	Sector 1	Ⅳ	Ⅲ	Ⅱ	Ⅰ
	Sector 2	Ⅲ	Ⅳ	Ⅰ	Ⅱ
Country B	Sector 1	Ⅱ	Ⅰ	Ⅳ	Ⅲ
	Sector 2	Ⅰ	Ⅱ	Ⅲ	Ⅳ

(*a*) Basic Inter-Country Input-Output Table



(*b*) Industrial Complex Network Model

Fig. 2.3 Four trade types in forms of ICIO table and network

are delegated by the left and right blue edges. Type III and Type IV manifest those IO relations existing in the same countries, but the former strides across sectors (as the top and bottom red edges) and the latter just happens within one sector (as the purple self-loops in the network). However, the trade types proposed in this chapter are not precisely identified to depict commercial behavior. Sectors may play several roles of trade simultaneously and contribute to transferring economic information from different angles.

2.2.2 *Decomposition of Trade Roles*

Enlightened by analysis on brokerage in SNA, five types of ***Trade Brokerage Property (TBP)*** in GIVCN model are proposed in Fig. 2.4.

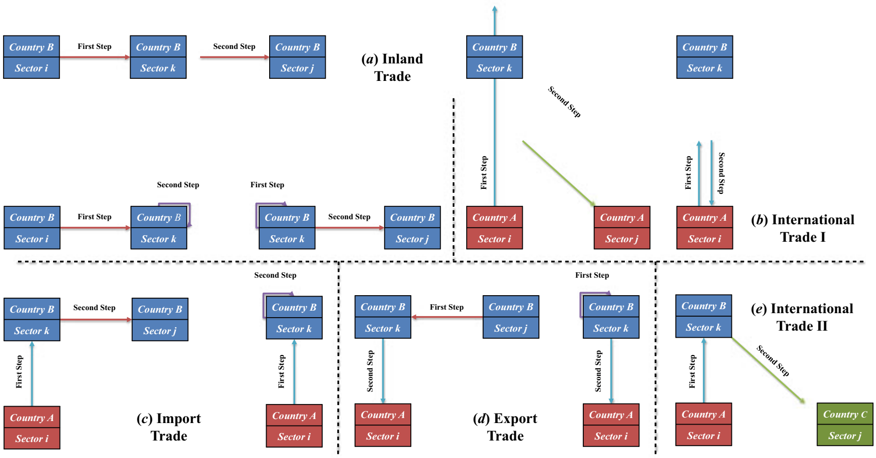


Fig. 2.4 Decomposition of trade brokerage property in GIVCN model

Figure 2.4 inherits the features of Figs. 2.1 and 2.3 and reflects four pairs of factors in each scenario of trade, including inter-country or inter-industry transfer, upstream or downstream sector, import or export goods, and inputs or outputs. Sector k of country B plays different roles of trade in each sub-Fig., and a detailed explanation about this sector is as follows.

Inland Trade, denoted by ***TBP1***, means that sector k and its upstream and downstream sectors all belong to the same country. For instance, both inputs and outputs of sector *k* are within the economic system of a single country (see Fig. 2.4a). Also, self-consumption can be treated as either inputs from the upstream sector or outputs to the downstream sector.

International Trade I, denoted by ***TBP2***, means that sector k belongs to one country and its upstream and downstream sectors belong to another country (see Fig. 2.4b). For instance, sector *k* imports inputs from another economic system and then exports outputs back to it (just like OEM). It doesn't matter whether oversea providers and consumers are the same. Besides, *TBP2* also includes a certain proportion of re-import and re-export trade.

Import Trade, denoted by ***TBP3***, means that sector k and its downstream sector belong to the same country, or itself as downstream sector consumes part of its output, while its upstream sector belongs to another country (see Fig. 2.4c). For instance, the inputs are imported from the oversea market and then sold inside home market after the value-added process.

Export Trade, denoted by ***TBP4***, means that sector k and its upstream sector belong to the same country, or itself as upstream sector provides part of its input, while its downstream sector belongs to another country (see Fig. 2.4d). For instance, the inputs are acquired inside the home market and then exported to the overseas market after the value-added process.

International Trade II, denoted by ***TBP5***, means that none of sector k or its upstream and downstream sectors belong to the same country (see Fig. 2.4e). It can better reflect the character of vertical specialization than *TBP2*. For instance, intermediate goods may be produced in Japan and then shipped to China for assembly into final goods that will be consumed in the United States; the relevant sector in China plays the role of TBP5 in this process.

2.3 Measurement

2.3.1 Statistical Inference on TBPs

TBPs cover all the roles in the process of vertical specialization and value-added production, and sectors always own several *TBPs* at the same time. As we all know, ICIO data for modeling ICN is too comprehensive and sophisticated to directly measure *TBPs* of each sector, which locates in a huge quantity of inseparable local economic systems (overlapping ego networks) simultaneously as a broker. Moreover, merely analyzing specific sector's *TBPs* one after another is meaningless as well. Research framework proposed here is based on probability sets, which describe *TBPs* ratio of sectors locating on the GVC. The derivation of the probability distribution of *TBPs* is as follows.

Step 1 Given that m countries/regions $(u, v = 1, 2, \ldots, m)$ in GIVCN model constitute a complete set, denoted by $\{R_u\}$.

Step 2 Given that all n sectors within one country/region constitute $\{z_k\}$ when they play the role of broker on the GVC, i.e., the sector k denoted by z_k is on the midstream level of IVCs. In which, $k \in \tau(u)$ and $\tau(u)$ is a set of numbers standing for the row sequence number of a certain country/region in the adjacent matr Z^{uv} ix. For instance, China is the 8th nation, and the United States is the 43rd one in ADB2019, so $\tau(8) = \{246, 247, \cdots, 280\}$ and $\tau(43) = \{1471, 1472, \cdots, 1505\}$ since each economy owns $n = 35$ sectors.

Step 3 Given that the upstream sectors of z_k (which provide raw materials or intermediate goods to z_k) constitute $\left\{s_{1,}s_{2,\cdots,}s_{a_u}\right\}$ and its downstream sectors (which consume intermediate goods from z_k) constitu $\left\{t_{1,}t_{2,\cdots,}t_{b_u}\right\}$ te. In which, $a_u = max(\tau(u))$, and $b_u = max(\tau(u))$ too.

Thus, the relation of any sector belonging to the upstream set on the IVCs could be presented as:

$$\begin{aligned} &\left\{\mathrm{s}_{1,}\mathrm{s}_{2,\cdots,}\mathrm{s}_{\mathrm{a}_1}\right\} \subseteq \mathrm{R}_1, \\ &\left\{\mathrm{s}_{\mathrm{a}_{\mathrm{u}-1}+1,}\mathrm{s}_{\mathrm{a}_{\mathrm{u}-1}+2,\cdots,}\mathrm{s}_{\mathrm{a}_\mathrm{u}}\right\} \subseteq \mathrm{R}_\mathrm{u}, \\ &\left\{\mathrm{s}_{\mathrm{a}_{\mathrm{m}-1}+1,}\mathrm{s}_{\mathrm{a}_{\mathrm{m}-1}+2,\cdots,}\mathrm{s}_{\mathrm{a}_\mathrm{m}}\right\} \subseteq \mathrm{R}_\mathrm{m}. \end{aligned}$$

Similarly, the relation of any sector belonging to the downstream set on the IVCs could be presented as:

$$\begin{aligned} &\left\{t_{1,}t_{2,\cdots,}t_{b_1}\right\} \subseteq R_1, \\ &\left\{t_{b_{u-1}+1},\, t_{b_{u-1}+2,\cdots,}t_{u_1}\right\} \subseteq R_u, \\ &\left\{t_{b_{m-1}+1,}t_{b_{m-1}+2,\cdots,}t_{b_m}\right\} \subseteq R_m. \end{aligned}$$

Step 4 Given that $\forall\{z_k\} \subseteq R_u, A_u$ denotes the sector k in the upstream set belonging to R_u to some degree, and B_u denotes the sector k in the downstream set belonging to R_u to some degree. Then, this kind of affiliation relation would be quantified by probabilities of events A_u and B_u as follows:

$$P(A_u) = \frac{\sum_{i=a_{u-1}+1}^{a_u} w_{s_i z_k}}{\sum_{k=1}^{a_m} w_{s_k z_k}} = \frac{\sum_{i\in\tau(u)} w_{s_i z_k}}{\sum_{k=1}^{N} w_{s_k z_k}}. \tag{2.1}$$

where $w_{s_i z_k}$ is the weight of edge starting from s_i reaching to z_k, $\sum\limits_{j\in\tau(u)} w_{s_i z_k}$ represents the gross of intermediate goods from all the upstream sectors to the midstream sector

k when they are in the same country/region R_u, and the function of denominator is to normalize the formula.

$$P(B_u) = \frac{\sum_{j=b_{u-1}+1}^{b_u} w_{z_k t_j}}{\sum_{k=1}^{b_m} w_{z_k t_k}} = \frac{\sum_{j\in\tau(u)} w_{z_k t_j}}{\sum_{k=1}^{N} w_{z_k t_k}}. \tag{2.2}$$

where $w_{z_k t_j}$ is the weight of edge starting from z_k reaching to t_j, $\sum\limits_{j\in\tau(u)} w_{z_k t_j}$ represents the gross of intermediate goods from the midstream sector k to all the downstream sectors when they are in the same country/region R_u, and the function of denominator is to normalize the formula.

Step 5 Obviously, events A_u and B_u are mutually independent. Considering the definition of brokerage and above conditions, the probability distribution of each *TBP* is:

$$P\left(z_k^{TBP1}\right) = P(A_u \cap B_u) = P(A_u)P(B_u) \tag{2.3}$$

$$P\left(z_k^{TBP2}\right) = \sum_{u=1, v\neq u}^{m} P(A_v \cap B_v) \tag{2.4}$$

$$P\left(z_k^{TBP3}\right) = [1 - P(A_u)]P(B_u) \tag{2.5}$$

$$P\left(z_k^{TBP4}\right) = P(A_u)[1 - P(B_v)] \tag{2.6}$$

$$P\left(z_k^{TBP5}\right) = \sum_{v=1, v\neq u}^{m} P(A_v)[1 - P(B_u) - P(B_v)] \tag{2.7}$$

where five sorts of probability delegate the ratio of roles that certain sector plays on the GVC, in detail, $P\left(z_k^{TBP1}\right)$ stands for inland trade, $P\left(z_k^{TBP2}\right)$ for international trade I, $P\left(z_k^{TBP3}\right)$ for import trade, $P\left(z_k^{TBP4}\right)$ for export trade, and $P\left(z_k^{TBP5}\right)$ for international trade II.

2.3.2 Measurment of Dependency

The concept of GVC helps expand the application of ICIO data and enabled the interdependence of different industries in different countries to be measured. Related studies mainly focus on two aspects: On the one hand, some of them estimated the input share of direct import in production or total investment to embody the foreign intermediate goods used in the domestic production. For example, Feenstra and

Hanson proposed the S_M index to measure the degree of manufacturing outsourcing [12]. On the other hand, scholars emphasized the value of directly and indirectly imported inputs embodied in goods that are exported such as the *VS* index proposed by Hummels in 2001, which applies to those whose production is completed in two or more countries and goods cross the border at least twice [13]. In this section, we try to redefine these two types of indices from the perspective of SNA.

Both *TBP1* and *TBP3* reflect the role of an industrial sector in promoting the production of its domestic downstream ones. However, the difference lies in whether its obtained intermediate goods come from the inside or outside of nation, which respectively reflects the extent to which it relies on the domestic and international IVC while exerting the function of value transformation. Drawing lessons from the expression form of S_M, we construct a new one based on *TBP1* and *TBP3* to measure the ***Import Share of Domestic Total Consumption***, denoted as ***IMS***. Its formula is as follows:

$$IMS(k) = \frac{P\left(z_k^{TBP3}\right)}{P\left(z_k^{TBP1}\right) + P\left(z_k^{TBP3}\right)} \times 100\% \tag{2.8}$$

where $IMS(k)$ denotes the import share of total consumption of a given sector k while providing the intermediate goods for its domestic IVC.

Both *TBP2* and *TBP5* reflect the outsourcing role played by an industrial sector in the process of global multi-stage production. Although their difference lies in whether its upstream and downstream sectors are in the same other country or in different other countries, it is the same for the sector in the middle. Therefore, we combine *TBP2* and *TBP5* to measure the ***Degree of Vertical Specialization***, denoted as ***VSD***. Its formula is as follows:

$$VSD(k) = P\left({z_k}^{TBP2}\right) + P\left({z_k}^{TBP5}\right) \tag{2.9}$$

where $VSD(k)$ denotes the frequency of a given sector k being in the middle of many three-stage IVCs while its imported intermediate goods are used to produce the export ones.

In sum, *IMS* and *VSD* reflect how much a given sector/economy relies on foreign trade when it participates in the vertical specialization from two perspectives. One is its dependence on the input of internationally produced intermediate goods (import trade), and the other is its dependence on the output of domestically produced intermediate goods (export trade).

2.4 Empirical Analysis: Economies' Two Sorts of Dependence on Foreign Trade

According to the *IMS* and *VSD* proposed above, this section firstly summarizes the foreign trade dependence on the national and sectoral levels, then briefly analyzes the situation of several countries' participation in the domestic and foreign economic cycles, and finally focuses on the reasons behind the developmental heterogeneity of China.

2.4.1 Statistics on All Economies

We focus on three sorts of industrial sectors, which are ***Primary (P)*** sectors, ***Low Tech (LT)*** sectors, and ***High and Medium Tech (HMT)*** sectors according to ERDI Aggregation Level 2, and then carry out statistics on *IMS* and *VSD* of all the economies in GIVCN-ADB2019-2019. The results are shown in Fig. 2.5.

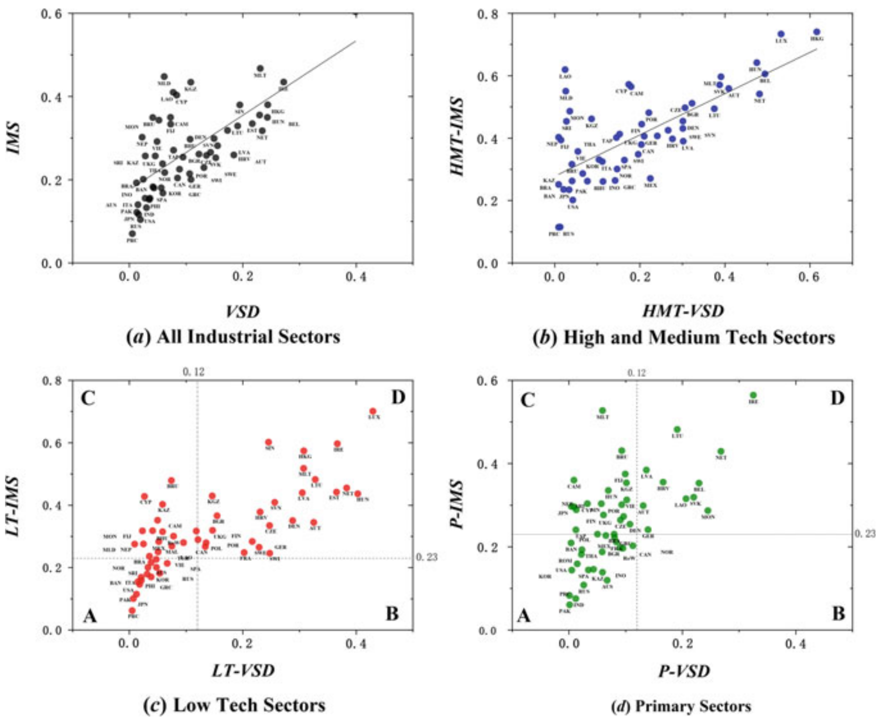


Fig. 2.5 Dependency Indices by Countries and Industrial Sectors in GIVCN-ADB2019-2019. *Notes* The distributions of P and LT sectors are more scattered than the other two, so the countries are divided into four areas

By fitting the *IMS* and *VSD* of all the industrial sectors within economies as shown in Fig. 2.5a, we find that they are positively correlated, indicating that the external dependence of domestically economic circulation (internal loop) is consistent with internationally economic circulation (external loop). That is, the higher the proportion of imports of intermediate goods required by the NVC/RVC of country/region, the more its industrial sectors tend to export the domestically produced products and services. The development of GVC makes it possible for developing countries to move forward from only exporting unprocessed primary products to those with multiple kinds of technological content. Imaging that, what if there was no GVC for the world? A country had to master the production of a whole product to meet its own demands, which is almost impossible. The GVC allows countries to specialize in a particular activity and join a global production network. As a developing country starts to export a variety of goods to other countries via GVC, the ratio of domestic value-added to gross export value is not only very small but also tends to fall, since they are often at the end of IVCs with labor-intensive assembly of parts produced elsewhere. As a result, some of them aspire to increase their value-added contribution to exports, without relying on the intermediate goods import and the advanced technology input from developed countries, which is, however, not realistic. It may seem like simple math that a higher domestic value-added share means more total value-added exported and hence more ***Gross Domestic Products (GDP)***. But that simple idea ignores the reality that imported goods and services are a key support to a country's competitiveness. If a country artificially replaces key inputs with inferior domestic versions, the final result is likely to be fewer gross exports and less, not more, total value-added exports [14].

The participation of the HMT sectors for countries in domestic and international economic circulations follows a similar distribution to that of all industrial sectors. As shown in Fig. 2.5b, the *IMS* and *VSD* of HMT sectors across 62 countries around the world are mostly positively correlated, with only a few countries deviating from the fitted line. This is because of the high technology factor needed for each component/ingredient used to produce the final product, which necessitates collaborative production achieved through technology integration on a global scale. In general, the higher the *VSD* of an economy's HMT sectors on the GVC, the less likely it is to easily realize a closed domestic circulation. Of course, there are exceptions to this rule. For example, the United States, China, and Russia are all located in the lower region, deviating far from the fitted line in Fig. 2.5b, with their HMT sectors scoring low on both *VSD* and *IMS*. We believe that this is largely due to their respective ultra-domestic markets and relatively well-developed industry layout, leading to domestic trade (measured by *TBP1*) taking up a greater proportion, which enables less dependency on the international markets. Meanwhile, smaller economies (such as Laos, Cambodia, Cyprus, and Maldives) are above the fitted line, i.e., the *IMS* of the HMT sectors is much greater than the *VSD*, which indicates that their high-tech product needs cannot be satisfied by domestic production, and that the relevant processing trade accounts for only a small proportion overall. Both of these factors would restrict their economic development.

In Fig. 2.5c, most countries are distributed in the low-*VSD*, high-*IMS* Quadrant C, and the high-*VSD*, high-*IMS* Quadrant D. This distribution shows that the LT sectors remain the main body of transnational technology transfer with relatively unimpeded import and export trade of related products. This also indicates that the countries distributed in Quadrant D are strongly dependent on foreign trade both in domestic and international circulations. Most of these Quadrant D countries are EU member states with smaller economies and their NVC is heavily embedded in European RVC, forming a closely-knit economic community with intensive internal cooperation.

In Fig. 2.5d, most countries are distributed in the low-*VSD*, low-*IMS* Quadrant A, and the low-*VSD*, high-*IMS* Quadrant C. We know that P sectors mainly includes agriculture, forestry, fishery, animal husbandry and mining. These industries possess characteristically short production chains, so participation in international circulation is relatively low. Some countries (such as Malta) suffer from low domestic resources, and need to import large amounts of resource products (such as food and minerals) to maintain normal domestic productions, consequently giving them high *IMS*. Ireland is located at the top right of Quadrant D because it is the largest exporter of dairy and beef in Europe, and its agri-food is one of its most important domestic manufacturing industries.

2.4.2 Significance of Dual Circulation

China's industrial added value increased from 23.5 trillion yuan to 31.3 trillion yuan during the "13th Five-Year Plan" period, and its contribution to the world's manufacturing industry was close to 30%. From 2010 to 2020, China has become the world's largest manufacturing country for 11 consecutive years, and it can be said to be a "world manufacturing giant". At the same time, the average growth rate of China's high-tech manufacturing sectors added value reached 10.4%, indicating that China is transforming into a "world manufacturing power". However, there is still a big gap in the development level of high-end technology between China and the United States, and China's huge population base hinders the speed of economic development—of course, also represents a huge domestic consumption capacity for final products. Besides, China' complete industrial system represents a strong ability to transform domestic intermediate goods, which makes its market potential unpredictable. According to data reported by the China Development and Reform Commission, China's total social consumer goods totalled 40 trillion yuan for the first time in 2019, with China surpassing the United States to become the world's largest consumer goods retail market.

On the one hand, as the second largest economy in the world, China has a high proportion of domestically economic circulation, a complete domestic industrial chain, mature industrial trade network, and huge market potential. Chinese people's need for a better life can create huge domestic demand [15]. With its increased status in the international division of labor and its influence on the GVC, China is gradually losing the original advantage of low factor costs and the momentum in the internationally economic cycle. On the other hand, China's four-decade-long high-speed development is inseparable from the scale and intensity of its international circulation, through which China was able to enhance its economic prowess while it exchanged resources with foreign markets. Externally, while China's economy has steadily improved, the global industrial chain has also undergone strong shocks and adjustments. For example, the digital technology has reduced labor costs and boosted the reflux of labor-intensive industries from developing countries back to developed ones. The COVID-19 pandemic has only intensified the trend of decoupling from China in some developed countries. In recent years, the overall sluggishness of GVC has also led to a worse external market environment for China [16]. In a word, the shift to a domestic cycle is the inevitable path for its current economic development, and stimulating the domestic economic cycle is a solution to its current dilemma in face of the unfavorable international political and economic environment in the post-pandemic era. The domestic industrial environment needs to be improved, by dint of an improved competition mechanism and flexible trade in domestic industries, so as to stimulate innovation momentum, boost domestic demand, and promote sustainable economic growth [17, 18].

In the face of an external environment characterized by rising protectionism, global economic downturn, and a shrinking international market, the Political Bureau of the Communist Party of China Central Committee propose that: China need to pool resources and concentrate on managing the country's affairs well, and give full play to the advantage of a huge domestic market, so as to accelerate the establishment of a "**Dual Circulation**" development pattern in which domestic loop plays a leading role while international loop remains its extension and supplement. From a realistic point of view, not all countries have the economic foundation to implement a dual circulation strategy. Looking at the history of global development, China today is highly similar to the United States at the turn of the twentieth century. Before entering the dual-circulation pattern, both the United States at that time and China today had access relatively well-developed local industrial chains and a stable and expansive inland market. After the transition to "dual-circulation" in 1913, the United States gradually formed a new paradigm of relying on its domestic circulation as the main factor, all the while benefiting from, but not subject to, international circulation. This shift allowed the United States to grow rapidly in spite of its adversities. Therefore, for China, a successful inward shift from its international circulation to a domestic circulation, and a realized dual-circulation economic development mode is a key step for China coming out of its present predicament, and transitioning from a big country to a major global participant.

2.4.3 Economic Meanings of Network-Based Dependency

In examining China's new "dual-circulation" development, experts and scholars have come to some important conclusions through well-grounded research. Yu believes that although China faces many challenges such as the escalation of Sino-US trade friction and the stagnation of multilateral cooperation, it nonetheless possesses many advantages to carry out dual circulation, including well-clustered domestic industrial chains, a sizable domestic market, and deep integration of GVC [19]. Li, et al. made the argument that as some developed countries show anti-globalization tendencies, China's manufacturing industry urgently needs to transition away from being passively embedded to the GVC [20]. Ding, et al. looked for general patterns of international or domestic circulation-oriented preference since the Reform and Opening-up, pointing out that at present, China's capital-intensive industries are mainly domestic-circulation oriented, while its labor-intensive industries are mainly international-circulation oriented [21]. Ma, et al. showed that China's industry is facing the combined risks of being stuck at the bottom of the value chain curve and the overall downward shift of the curve [22]. Xu, et al. argued that the "dual circulation" is a continuation of supply-side reform and emphasized that "the formation of a strong domestic market should be promoted" [23]. These scholars have argued for the necessity and feasibility of "dual-circulation" strategy from different perspectives, but few have directly studied the international dependence in economic circulations, Chinese or otherwise, likely as a result due to limitations in research scope or differences in historical backgrounds.

As a large-scale economy, China will inevitably cause impacts to its NVC, and even RVC and the GVC, as it shifts its economic center of gravity, and adjusts its internal and external driving forces. Under this background, it has become vitally important to study the degree of Chinese industrial sector's participation in domestic and international circulations, that is, the degree of dependence on foreign trade. Grassman proposed to measure foreign trade dependency through the ratio of total import and export to GDP of a country or region within a given period [24]. Although his method has been widely applied, there are some doubts regarding its ability to adequately comprehensively assess the extent of an economy's foreign dependencies [25, 26], i.e., the question of "who produces for whom" [27]—in other words, it did not take into account the intermediate goods that have become ever more important in global trade[28]. Fortunately, the GVC value-added trade accounting can make up for this shortcoming and accurately calculate the degree of dependence on foreign trade, which is mainly based on the ICIO model [29–31]. For instance, Belke and Wang used the value-added trade volume (the sum of value-added exports and value-added imports) instead of the customs trade volume to study the influencing factors of external dependence [32]. Lin used an international input–output model to calculate South Korea's overall foreign trade and Chinese trade dependence, and reached the conclusion that South Korea's economy is vulnerable to external negative impacts through its value-added foreign trade dependence [33]. Larudee recalculated Mexico's dependence on foreign countries based on the input–output model, and found that Mexico's dependence on foreign crops has actually increased year by year [34]. Liu analyzed China's foreign dependence and mapped its spatial distribution based on the input–output data from 1995 to 2011, which showed that China has the highest degree of dependence to the United States [35]. These studies were conducted in large part due to the realization of gaps to the traditional foreign dependency models. Through applying the new model, scholars sshave also readjusted previous estimates. However, there research did not pay close attention to the brokerage role played by the industrial sectors in the GVC.

All in all, the netwosssrk-based measurement of dependency is a good supplement to previous studies in this area. It is characterized by focusing on the production role played by the industrial sector on the GVC from the perspective of SNA, and simultaneously measuring the impacts of globally vertical specialization on the internal and external loops of the economy.

2.5 Summary

The GIVCN model can be used as the general analytical framework to interpret and illustrate various types of international and domestic trade. According to the affiliation on the national level and sectoral level, trade process can be divided into four types with economic implication. Also, these trade types can be embodied in both forms of IO table and network model, bridging the ICIO data and complex network structure.

For the purpose of distinguishing the different medium roles that industrial sectors play on the GVC, we introduce five types of *TBPs* to enumerate all the possible combinations and provide a set of calculation formula to quantify their ratios. In detail, a given industrial sector's *TBPs* depend on:

(1) where (domestic or foreign markets) its inputs are gotten from;
(2) where (domestic or foreign markets) its outputs are sent to;
(3) whether its upstream and downstream sectors belong to the same nation or not.

The first two "where" can have trade classified into four basic types: inland trade, international trade, import trade, and export trade. And the "whether" can have international trade further divided into international trade I and II, the latter of which is better to embody global economic integration. One thing to note here is that inputs obtained in domestic markets are possibly from consumers themselves, and this part is also contained within inland trade, import trade, and export trade.

Limitations still exist in the analytical framework of this chapter. One of them is that there is no discrimination between the vertical and horizontal trades in the application of *TBPs*. For instance, horizontal trade has been here incorporated into four types of international trade except for inland trade; hence, *TBPs* can't be directly used to measure vertical specialization at present. To alleviate this problem, we design two indices based on *TBPs*, i.e., *IMS* and *VSD*, to illustrate how much a given sector/economy relies on foreign trade when it participates in the vertical specialization. Also, we believe they are useful to quantify and compare the dependence on both domestically and internationally economic circulation.

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Chapter 3
Probe the Industrial Linkages Reasonably and Effectively

3.1 Introduction

As Porter put it, the value chain represents the value-adding process at every stage of production, from R&D and design down to delivery and customer service. This process may just happen within a country or a region, but it is becoming increasingly international and sophisticated as a result of globalization nowadays. It is, thus, a bold attempt to measure the industrial sectors' position as well as the consequent function on the GVC.

To tackle this problem, scholars from world economics have offered definitions and frameworks based on the ICIO database. Fally proposed two separate measures, namely "the number of stages required for production" and "the number of stages between production and final consumption" [2], which constitute the theoretical basis of upstreamness and downstreamness respectively. Antràs, et al. defined the production length as the number of stages on a value chain, which now becomes an indispensable tool to assess the degree of specialization of countries [3]. Antràs [4] and Miller [5] adopted upstreamness and downstreamness to measure a sector or country's position in a global production process from different angles. Specifically, Antràs and Chor argued that countries and country-industries far removed from final demand also tend to be far removed from the use of primary factors in production due to the reduction in trade costs and the increase in the share of world spending on services [6]. The key trait of the above studies is that their measures start from a sector's gross outputs and are defined as absolute ones, based on the Average Propagation Length (APL) proposed by Diezenbacher, et al. [7]. By contrast, Wang, et al. defined the average production length of a value chain as the average number of times of value-addition created by the production factors in a national sector. They considered "production position" a relative concept to be determined by comparing production length measured by forward and backward inter-industry linkages [8]. Some scholars, inspired by these frameworks, applied new methods to enhance the validity and practicality, such as Muradov's weighted average number of production stages [9].

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There is no doubt that the measurement of length and upstreamness /downstreamness contributes to the studies of vertical specialization. In our opinion, network-based algorithms and indices will surely help understand the industrial sector's position and function in consideration of the network-form architecture of GVC. However, only a few studies, including those of Mesa-Arango, et al. [10] and Cingolani, et al. [11], adopted this method to analyze countries' positions in the global value networks till now.

The dynamic of value chain acts like that of a supply chain in essence [12], because value stream can be regarded as a material flow after converting into cash. Against this background, we are enlightened by solutions for the bullwhip effect. This chapter makes three contributions to the literature. Firstly, an optimal path algorithm is presented to embody the non-linearly relations in the economic system and is used to measure the flow efficiency of inter-industry intermediate goods on the GVC. Secondly, we develop three path-based indices to measure the independence and relative position of sectors according to the nature of closeness centrality. Thirdly, our methodology can be and already is applied to carry out an empirical analysis of the topological structure of the globally economic system.

3.2 Methodology

Although many network-based measures have been proposed for weighted networks, few of them can process those networks made up of edges with similarity weight, just like GIVCN model. On the one hand, from the view of the network, all edges have a strength naturally associated with them that differentiates the number of intermediate goods, which has been operationalized as weight. On the other hand, based on IO theory, Leontief and Ghosh models are widely used to quantify the length or position of production networks [13].

In this section, we propose a network-based framework that relies on the first principle to detect inter-industry relevance. In detail, the information of sector's function and inter-industry relative position on the GVC is already embedded in the topological structure of GIVCN model, so the first thing is to redefine the optimal path to reflect the propagation process of intermediate goods on the premise of considering the properties of the economic system.

3.2.1 Path Issue in Similarity-Weight Network

Both ***Betweenness and Closeness Centrality*** rely on identifying optimal paths, which in the case of binary data can be unproblematically identified as shortest paths. But if the edges are weighted, there are a variety of possibilities in assessing the optimality of a path [14]. In other words, there is no one-size-fits-all generalization for weighted networks, and it all depends on what kinds of network processes we are studying.

For many researchers studying ICIO networks, the most common style they used is to binarize the weighted edges and run the traditional ***Breadth-First-Search (BFS)*** algorithms, in consideration of the computational intension. Besides, someone defined the optimal path as the maximum shortest path length between any two pairs [15], and took the minimum shortest path length based on taking the reciprocal of weights. They did so in part because they wanted to obtain the metric of consecutive paths, which is inappropriate.

3.2.2 Revised Floyd-Warshall Algorithm

In network science, path plays a central role, and many network-based indicators are developed around it. The ***Shortest Path*** between nodes i and j, also known as ***Distance*** or ***Geodesic Path***, is the path with the fewest edges linking to them, as denoted by d_{ij}. If there is no such path between them, it means $d_{ij} = \infty$. Besides, multiple shortest paths of the same length d_{ij} are possible to be found. In general, ***Floyd-Warshall Algorithm (FWA)*** as a classical BFS algorithm is used to find all inter-node shortest paths in a recursive way, which means it compares all possible paths through the network between each pair of nodes by incrementally improving an estimate on the shortest path until the estimate is optimal [16]. The core formula of FWA is:

$$d_{ij}^{(k)} = \min_{i,j,k \in \{1,2,\ldots,N\}} \{d_{ij}^{(k-1)}, d_{ik}^{(k-1)} + d_{kj}^{(k-1)}\}(i \neq j) \tag{3.1}$$

Equation (3.1) works by first computing $d_{ij}^{(k)}$ for all pairs of source-to-sink nodes for $k = 1$, then $k = 2$, etc. This process continues until $k = N$, and we have found the shortest path using any intermediate nodes.

Nevertheless, in weighted networks, particularly those with similarity weights such as the IO system, we could use neither the objective function of minimization nor the iterative accumulation of paths. In other words, geodesic-based indicators don't work for similarity-weight network anymore. This is because if this is taken only as a maximization problem, the least efficient channel of intermediate goods will inevitably lead to an infinite result. Hence, a fast and highly effective restraining algorithm is needed to solve this operational problem about tracking network flow. It is possible to create a method to reconstruct the actual path between any two endpoint nodes with simple modifications to FWA, just like what scholars have done [17].

First of all, it is time to back to the realization that the nature of dissimilarity weight and similarity weight. Enlightened by the Bullwhip Effect, we take quantitative relations of each relevant step and the length of path as key factors into consideration before searching optimal paths in the similarity-weight network. Taking the simplest example that there is one more node k in addition to nodes i and j, the product of edge weights $w_{ik}w_{kj}$ is used as a positive measure for effectiveness, as well as the summation $w_{ik} + w_{kj}$ as the negative measure. On the one hand, their product helps to amplify the influence of every single redundant step. On the other hand, summation counts in the number of relevant steps and more steps will result in larger summation. We, therefore, divided $w_{ik}w_{kj}$ into $w_{ik}+w_{kj}$ and named the result the ***Relevance Path Length (RPL)***. After transformation, $RPL_{ij} = 1/\left(1/w_{ik}+1/w_{kj}\right)$. Different from edge weights that stand for the monetization of intermediate goods from sectors i to j, the *RPLs* in GIVCN model are not used to measure inter-industry relations in economic terms, but instead the gauge of spreading effectiveness of all paths. In sum, one *RPL* between nodes i and j is mathematically equivalent to the reciprocal of the summation of the relevant edge weights' reciprocals, namely:

$$RPL_{ij} = \left(\frac{1}{w_{ik}} + \frac{1}{w_{kl}} + \cdots + \frac{1}{w_{lj}}\right)^{-1} = \left(\sum_{i,j,k,l\in\{1,2,\cdots,N\}} w_{kl}^{-1}\right)^{-1} \tag{3.2}$$

where w_{kl} is the weight of an edge on the path connecting nodes i and j, and the exact number of RPL_{ij} is up to that of possible paths delivering the inter-industry intermediate goods. This formula is similar with parallel resistors. As for the self-loops in some networks, e.g. the ICIO network, $RPL_{ii} = w_{ii}$ according to the Eq. (3.2).

Then, to find the optimal *RPL*, the ***Strongest Relevance Path Length (SRPL)*** is proposed, which is the synthetic gauge of spreading the effectiveness and efficiency of a given path. For this purpose, we put forward the ***Revised Floyd-Warshall Algorithm (RFWA)***[1] as an iterative and convergence algorithm based on operations research:

$$SRPL_{ij}^{(k)} = \max_{i,j,k\in\{1,2,\ldots,N\}} \left\{ w_{ij}^{(k-1)}, \frac{w_{ik}^{(k-1)} w_{kj}^{(k-1)}}{w_{ik}^{(k-1)} + w_{kj}^{(k-1)}} \right\} \tag{3.3}$$

where $SRPL_{ij}^{(k)}$ is the *SRPL* between nodes i and j, representing the IVC with the maximum efficiency and effectiveness. If it is greater than $w_{ij}^{(k-1)}$, we keep the record as it is, otherwise just equalize it to $w_{ij}^{(k-1)}$. When the $SRPL_{ij}^{(k)}$ happens to be equal to $w_{ij}^{(k-1)}$, it means the optimal path is just the most direct one between nodes i and j. In other words, there is no need to take even one more step via another node. Due to the nature of *RPLs*, the selected *SRPL* converges when the maximum is reached. Given that the self-loops contain non-negligible topological information, such as self-consumption of industrial sectors in the ICIO network, we, therefore, incorporate this edge into the comparison process, enabling the source node to be the same as the sink node of certain *RPLs*.

RFWA with parameter-free property is self-explanatory whereas the running time scales as network size exponentiated. Luckily, the number of industrial sectors is not very large in the current ICIO database; hence, we just need to handle GIVCN

[1] Note that, the RFWA with parameter-free property is self-explanatory whereas the running time scales as network size exponentiated. If it took too long to compute, we can change the RFWA with the Shortest Path Faster Algorithm (SPFA), which will greatly shorten the operation use time.

models with thousands of nodes and millions of edges in reasonable running times on a typical desktop workstation. As international trade data volume up, we develop a local optimization algorithm for realizable computation.

We abstract two sorts of matrix from any given similarity-weight network based on RFWA, in which $SRPL'$ is a numerical matrix, and $SRPL''$ is a string matrix:

$$SRPL' = \begin{pmatrix} SRPL_{11}^{(N)} & \cdots & SRPL_{1N}^{(N)} \\ \vdots & \ddots & \vdots \\ SRPL_{N1}^{(N)} & \cdots & SRPL_{NN}^{(N)} \end{pmatrix} \tag{3.4}$$

$$SRPL'' = \begin{pmatrix} Str_{11}^{(N)} & \cdots & Str_{1N}^{(N)} \\ \vdots & \ddots & \vdots \\ Str_{N1}^{(N)} & \cdots & Str_{NN}^{(N)} \end{pmatrix} \tag{3.5}$$

where $SRPL_{ij}^{(N)}$ is the value of the $SRPL$ between nodes i and j after global searching, and $Str_{ij}^{(N)}$ embodies the concrete details of this path in sequence by a string, which begins from the very first character with the name of node i and ends with the very last character with the name of node j.

The empirical analyses of this chapter and next chapter are based on these two sorts of matrices, so we share the results of 56-sector and 4-category version on the website.

3.2.3 Theoretical Basis of SRPL in GIVCN Model

By Porter's definition in 1985, an IVC is a physical representation of the various processes in producing goods (and services), starting with raw materials and ending with the delivered product. It is based on the notion of value-added at the stage of production. Wasilly Leontief's IO table, published in the 1950s, estimated the relative importance of every individual link in industry-level value chains. In recent decades, in pursuit of better efficiency and profits, multinational enterprises locate a lot of activities, such as research, development, design, assembly, production of parts, marketing and branding, in different countries around the globe. It is the epitome of comparative advantage in the context of globalization, so here comes the concept of GVC. Furthermore, analytical tools stemming from complex networks have been proven to be very effective in the analysis of GVC, so the *SRPL* is proposed to find the optimal path for intermediate goods propagation based on theories and models as shown in Fig. 3.1.

It should be noted that the RFWA uses the experience of gravity model in the field of international economics for reference. Gravity models are often used in social science to predict and describe certain behaviors that mimic gravitational interaction

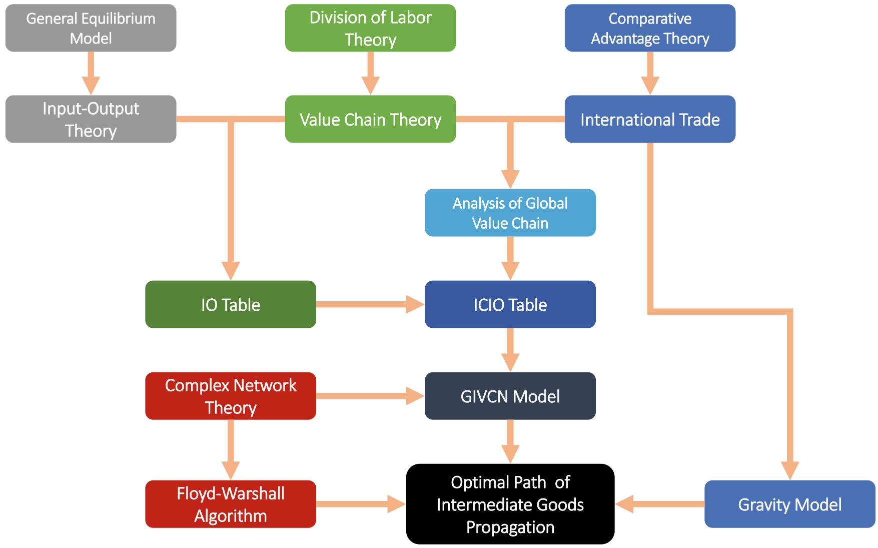


Fig. 3.1 Theoretical basis of SRPL

as described in Isaac Newton's law of gravity. Generally, the models employed in social science contain some elements of mass and distance, which leads them to the metaphor of physical gravity. A gravity model can help estimate the volume of flows of, for example, goods, services, or people between locations. This can be the population movement between cities or the volume of trade between countries [18].

The gravity model of international trade in international economics, first introduced in world economics by Walter Isard in 1954 [19], can predict, in its traditional form, bilateral trade flows based on economic sizes and distance between two units. The basic model for trade between two countries i and j takes the form of

$$T_{ij} = \frac{A \times Y_i \times Y_j}{D_{ij}} \tag{3.6}$$

where A is the constant, T_{ij} stands for trade flow, D_{ij} the distance, and Y_i, as well as Y_j, stands for the economic dimensions of the countries that are being measured, often using GDP as a measure.

In econometric applications, this model is customary to specify

$$T_{ij} = \frac{A \times Y_i^a \times Y_j^b}{D_{ij}^c} \tag{3.7}$$

where a, b and c as adjustable parameters are used to optimize the approximation estimation of the model.

Whereas the fundamental difference between RPL and many frameworks based on gravity law is: RPLs in the similarity network reflect how inter-node linkages, instead of nodes themselves, derive commuting, trade, and mobility fluxes. In other words, some nodes with specific metrics determine the character of edges and create them, finally forming a network structure; in other cases, it is edges that provide exiting meaning to nodes. This explanation makes it seem like a chicken-egg problem, only it is not. We can image how many communities are built near the freeway in recent years, just like the freeway is the lifeblood to cities' development.

In the field of economics, for instance, customers on the demand-side ask for goods and service from the supply-side, and then activities of production and delivery are self-organized according to market rules, which means the synthetic division of industrial sectors is essential to boost the national economic statistics, not based on natural occurrence. We believe that the inter-industry quantitative relation reflected by the IO value is better to be the gauge of the value-added process than the sector itself. Intuitively, we decide to measure the positive transfer probability with edge weight instead of node strength. Also, we notice that the number of passing edges contains the information of distance decay in an economic sense.

Many similar studies didn't take the length of the value chain into account, making them overly qualitative or even groundless. Then, the formula of gravity model sheds light on the principle of our BFS algorithm. That is to say, an intermediate goods transfer path is directly proportional to the relevant IO relations and inversely proportional to the length of the value-added process. $Y_i \times Y_j$ is then replaced with $w_{ik}^{(k-1)} w_{kj}^{(k-1)}$ to measure the influence from the industrial structure, and D_{ij} with $w_{ik}^{(k-1)} + w_{kj}^{(k-1)}$ to provide distance information (the denominator of RPLs of two or more steps incorporates the number of relevant steps after employing fractionation, and increasing steps yield more transaction cost as well), explaining the dynamics of intermediate goods transferring from upstream sectors to downstream ones (sometimes the two are the same). **As a result, *SRPL* based on RFWA bears two economic meanings: one is to find all the optimal propagation paths of intermediate goods with both higher IO relation and lower transaction cost between any pairs of sectors (including self-loops); another is to measure the inter-industry (maybe intra-industry) relation strength from the standpoint of an integrated value chain.**

Note that, as the gravity model cannot accurately predict flows, there is large room for improvement in our method. First, it is necessary to set up a constant, the formula of *RPL* remains to be tailored to the actual economic data in our future studies, for example:

$$RPL_{ij} = P \times \left(\frac{1}{w_{ik}^{\alpha}} + \frac{1}{w_{kl}^{\beta}} + \cdots + \frac{1}{w_{lj}} \right)^{-1} \tag{3.8}$$

where P represents the constant waiting for further definition, α, β and χ are positive adjustable parameters measuring how different IO relations produce effects on the value chain.

3.2.4 Computation of SRPL in Consideration of Self-loops

The following example is to explain how we pick an inter-node *SRPL* from various existing paths. As shown in Fig. 3.2a, b, a five-nodes network is designed with the purpose to find the *SRPL* paths between any pair of source and sink nodes, and we then provide detailed explanation through the source node A and the sink node C.

For illustration, this network is split into 12 interconnected weighted paths as in Fig. 3.2c; the number of steps from A to C are 1, 2, 2, and 3. Intuitively, the first path directly connecting A and C is the shortest without regard to the adhering weights, but it may not be the optimal path to pass on intermediate goods in GIVCN model. So every path's *RPL* is calculated to find the *SRPL*. By comparing *RPLs* in Fig. 3.2d, the following phenomena shows up:

Firstly, the *RPL* of path $A \rightarrow C$ is bigger than that of $A \rightarrow B \rightarrow C$ because one more step brought by broker B blocks the spread of information, even though the second step owns a better effect. It is easy to prove that if the weight of any part of an indirect path is no more than the direct one, its *RPL* will not be *SRPL*.

Secondly, as the weaker step's spreading effect goes up, the RPL of path $A \rightarrow D \rightarrow C$ exceeds that of $A \rightarrow B \rightarrow C$, even though the total weight of all paths is the

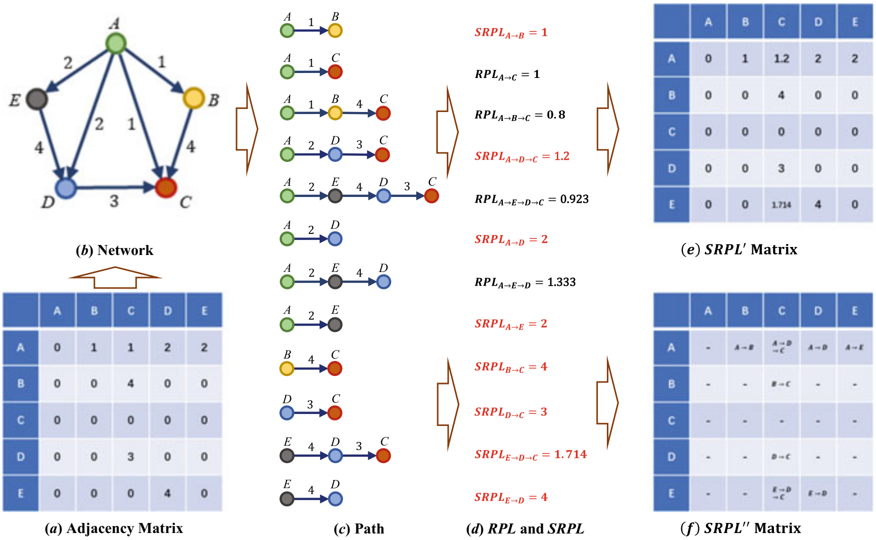


Fig. 3.2 How to select an inter-node SRPL

same. For instance, if the edge weights represent the capacities of pipes, the optimal paths hinge on the weakest link in the path.

Thirdly, the RPL of path $A \rightarrow D \rightarrow C$ is also beyond that of $A \rightarrow E \rightarrow D \rightarrow C$, the reason for which is similar to the first case.

Finally, by repeating the above process, we will figure out all the SRPL paths in this five-nodes network and get a numerical matrix SRPL$'$ and a string matrix SRPL$''$, which are as shown in Fig. 3.2e, f. Although all the rest of SRPL paths are the shortest ones linking nodes, it is sure to find more of them with the same situation of path A $\rightarrow$ D $\rightarrow$ C in other networks.

Why are some indirect connect such as path $A \rightarrow D \rightarrow C$ even more effective than those direct ones? We attempt to answer this question employing SNA. Considering the synthetic effect of structural holes [20] and the strength of ties [21], we believe that **the optimal paths in ICNs, even the most direct ones, carry inter-industry intermediate goods with limited strong relevance, rather than lesser weak relevance.** So it suffices to say that RFWA can figure out all the inter-industry SRPLs combining propagation efficiency and effectiveness of intermediate goods. Since the bullwhip effect will be automatically eliminated under market regulation, we argue, from a global perspective, that irrespective of whether it is the value stream or the material flow that is between specific upstream and downstream, industrial sectors tend to propagate along the SRPL, instead of expanding randomly.

Because of the nonnegligible importance of the self-loop's function to many complex network analyses, another group of examples is taken to describe the impact of self-loop on an inner-node SRPL, as shown in Fig. 3.3.

Self-loop looks like the most direct path to itself, but not necessarily the optimal one. If the strong linkages outside this node constituting a closed-loop path are in relatively low number, as shown in Case 1 A $\rightarrow$ B $\rightarrow$ C $\rightarrow$ A, the SRPL maybe not its self-loop. Otherwise, inner-node SRPL is more likely to be the self-loop with an increasing number of relevant paths outside this node, even though only one link is weaker as shown in Case 2 A $\rightarrow$ A.

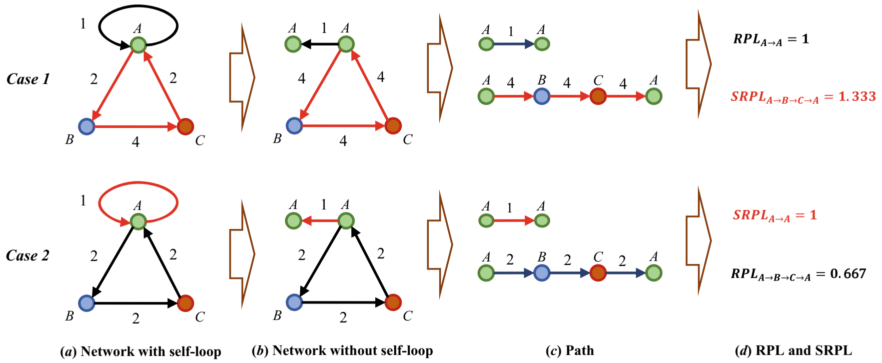


Fig. 3.3 The impact of self-loop's weight on inner-node SRPL

SRPL method has yielded widely varying measures and interpretation about the comprehensive relations between pairs of nodes because this optimization idea considers not only direct and indirect steps linking the source node and sink node, but also more restricted conditions, i.e., stronger linkage as well as fewer steps, which are both crucial to the final transmission efficiency of various flows.

3.3 Empirical Analysis: Fragments of GVC

Motif analysis is usually applied to the investigation of huge network structures, such as transcriptional regulatory networks, gene networks, food webs [22, 23], etc. Although the topological structure of GVC is smaller than those huge ones and relatively well understood due to extensive study by economists, its microstructure is still not clear. At the smallest scale, we can divide the basic composition of GVC into three sorts of motifs, which are ***Single-Tuple Motif*** (nodes and industrial sectors), ***Two-Tuple Motif*** (dyads and IO relations), and ***Triple-Tuple Motif*** (triad and *TBPs*).

3.3.1 Single-Tuple Motif

At the first step, we wonder the occurrence frequency of nodes in the string matrix of *SRPL*, which fall in four categories of industrial sectors or 44 economies (including 43 countries/regions and ROW). It is another representation of the betweenness centrality of nodes, which is based on the time that nodes appear on specific paths rather than paths passing through specific nodes.

According to the statistics on single-tuple motifs (see Fig. 3.4), there is no obvious change in the general proportion of occurrence frequency from 2000 to 2014. On the level of industrial sector, the proportion of the agriculture and mining sectors remains virtually unchanged, and that of services has been on the rise, eroding the part of manufacturing. On the level of the country, Germany has the most occurrences, followed by the United States. It should be noted that, in the year of 2010, the United States has the lowest value among the given four years, and Germany is at its highest, indicating that the former did not recover from the Subprime Crisis, and the latter was playing an additional part once belonged to the former on the GVC.

3.3.2 Double-Tuple Motif

In the second step, we wonder the occurrence frequency of dyads (pairs of nodes and edges with direction and weight between them) in the string matrix of *SRPL*, which are 16 pairs of four-sector categories or 1936 pairs of economies. Accordingly, it is another representation of the betweenness centrality of edges, which is based on

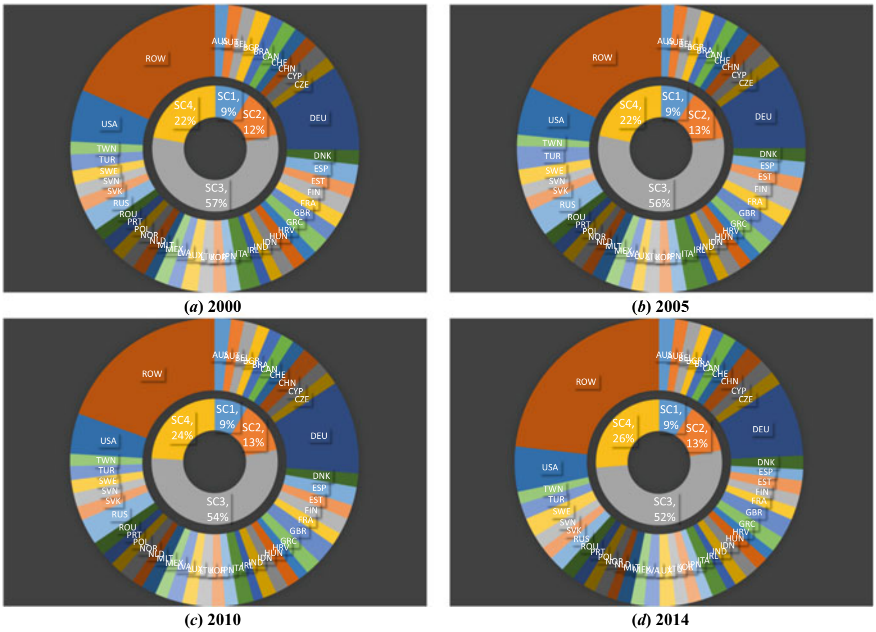
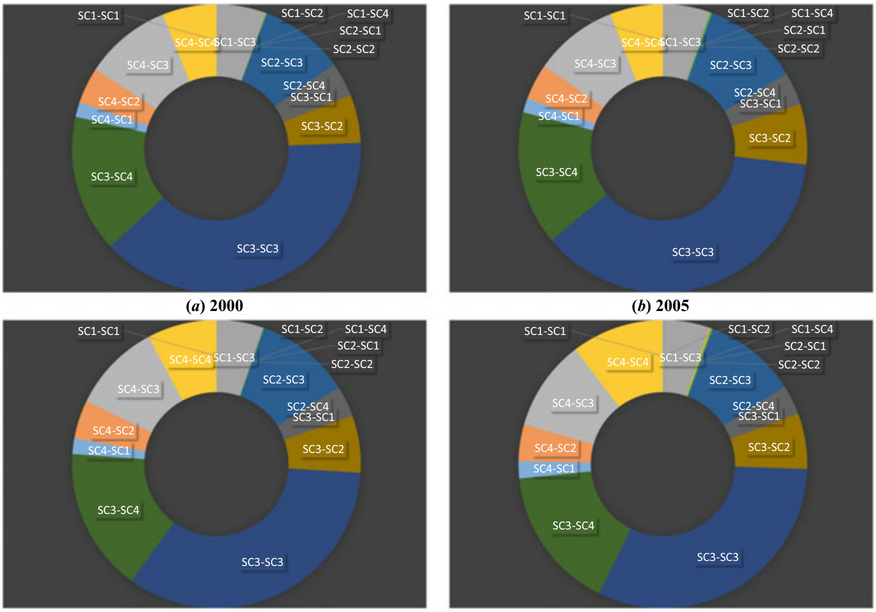


Fig. 3.4 Single-Tuple motifs on the national level and sectoral level in GIVCN-WIOD2016SC4 Models

the time that edges appear on specific paths rather than paths pass through specific edges.

According to the statistics on double-tuple motifs on the level of industrial sector as shown in Fig. 3.5, it is obvious that the most important ICIO relation is inside the manufacturing itself (SC3 $\rightarrow$ SC3), followed by SC3 $\rightarrow$ SC4, SC2 $\rightarrow$ SC3, SC4 $\rightarrow$ SC3, SC4 $\rightarrow$ SC4, SC3 $\rightarrow$ SC2 and SC1 $\rightarrow$ SC3 which are nearly all closely related to the manufacturing. Therefore, there is no doubt that the micro foundation of GVC is manufacturing oriented ICIO relations. Besides, although services still retain a strong symbiotic relationship with manufacturing, intra-services relation is increasingly important, even beyond several manufacturing-centered ones, which means some emerging formats within the services have begun to break away from absolute dependence on manufacturing. Relatively speaking, no matter the agriculture-centered relation or intra-agriculture relation is becoming less and less important to the whole economic system.

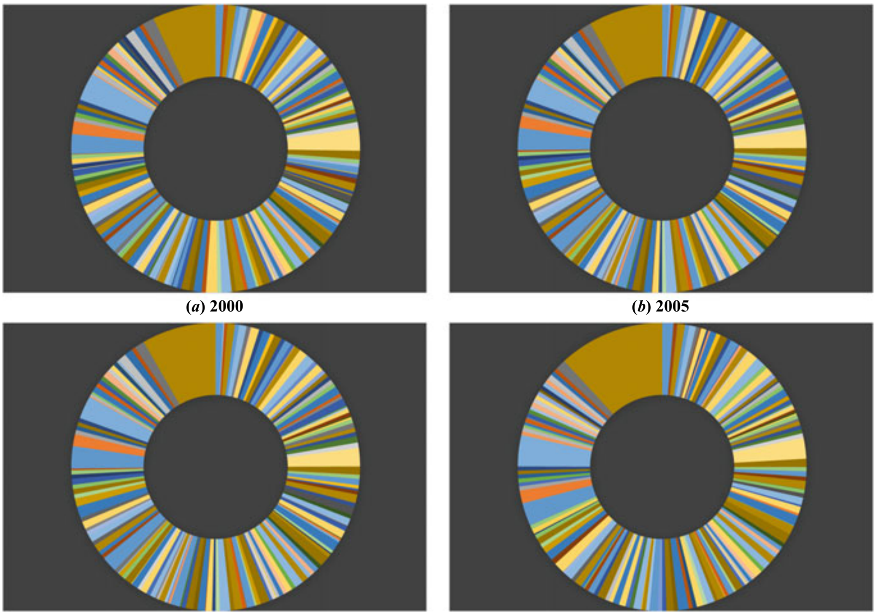
As for economies, there are three significant features from Fig. 3.6 and Table 3.1. Firstly, the intra-ROW IO relations are becoming more crucial than ever before, reflected by the absolute quantity (the occurrence frequency of ROW $\rightarrow$ ROW in all the double-tuple motifs went up from 9868 in 2000 to 17,472 in 2014) and relative ratio (the occurrence rate went up from 7.08% in 2000 to 11.85% in 2014), which means the developing countries have experienced rapid growth in recent years and gradually established their economic status on the GVC. Secondly, some domestic



(*a*) 2000 (*b*) 2005

(*c*) 2010 (*d*) 2014

Fig. 3.5 Double-Tuple motifs on the sectoral level in GIVCN-WIOD2016SC4 models



(*a*) 2000 (*b*) 2005

(*c*) 2010 (*d*) 2014

Fig. 3.6 Double-Tuple motifs on the national level in GIVCN-WIOD2016SC4 models

Table 3.1 Top 10 pairs of Double-Tuple motifs on the national level in GIVCN-WIOD2016SC4 Models

Rank	2000		2005		2010		2014	
	Dyad	Num.	Dyad	Num.	Dyad	Num.	Dyad	Num.
1	ROW → ROW	9868	ROW → ROW	12,141	ROW → ROW	14,007	ROW → ROW	17,472
2	ROW → DEU	4399	ROW → DEU	3770	ROW → DEU	4646	ROW → DEU	5170
3	DEU → ROW	3498	USA → USA	3664	DEU → ROW	3576	USA → USA	3777
4	USA → USA	3122	DEU → ROW	3020	USA → USA	3117	DEU → ROW	3448
5	USA → ROW	1996	RUS → RUS	2582	ROW → USA	2589	USA → ROW	2120
6	RUS → RUS	1901	USA → ROW	1960	RUS → RUS	2408	AUS → AUS	1856
7	ROW → USA	1836	TUR → TUR	1911	USA → ROW	2162	SWE → SWE	1808
8	GRC → GRC	1750	GRC → GRC	1750	DEU → RUS	2032	GRC → GRC	1750
9	LUX → LUX	1744	LTU → LTU	1738	GBR → GBR	1939	GBR → GBR	1747
10	BGR → BGR	1576	ROW → USA	1664	AUS → AUS	1922	LVA → LVA	1738

and international IO relations are higher than the others, such as ROW → DEU, DEU → ROW, USA → USA, etc., indicating that Germany has established a close trade network with many countries and played a key role in promoting the circulation and value-added process of intermediate products worldwide. Relatively speaking, the United States is more inclined to enhance its internationalization ability through the integration of domestic value chains, although its two-way relationship with ROW is also frequent. Thirdly, some medium-scale economies have performed powerful cohesive functions through their domestic value chain integration in recent years, such as Australia, Switzerland, Greece, United Kingdom, and Latvia, etc.

3.3.3 Triple-Tuple Motif

In the third step, we wonder the occurrence frequency of 5 sorts of triads based on the concept of *TBPs*, which can effectively and simply reflect the microstructure of GVC. If we compare the GVC to DNA, the *TBPs* will be its base pairs. As we mentioned above, *TBP1* stands for inland trade (for instance, AUSS1 → AUSS3 → AUSS4), *TBP2* for international trade I (AUSS1 → AUTS3 → AUSS4), *TBP3* for import trade (AUSS1 → AUTS3 → AUTS3), *TBP4* for export trade (AUSS1 → AUSS3 → AUTS3), *TBP5* for international trade II (AUSS1 → AUSS3 → BELS3).

In detail, all the consecutive-three-strings fragments on all the *SRPLs* are first identified according to the concept of *TBPs*, and then statistics of triple-tuple motifs are examined according to the names of industrial sectors and economies. For instance, we can get S1 → S3 → S4 and AUS → AUS → AUS from AUSS1 → AUSS3 → AUSS4, S1 → S3 → S4 and AUS → AUT → AUS from AUSS1 → AUTS3 → AUSS4, etc. The frequency for all the possible combinations of triad on both the national level and sectoral level can be obtained under the circumstances of five *TBPs*. At last, we add up the same sort of *TBP* to produce new indicators named ***Cumulative Trade Brokerage Property (CTBP)***. Notice that, due to this cumulation process, only one set of *CTBPs* is obtainable.

The most obvious feature in Fig. 3.7 is the proportion of CTBP2, indicating it is rare that countries provide value-added services of intermediate goods for another one (i.e., they import intermediate goods from other countries and then export them to the same one after further processing). In contrast, it is the trend that countries also acquire industrial resources on the GVC through import and export trade (the ratio of both CTBP3 and CTBP4 is basically stable in one-third), and cooperate with upstream and downstream countries on the GVC (the ratio of CTBP5 is 23.44%, which shows a downward tendency during 15 years) to ensure the sustainable development of the global economic system (although there has been a certain degree of anti-globalization in recent years).

From the statistics of triads on the sectoral level (see Table 3.2), the most frequent triple-tuple motifs are based on the top 5 manufacturing and services, which once again certify that the manufacturing-related IVC links constitute the GVC as the most important microstructural basis. Since the year of 2000, the top 3 triple-tuple motifs

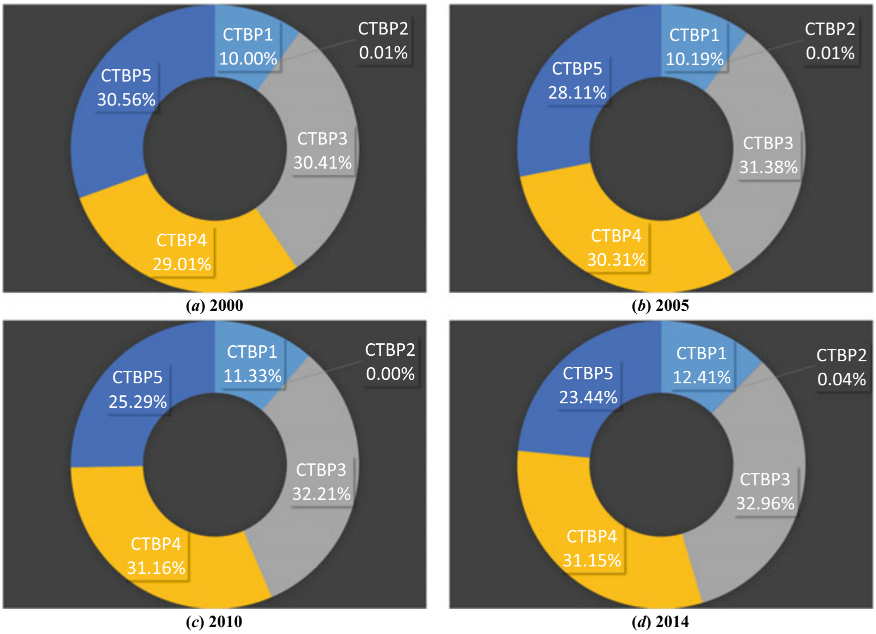


Fig. 3.7 Triple-Tuple motifs on the global level in GIVCN-WIOD2016SC4 models

are always SC3 → SC3 → SC3, SC3 → SC3 → SC4, and SC4 → SC3 → SC3. However, it is scarcely seen that three industrial sectors of a triad all belong to manufacturing appears less and less, reducing from 26,105 times in 2000 to 20,633 times in 2014. The rankings of the following triple-tuple motifs are constantly changing, and the overall frequency is higher than that in 2000. It is thus crystal clear that the global industrial structure has been in an ongoing process of adjustment. It will be further analyzed in subsequent research according to the classification of 56 sectors.

From the statistics of triads on the national level (see Table 3.3), double-tuple motifs have strong logical and quantitative relations with triple-tuple ones, but the former presents richer microscopic features of topological structure. In terms of serving developing countries, Germany's influence on the GVC was stronger than that of the United States in 2000. Then, the United States not only surpassed Germany but also began to provide high-value-added intermediate goods to developing countries through cooperation between its upstream and downstream sectors interiorly in 2005. Following Germany and the United States, China demonstrated its growing influence on developing countries around the world with a rapid development momentum in 2010. However, the United Kingdom and Switzerland surpassed China in this aspect in 2014. From the opposite perspective, countries such as Russia, the United States, Turkey, and Italy have made full use of industrial resources from developing countries through the continuous extension of GVC. Of course, more accurate analysis of the inter-country industrial partnership needs to be based on high-dimensional data,

Table 3.2 Top 10 pairs of triple-tuple motifs on the sectoral level in GIVCN-WIOD2016SC4 Models

Rank	2000		2005		2010		2014	
	Triad	Num.	Triad	Num.	Triad	Num.	Triad	Num.
1	SC3 → SC3 → SC3	26,105	SC3 → SC3 → SC3	26,256	SC3 → SC3 → SC3	21,573	SC3 → SC3 → SC3	20,633
2	SC3 → SC3 → SC4	13,150	SC3 → SC3 → SC4	12,734	SC3 → SC3 → SC4	13,621	SC3 → SC3 → SC4	13,233
3	SC4 → SC3 → SC3	9444	SC4 → SC3 → SC3	8843	SC4 → SC3 → SC3	10,336	SC4 → SC3 → SC3	9588
4	SC2 → SC3 → SC3	6932	SC3 → SC2 → SC3	7946	SC2 → SC3 → SC3	7767	SC3 → SC4 → SC4	9133
5	SC1 → SC3 → SC3	5736	SC2 → SC3 → SC3	7261	SC3 → SC4 → SC4	7523	SC4 → SC4 → SC3	8670
6	SC3 → SC4 → SC4	5575	SC3 → SC3 → SC2	6516	SC3 → SC2 → SC3	7350	SC3 → SC2 → SC3	7077
7	SC3 → SC2 → SC3	5377	SC1 → SC3 → SC3	6057	SC3 → SC3 → SC2	6331	SC2 → SC3 → SC3	5947
8	SC3 → SC3 → SC2	4989	SC3 → SC4 → SC4	5796	SC4 → SC4 → SC3	6322	SC2 → SC3 → SC4	5742
9	SC3 → SC4 → SC2	4495	SC2 → SC3 → SC4	5637	SC1 → SC3 → SC3	5335	SC1 → SC3 → SC3	5226
10	SC3 → SC3 → SC1	4210	SC3 → SC4 → SC2	4840	SC2 → SC3 → SC4	5000	SC3 → SC3 → SC2	4993

Table 3.3 Top 10 pairs of triple-tuple motifs on the national level in GIVCN-WIOD2016SC4 models

Rank	2000		2005		2010		2014	
	Triad	Num.	Triad	Num.	Triad	Num.	Triad	Num.
1	DEU → ROW→ ROW	1587	USA → ROW → ROW	1653	ROW → ROW → USA	2176	ROW → ROW → ROW	2778
2	ROW → RUS → RUS	1363	ROW → ROW → ROW	1577	DEU → ROW → ROW	2088	DEU → ROW → ROW	2302
3	ROW → ROW → ITA	1105	ROW → ROW → USA	1562	USA → USA → ROW	2007	ROW → ROW → DEU	2184
4	ROW → USA → USA	999	USA → USA → ROW	1456	USA → ROW → ROW	1952	USA → USA → ROW	1968
5	USA → ROW → ROW	989	DEU → ROW → ROW	1296	DEU → RUS → RUS	1860	USA → ROW → ROW	1854
6	ROW → ROW → ESP	856	ROW → RUS → RUS	1264	ROW → ROW → DEU	1753	GBR → ROW → ROW	1188
7	ROW → ROW → ROW	758	ROW → TUR → TUR	1132	ROW → ROW → ROW	1477	AUS → AUS → AUS	830
8	ROW → ROW → TUR	756	ROW → ROW → ITA	1072	AUS → AUS → AUS	874	ROW → ROW → ITA	786
9	GRC → GRC → GRC	702	DEU → RUS → RUS	768	CHN → ROW → ROW	872	SWE → SWE → ROW	740
10	LUX → LUX → LUX	697	ROW → USA → USA	759	ROW → DEU → RUS	832	CHN → ROW → ROW	738

so that complex value stream transmission mechanisms can be summarized at the micro-level.

3.4 Summary

This chapter designs an analytical framework according to the ***First Principle*** based on econophysics to redefine the propagation process of intermediate products on the GVC, optimizes the FWA, put forward the concept of *SRPL* and mined the strongest value conduction path between industrial sectors on the GVC network and upstream and downstream sectors. Contributions of this chapter are as follows:

(1) **Develop the optimal path algorithm and measurement in similarity-weight networks**. Many network-based measures have been proposed for weighted networks, but not like our GIVCN model. Most of the previous measures could not process those networks made up of edges with similarity weight. We introduce the *RPL* as a counterpart of paths in non-weighted networks to quantify the effectiveness of the value chain that intermediate goods passing through, which is mathematically equivalent to the reciprocal of the sum of the reciprocals of relevant edge weights. Then, we define the most optimal one among *RPLs* as *SRPL*, which boasts the most rapid transfer and the lowest distortion of information in similarity-weight networks. For this purpose, we put forward the RFWA to figure out all the inter-industry *SRPLs* combining both propagation efficiency and the effectiveness of intermediate goods. For example, in ICNs, the optimal paths carry inter-industry intermediate goods via a limited number of strong relevance, rather than lesser weak relevance.

(2) **Apply motif analysis on the micro-structure of GVC based on *SRPL* string matrix**. In general, the standard approach for complex network analysis is to conduct statistics of common properties, such as all kinds of centralities, clustering coefficient, network diameter, and entropy, etc., but they often fail to find the essential difference between different networks. In the case of this book, it is hard to analyze the whole GVC network, or even compare sub-networks made of industrial sectors within the same country because of the high network density and heterogeneity. In other words, the GIVCN model should be investigated with more precise and structure-sensitive methods. There is no doubt that one of the most prominent is motif analysis for its explanatory ability on the most basic network component. After decomposing the GVC into three types of motifs, we conduct statistics to see what happened to its micro-structure in the period from 2000 to 2014, which is different from other studies in the field of the world economy.

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Chapter 4
Find the Vital Industrial Sectors and IO Relations

4.1 Introduction

Centrality is one of the most important concepts in complex network analysis. Numerous measures have been developed, including betweenness and closeness [4], flow betweenness [5], eigenvector centrality [6], and random walk centrality [7], leading to implicit assumptions on how information flows in a network. This chapter examines the topology structure of the ICIO network through the centrality index based on the *SRPL*, identifies the network's internal critical industry value chain, and then measures the function of industrial sectors.

This analytical framework is split into three hierarchical classifications (see Fig. 4.1): ***Network Level***, ***Node Level***, and ***Edge Level***. Also, it uses three statistical methods that are algorithms based on the path and value of *SRPL* and simulations via removing edges in certain kinds of sequences. More importantly, we carry out empirical analyses in three terms, which are the measurement of the ICIO network, the source of the comparative advantage and their relations in the economic sense.

Comparative advantage is the economic reality describing the work gains from trade, which exists because individuals, firms, or nations have different factor endowments or technological progress. The GVC exactly stems from the comparative advantage of nations all around the world, and *SRPL* can be used to identify these important value chains from the ICIO network. It then becomes feasible to measure with *SRPL*-based indicators and forecast through simulation. As results, we can propose international trade policies from the perspective of econophysics.

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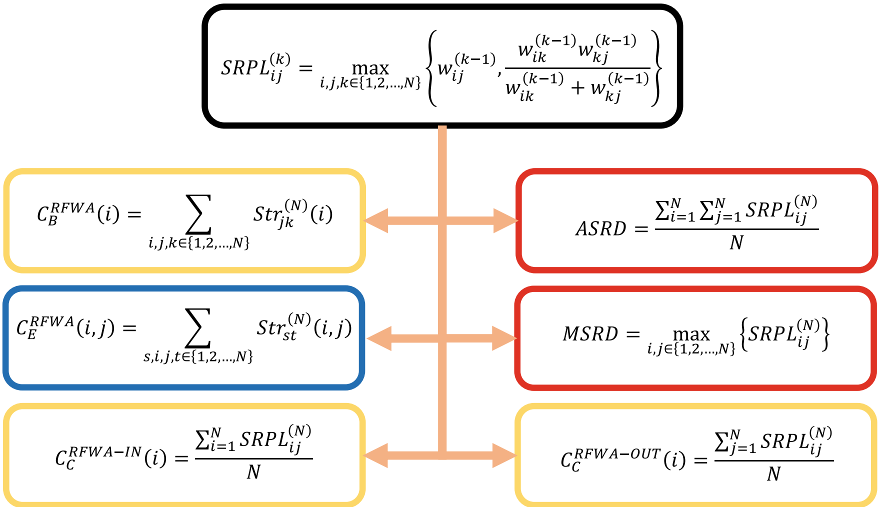


Fig. 4.1 Analytical framework based on SRPL. *Notes* Red border stands for the network-level indices, yellow border the node-level indices, and blue border the edge-level indices

4.2 Measurement

4.2.1 Average/Maximum Strongest Relevance Degree

In non-weighted networks, the ***Average Path Length (APL)*** of the whole network can be calculated via FWA, depicting the degree of separation of nodes. As a counterpart in GIVCN model, the average of $SRPL'$ matrix is chosen to measure the overall flow efficiency of the economic system, i.e., the ***Connectedness of Industrial Value Chain***. The ***Average Strongest Relevance Degree (ASRD)*** is proposed, namely:

$$ASRD = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} SRPL_{ij}^{(N)}}{N} \tag{4.1}$$

where $SRPL_{ij}^{(N)}$ is the *SRPL* between nodes i and j within the scope of the whole network. We allow for self-loops, and the denominator thus incorporates two parts, i.e., edges and self-loops.

$$N = N_e + N_s = N_n(N_n - 1) + N_s \tag{4.2}$$

where N_e stands for the number of normal edges, N_s for self-loops, and N_n for nodes.

Furthermore, to observe its impact on the uppermost branch of GVC, another measuring method named the ***Maximum Strongest Relevance Degree (MSRD)*** is here designed, namely:

$$MSRD = \max_{i,j \in \{1,2,\cdots,N\}} \left\{ SRPL_{ij}^{(N)} \right\} \quad (4.3)$$

In a mathematical sense, *MSRD* is the highest value in $SRPL'$ matrix, and there exists a complicated process of intermediate goods propagation behind it. Different from *ASRD*, *MSRD* only depends on a single value chain that covers the most significant spreading effect across industrial sectors—just like a threshold value of the ***Compactness of Industrial Value Chain***. Correspondingly, both upstream and downstream sectors are respectively the source and sink nodes of this max-*SRPL* path. Under normal circumstances, the random small-scale industrial fluctuation is not supposed to shake the closest economic connection in the global or regional economic system, and this kind of special IVC will in turn drive the development of all relevant industrial sectors and even the entire industrial network.

As previously discussed, the region of inter-country inter-industry use and supply in the ICIO table is taken to build GIVCN models. Furthermore, if this network corresponds to the entire global production system, sub-networks composed of all the IO relations within each country can also be treated as independent ones. Thus, *ASRD* and *MSRD* are adopted to measure and compare the local flow efficiency of intermediate goods. Besides, each pair of upstream and downstream sectors in the local network may change with national industrial restructuring and global industrial transfer.

4.2.2 Betweenness Centrality of Node

Betweenness Centrality denoted by C_B measures how frequently a given node falls along the shortest path between two other nodes. In detail, it is calculated for a given hub node by computing, for each pair of nodes other than the hub node, the proportion of all the shortest paths from one to the other that pass through the hub node. These proportions are summed across all pairs and the result is a single value for each node in the network. The formula for the betweenness centrality of node i is given by:

$$C_B(i) = \sum\nolimits_{i,j,k \in \{1,2,\cdots,N\}} \frac{d_{jk}(i)}{d_{jk}} (i \neq j, i \neq k, j \neq k) \quad (4.4)$$

where $d_{jk}(i)$ is the number of shortest paths connecting nodes j and k through node i, and d_{jk} is the total number of shortest paths connecting nodes j and k. A node's betweenness is zero when it is never along the shortest path between any pair of others. Besides, this formula applies to directed networks.

Betweenness centrality is a measure of the influence of a node ore a path over the flow of information between other nodes, especially where information flow over a network primarily follows the shortest available path. The concept is therefore usually interpreted as the potential controlling flows in the network, i.e., playing a brokerage role. Nodes with high betweenness centrality can threaten the network with disruption of operations, so as the edges. In extreme cases, betweenness centrality reaches its maximum value when the given node or edge almost lies along every shortest path between every pair of other nodes.

In a similarity-weight network, however, the basis of information propagation differs from that of a Boolean network, thus we propose the ***Weighted Betweenness Centrality of Node based on RFWA*** and denote it by C_B^{RFWA}. An important question then arises: how do we treat those nodes located on both ends of every single *SRPL*? They cannot be simply ignored. As the framework has been expanded to multi-layer one, in this case, all the industrial sectors processing value-added are between value-added level units and final demand level units. Correspondingly, they are neither on the highest nor on the lowest part of the value chain. Therefore, instead of being caught in the function of source nodes or sink nodes on the SPRLs, just focus on the frequency of their appearance in *SRPL*-related strings. We assign different meanings or usages to source nodes and sink nodes when running more complex applications. The formula of C_B^{RFWA} is:

$$C_B^{RFWA}(i) = \sum\nolimits_{i,j,k\in\{1,2,\cdots,N\}} Str_{jk}^{(N)}(i) \tag{4.5}$$

where $Str_{jk}^{(N)}(i)$ is the number of *SRPLs* within the scope of the whole network, which connect any pairs of others across a given node i. Of special interest is how to measure the node with self-loop of being a *SRPL*. The frequency seems to be 2 because this node appears as both the source node and sink node on this special path, which is, however, irrational. Thus, we set a rule that the number of appearances of the node on the same path is less than or equal to 1.

According to Eq. (4.5), the most significant difference is that we do not normalize it by totality anymore, because we are more concerned with industrial sectors' propagation function on the GVC rather than their weakened heterogeneity reflected by ratio. Above all, we adopt it to measure the ***Value-Added Pivotability of Industrial Sectors***, with the purpose to evaluate the level of the brokerage in the process of the intermediate goods turnover. For example, suppose that a given sector owns high pivotability, many sectors will go through it to reach others via efficient and effective paths. In principle, this sector has power because it can threaten to stop transferring, making sectors use less efficient and effective paths to reach one another, just like brokers with information superiority and more intermediate interests in Burt's Structural Holes theory [8]. But this superiority only works if the other sectors cannot easily enter new trade relations around the world. In other words, not only can we use pivotability to evaluate the current global economic situation, but also offer favorable suggestions for the future.

4.2.3 Betweenness Centrality of Edge

Newman generalized Freeman's betweenness centrality to edges and defined the ***Betweenness Centrality of Edge*** as the number of shortest paths between pairs of nodes that run along it [9], namely:

$$C_E(i,j) = \sum\nolimits_{s,i,j,t\in\{1,2,\cdots,N\}} \frac{d_{st}(i,j)}{d_{st}} (i \neq j, s \neq t) \tag{4.6}$$

where $d_{st}(i,j)$ is the number of shortest paths connecting nodes s and t through $e(i,j)$, and d_{st} is the total number of shortest paths connecting nodes s and t.

To find the most important inter-industry economic relations among numerous couples of sectors in GIVCN model, ***Weighted Betweenness Centrality of Edge based on RFWA*** is derived to measure the ***Value-Added Pivotability of Input–Output Relations***:

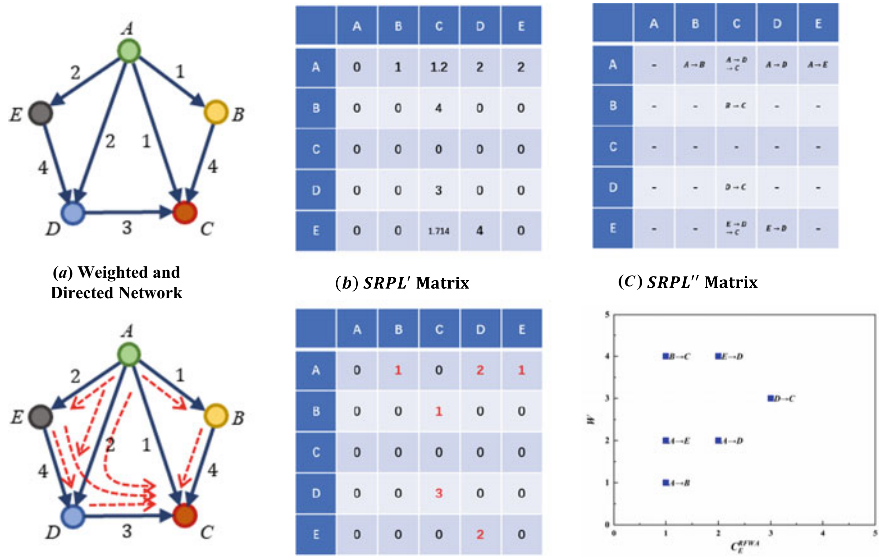
$$C_E^{RFWA}(i,j) = \sum\nolimits_{s,i,j,t\in\{1,2,\cdots,N\}} Str_{st}^{(N)}(i,j) \tag{4.7}$$

where $Str_{st}^{(N)}$ is the number of *SRPLs* within the scope of the whole network, which are connecting any pairs of others cross a given couple of nodes i and j. Self-loop serving as a *SRPL* will plus 1 to this indicator of itself.

Given that there is a five-nodes network as shown in Fig. 4.2a, we can calculate matrices $SRPL'$ and $SRPL''$ (see Fig. 4.2b, c) according to the Eq. (3.3), and find out 8 *SRPL* paths marked with red dashed lines exist (see Fig. 4.2d), incorporating 7 direct paths and 1 indirect path. Except for the path of $A \to C$, the other edges are passed through by at least 1 *SRPL* path and at most 3 *SRPL* paths. Then, we can get the matrix of C_E^{RFWA} based on the statistics on the *SRPL* paths (see Fig. 4.2e). For instance, $C_E^{RFWA}(D,C) = 3$ means there are 3 *SRPL* paths passing through it. Putting Fig. 4.2a, b and e together, we will find an interesting pattern that the edge weight equals to its corresponding *SRPL* value while its betweenness centrality exists.

Besides, it is worth to testify whether there is a correlation between the weight of edge and the C_E^{RFWA}. The truth is neither the edges with large weight nor the ones with small weight will certainly get a proportional C_E^{RFWA} (see Fig. 4.2f). Based on the theory of "The Strength of Weak Ties" introduced by Granovetter [9], we recognize that a weak tie connecting two heterogeneous communities will have a large betweenness centrality because it plays a crucial role of information bridge. If the background is set to a similarity-weight network, then there is likely to be such an edge: it has a small weight but a large C_E^{RFWA}, which we call the "***Crucial Weak Tie***". The path of $A \to D$ is of this type of edge, which is tied for fourth in the weight of edge and for second in the C_E^{RFWA}.

In reality, it is a part of IO relations, rather than certain industrial sectors, that are immediately affected by the development of economic globalization and changeability of international political situation, such as Brexit or trade disputes between



(*a*) Weighted and Directed Network

(*b*) *SRPL*′ Matrix

(*C*) *SRPL*″ Matrix

(*d*) *SRPL* Paths

(*e*) Matrix of Betweenness Centrality of Edge

(*f*) Correlation between Weight and Betweenness Centrality of Edge

Fig. 4.2 Betweenness centrality of edge in similarity-weight network

China and the United States. Through the cascading effect, the function and location of relevant industrial sectors will then present significant accumulated results. Therefore, it is important to analyze the fragments of GVC, which are quantified by the ICIO data, both for understanding the mechanism and enhancing the robustness of global production system.

4.2.4 Closeness Centrality of Node

The measure of Closeness Centrality relies on identifying the optimal paths in the network. In a non-weighted and non-directed network, a node's Closeness Centrality denoted by C_c is the inverse of APL from itself to others. The higher a node's the closeness centrality is, the shorter the APL from itself to others will be, and thus the better position it will be in to propagate information to the others. This can be viewed as the efficiency of each node in propagating information to all the rest, i.e.:

$$C_c(i) = \frac{N-1}{\sum_{j=1}^{N} d_{ij}} (i \neq j) \tag{4.8}$$

It is noted that Eq. (4.8) is inapplicable to either weighted or directed network, which means more needs to be done other than solving the shortest-paths problem of all pairs. This is because information propagates in a much more complicated way. New *SRPL*-based measures should be developed because the GIVCN model takes both weight and the direction of nodes into account to make maximum use of the ICIO data. Firstly, directed closeness centrality should be divided into two sorts: ***Weighted In-Degree Closeness Centrality*** **and** ***Out-Degree Closeness Centrality based on RFWA***. Denoted by $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$, according to nodes' position on the propagation path, they serve as a sink node and source node respectively. Secondly, the shortest paths can no longer effectively reflect the efficiency of information propagation in a weighted network as mentioned above, and *SRPLs* will become a substitute when computed. Finally, yet importantly, the relative position of numerator and denominator needs to be changed, because *SRPLs* reflect the most efficient ways in which information flows in a similarity-weight network, and the numerical value of closeness centrality should be proportional to its average value. Considering the above-mentioned, new closeness centralities in directed similarity-weight network based on RFWA are introduced:

$$C_c^{RFWA-IN}(i) = \frac{\sum_{i=1}^{N} SRPL_{ij}^{(N)}}{N} \tag{4.9}$$

$$C_c^{RFWA-OUT}(i) = \frac{\sum_{j=1}^{N} SRPL_{ij}^{(N)}}{N} \tag{4.10}$$

where the denominator has two kinds of settings: if node i is self-looped, the denominator represents the number of all the nodes that it links to, and thus $N = N_n$; if node i just owns links with the other nodes in the network, $N = N_n - 1$.

In order to quantify the closeness of relation among countries, we design two indicators at the national level based on the $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$, named the ***National Industrial Backward Closeness (NIBC)*** and ***National Industrial Forward Closeness (NIFC)***:

$$NIBC(u) = \sum_{i \in \tau(u)} C_c^{RFWA-IN}(i) \tag{4.11}$$

$$NIFC(u) = \sum_{i \in \tau(u)} C_c^{RFWA-OUT}(i) \tag{4.12}$$

where $NIBC(u)$ and $NIFC(u)$ are the backward closeness and forward closeness of country u, respectively.

According to the nature of Eqs. (4.9) and (4.10), the summation of all the backward linkages is just equal to that of the forward linkages, i.e., $\sum_{i=1}^{N} C_c^{RFWA-IN}(i) = \sum_{i=1}^{N} C_c^{RFWA-OUT}(i)$, so there is a kind of conservation relation between them in the closed economic system.

From the point of backward linkage, bigger $C_c^{RFWA-IN}$ means sectors rely much more on the intermediate goods from their upstream providers in the international division of labor. And from the opposite side, the bigger $C_c^{RFWA-OUT}$, the more intermediate goods that contribute to the downstream consumers. We define the $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$ as ***Backward Closeness and Forward Closeness of Industrial Sectors***, so as to quantify backward and forward inter-industry closeness degree starting from a given sector respectively. Note that, intra-industry self-consumptions denoted by self-loops in the network are included in both directions.

For simplicity, ***Relative Upstreamness Index (RUI)*** is proposed here under the concept of the combination of $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$, as a way to measure the industrial sector's relative interdependence with all the others distributing everywhere on the GVC. The formula of RUI is just the ratio of the industrial sector to other sectors:

$$RUI(i) = \frac{C_c^{RFWA-IN}(i)}{C_c^{RFWA-OUT}(i)} = \frac{\sum_{i=1}^{N} SRPL_{ij}^{(N)}}{\sum_{j=1}^{N} SRPL_{ij}^{(N)}} \tag{4.13}$$

Note that, as RUI increases, the sector's relative position transfers from the market end to the production end. Additionally, we set the boundary to be 1. That is, the sector locates in the upstream of GVC while its RUI is greater than 1, and the downstream while less.

In sum, the hypothesis is that the relative position of the industrial sector on the GVC could be reflected by backward closeness and forward closeness, and the specific comparative advantage brought by different locations. The major difference between our framework and the rest is that, in this framework, there is no starting point (R&D and design) or ending point (the delivery of final products or services to consumers) in the economic system. A single sector on the supply-side is called the upstream sector only if it directly or indirectly provides intermediate products or services to one consumer at least, while a sector on the demand-side is taken as the downstream sector only if it directly or indirectly consumes intermediate products or services, even from the sole provider. In other words, this positioning measurement is based on the industrial interdependence at a global scope rather than the production stages proposed by Fally, and the results could thus be quite different from those well-known studies.

4.3 Connectedness/Compactness of NVC

As GDP of each country increased, the value of the elements in ICIO tables represented in current US$ kept rising every year, so the SRPLs transformed from ICIO by RFWA grew numerically too. As result, ASRD and MSRD, reflecting the connectedness and compactness of GIVCN model, have similar situations as shown in Table 4.1. The MSRD-related upstream/downstream sectors are also listed in this table.

From an overall perspective, ASRD and MSRD rise all the way, expect the year of 2009 in GIVCN-WIOD2016 models. It is universally known that 2007 the United States' subprime mortgage crisis set off a rapid or even global economic tsunami.

Table 4.1 ASRD and MSRD of GIVCN-WIOD2016 models

Year	ASRD value	MSRD		
		Value	Upstream sector	Downstream sector
2000	76.125	151,475	USAS1	USAS5
2001	74.882	134,991	USAS1	USAS5
2002	78.649	137,903	USAS1	USAS5
2003	90.653	161,797	USAS1	USAS5
2004	107.580	255,479	USAS1	USAS5
2005	123.446	370,145	USAS4	USAS10
2006	139.390	510,204	USAS4	USAS10
2007	165.131	671,601	USAS4	USAS10
2008	188.872	600,942	USAS4	USAS10
2009	157.667	496,066	CHNS14	CHNS27
2010	178.738	605,595	CHNS1	CHNS5
2011	206.806	702,277	CHNS1	CHNS5
2012	206.535	795,656	CHNS1	CHNS5
2013	213.680	777,851	CHNS1	CHNS5
2014	216.552	800,356	CHNS1	CHNS5

Thus, this abnormal phenomenon reflects that both connectedness and compactness of GVC declined due to the damage of international and domestic trade networks.

To ensure the robustness of results, their changes on the national level are further investigated. ASRD and MSRD of two sub-networks standing for the United States and China are cross-compared and the results are shown in Figs. 4.3 and 4.4.

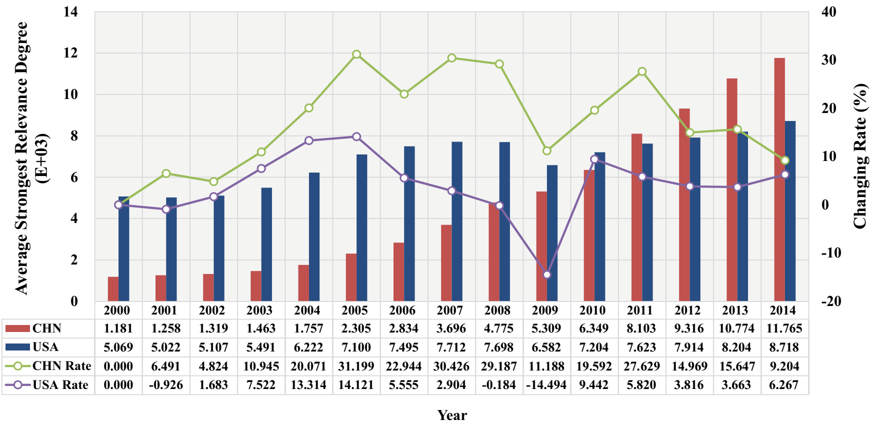
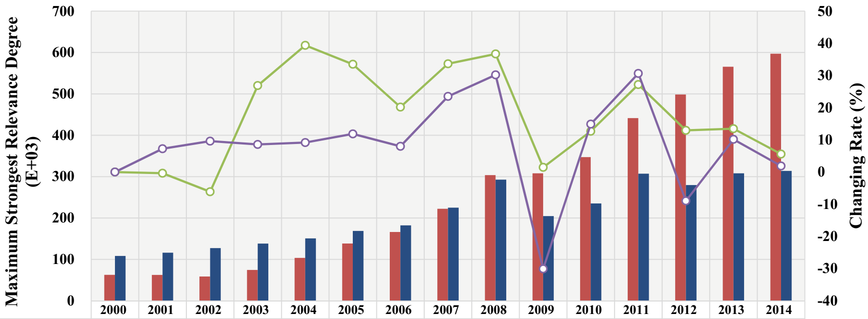


Fig. 4.3 ASRDs of the United States and China in GIVCN-WIOD2016 models



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
CHN	62.661	62.431	58.604	74.347	103.616	138.304	166.207	222.116	303.598	307.971	346.985	441.268	498.400	565.473	597.017
USA	108.244	116.081	127.221	138.123	150.766	168.621	182.080	224.846	292.711	204.627	235.066	307.088	279.552	307.934	313.709
CHN Rate	0.000	-0.367	-6.130	26.864	39.368	33.478	20.175	33.638	36.684	1.440	12.668	27.172	12.947	13.458	5.578
USA Rate	0.000	7.240	9.597	8.570	9.153	11.843	7.982	23.488	30.183	-30.093	14.876	30.639	-8.967	10.153	1.875

Year

Fig. 4.4 MSRDs of the United States and China in GIVCN-WIOD2016 Models

On the one hand, China's ASRD keeps a sustained upward trend since the beginning and surpassed that of the United States in 2011. On the other hand, the United States' ASRD troughs in 2009 and peaks in 2014, which is synchronized with the recovery process from the Subprime Crisis. From the angle of change rate, China has a higher changing rate than the United States all the time. Therefore, it naturally reaches to the conclusion that the industrial structure of China, compared to that of the United States, has benefited more from global economic integration and improvement in the domestic economic circulation, and promoted the economic development in turn.

For China and the United States, the year of 2009 is a clear watershed. China's MSRD already surpasses that of the United States in 2008 and gradually widens the gap in between since 2009. At the same time, the source and sink ends of corresponding IVCs change from "Manufacture of textiles, wearing apparel and leather products" (both the upstream and downstream sectors) to "Manufacture of computer, electronic and optical products" (both the upstream and downstream sectors), which presents a trend of shifting from labor-intensive sectors to capital intensive and technology-intensive ones. In contrast to the United States, the most compact IVC in 2009 is "Insurance, reinsurance and pension funding, except compulsory social security" (both the upstream and downstream sectors), which then changes to the one beginning with "Mining and quarrying" and ending at " Manufacture of coke and refined petroleum products", indicating that the source of power for its economic development also changed.

As to the whole network model, MSRD-related upstream and downstream sectors vary in certain years (see Table 4.2).

From the statistics on each pair of upstream and downstream sectors, we can see that the results are relatively stable. Most of the strongest industrial relevance in the global economic system exist in the United States and China, with the former occupies the earlier period and the latter the later period. Besides, the results over

Table 4.2 MSRD-related upstream and downstream sectors in GIVCN-WIOD2016 models

Period	Country	Upstream and downstream sectors
2000–2004	United States	From “Crop and animal production, hunting and related service activities” To “Manufacture of food products, beverages and tobacco products”
2005–2008	United States	From “Mining and quarrying” To “Manufacture of coke and refined petroleum products”
2009	China	From “Manufacture of other non-metallic mineral products” To “Construction”
2010–2014	China	From “Crop and animal production, hunting and related service activities” To “Manufacture of food products, beverages and tobacco products”

time also reflect the changes happening on the NVCs. For instance, the industrial gravity center of the United States that is about that of GVC turned from food-related sectors to energy-related sectors after 2005, which then gives way to the construction-related field of China, and after that to China’s food-related sectors again. According to the results, it can be concluded that the pair of sectors with the strongest relevance always belong to one of the national economic systems rather than emerging from international trade.

4.4 Pivotability of Industrial Sectors

4.4.1 Overall Statistics

The distribution of C_B^{RFWA} in two sorts of coordinates for all sectors in GIVCN-WIOD2016-2014 is shown in Fig. 4.5. This curve is heavy-tailed and obeys the

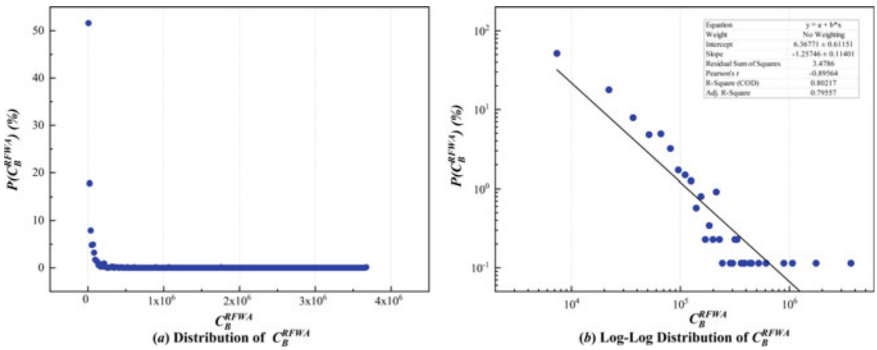


Fig. 4.5 Distribution and Log–Log Distribution of C_B^{RFWA} in GIVCN-WIOD2016-2014

Pareto distribution according to the linear fitting result in the log–log coordinate, which means the number of nodes with overwhelming C_B^{RFWA} is very small. This phenomenon means industrial sectors' pivotability varies tremendously, and that the tiny minority of industrial sectors own huge pivotability while the others are practically nil.

Top 20 sectors of pivotability excluding ROW in GIVCN-WIOD2016-2014 are shown in Table 4.3.

Based on the statistics, the "Manufacture of motor vehicles, trailers and semi-trailers" (S20) of Germany occupied the top position in 2014, then the United States' sectors took three of the top 5 spots. It is no surprise that most of the top 20 sectors play a crucial role in connecting their upstream and downstream sectors at home and abroad. Take DNKS32 as an example. Denmark owns the world's largest container shipping company, Maersk, which has customers in more than 110 countries and employs approximately 7,000 seafarers and approximately 25,000 land-based people. Correspondingly, the Danish "Water transport" sector benefit from superior domestic industrial resources and converts them into powerful capacity in transporting to many other countries. To facilitate the analysis on the geographical distribution of pivotability, 56 sectors in WIOD2016 are combined into four-sector categories as mentioned in the Sect. 1.4.3.

4.4.2 Cross-National Analysis

As shown in Figs. 4.6, 4.7, 4.8 and 4.9, there are large differences between the 4 sorts of the geographical distribution of national pivotability. Brazilian agriculture sectors, Russian mining sectors, German manufacturing sectors, and the United States' services sectors own the greatest pivotability and the following is an explanation from the perspective of their domestic industrial and foreign trade structures.

The pivotal nature of Brazilian agriculture is most prominent in all countries, due to the following two reasons. First, as the third-largest exporter of agricultural products in the world and the largest in South America, Brazil is a large agricultural country gifted with unique agricultural resources, with the exports of its agricultural products only second to the United States and the European Union. Brazil also enjoys the highest agricultural trade surplus, together with the largest export volume of orange juice and sucrose in the world. Second, with the acceleration of its industrialization process, Brazil has introduced many advanced technologies and equipment through the active development of foreign trade, which has promoted the rapid growth of its processed agricultural exports volumes. Exports of orange juice, candy, tobacco, and ethanol account for an ever-increasing share of Brazil's total agricultural exports. In other words, Brazil has not only obtained key technologies and products that promote its agricultural development on the GVC but also continuously expanded its global market share of agricultural products.

The high pivotability of the Russian mining sectors stems from its industrial structure and export trade. As one of the countries with the most abundant energy

Table 4.3 Top 20 sectors of pivotability in GIVCN-WIOD2016-2014

Rank	Abbr.	Country	Industrial sector	Pivotability
1	DEUS20	Germany	Manufacture of motor vehicles, trailers and semi-trailers	888,805
2	USAS10	United States	Manufacture of coke and refined petroleum products	607,852
3	USAS44	United States	Real estate activities	448,163
4	USAS27	United States	Construction	374,594
5	CHNS17	China	Manufacture of computer, electronic and optical products	324,201
6	USAS29	United States	Wholesale trade, except of motor vehicles and motorcycles	324,117
7	DEUS11	Germany	Manufacture of chemicals and chemical products	314,724
8	CHNS45	China	Legal and accounting activities; activities of head offices; management consultancy activities	305,377
9	USAS51	United States	Public administration and defence; compulsory social security	280,497
10	DEUS19	Germany	Manufacture of machinery and equipment n.e.c	236,201
11	RUSS4	Russia	Mining and quarrying	229,527
12	DNKS32	Denmark	Water transport	225,352
13	RUSS20	Russia	Manufacture of motor vehicles, trailers and semi-trailers	218,847
14	RUSS31	Russia	Land transport and transport via pipelines	218,054
15	CHNS10	China	Manufacture of coke and refined petroleum products	210,866
16	DEUS15	Germany	Manufacture of basic metals	209,126
17	NORS4	Norway	Mining and quarrying	201,031
18	LTUS10	Lithuania	Manufacture of coke and refined petroleum products	196,633
19	GBRS41	United Kingdom	Financial service activities, except insurance and pension funding	190,114
20	LUXS41	Luxembourg	Financial service activities, except insurance and pension funding	186,246

resources and the largest production capacity, Russia's reserves of coal, oil, natural gas, peat, and uranium are among the highest in the world. At the same time, Russia has always been committed to adopting high technology in extracting its energy resources and raw materials, and it is also the top priority of Russia's industrial restructuring. However, although this country is a large world trader, it is not a

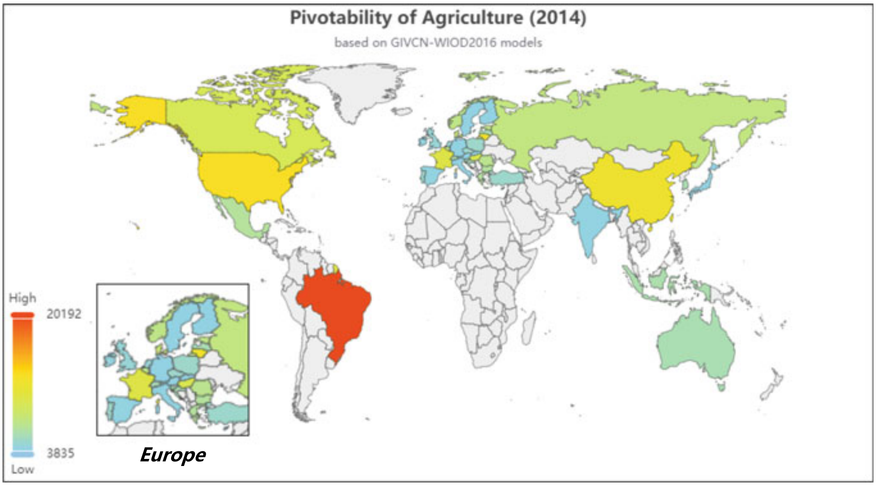


Fig. 4.6 Geographical distribution of pivotability of agriculture in 2014

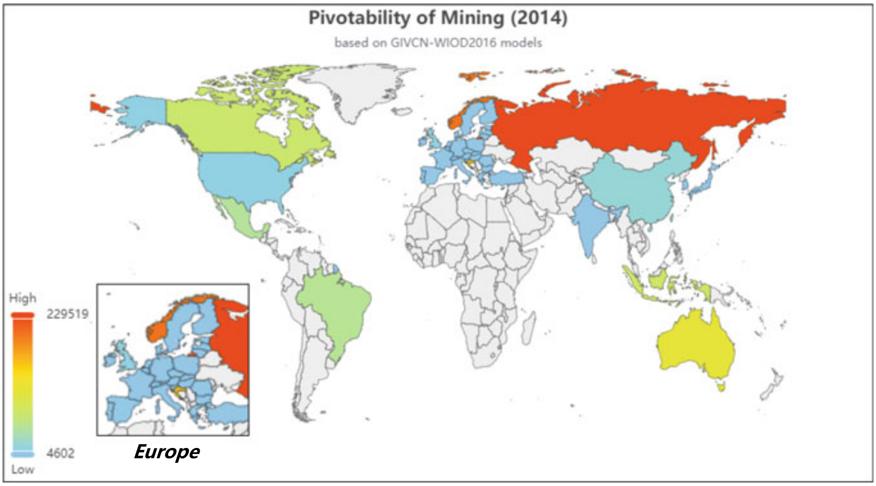


Fig. 4.7 Geographical distribution of pivotability of mining in 2014

trade power. This is because its export commodities are mainly low value-added energy-intensive products such as fuel and energy.

As is known to all, German manufacturing has an absolute advantage in its national economy, and occupies an important position in the world, as a prominent pivot on the GVC. Germany's automobile, electrics and electronics, machinery and equipment manufacturing, and information industries are the pillar industries of its economy, with outputs value accounting for more than a quarter of its GDP. German products are highly competitive in the international market, with automobiles and machinery

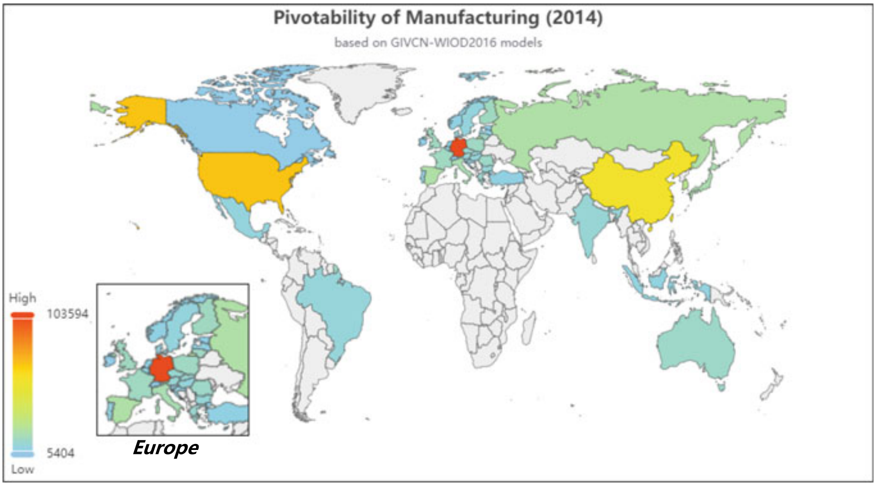


Fig. 4.8 Geographical distribution of pivotability of manufacturing in 2014

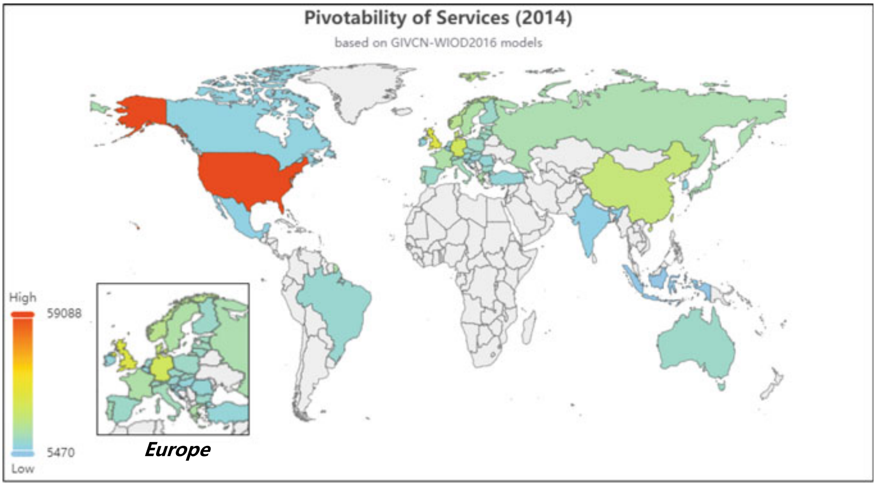


Fig. 4.9 Geographical distribution of pivotability of services in 2014

occupying a dominant position in exports. Also, the pharmaceutical industry, medical equipment, aero, and aerospace industry have developed rapidly into a new growth point for the German economy.

The United States has the most advanced service infrastructure in the world, which is both the most powerful support system for service trade and the fundamental source of the services sector's centrality. Since the 1990s, the United States' services sectors have gradually replaced its traditional industries such as steel, automobiles, and construction, becoming the main industry that supports the United States' economy.

At present, the United States has become the world's largest service trade country and surplus country and has largely eased the imbalance in international payments due to the huge trade deficit in goods.

In conclusion, if a certain sector in one country has a high centrality on the GVC, then it not only is at the core of the country's industrial structure and strongly promotes domestic economic development, but also occupies a large proportion in international trade as the main source of the country's trade surplus. Therefore, industrial sectors with high pivotability can be taken as the key points of GVC that bring their country great competitive advantages.

4.4.3 Robustness Analysis

Take GIVCN-WIOD2016-2014 as an example. Intentional removal of nodes has been performed to observe its impact on connectedness (*ASRD*) and compactness (*MSRD*) of the whole network. In detail, the removal has been carried out following the sequence from those with higher pivotability (C_B^{RFWA}) to those with lower ones, as compared to another experiment of random removals as reference. Figure 4.10 shows the results of implementing intentional removal and random failure (null model).

There is no doubt that the sectors with extremely high pivotability are crucial to the connectedness and compactness of GVC. In detail, the flow efficiency of intermediate goods falls by 50% when the proportion of nodes intentionally removed just reaches 2.801%; in the meanwhile, reference sets are far from this level of damage. This situation has become more evident in the case of *MSRD*, e.g., intentional failure on C_B^{RFWA} only at the level of 8.526% has reduced the value of *MSRD* by 67.958%, and in the meanwhile, it does not descend until random failure takes up a proportion of 51.157%. Although two types of curves are falling rapidly under cascading failures, the network has not suddenly disintegrated, proving, once again, the architecture of GIVCN model is neither centralized nor distributed but decentralized. But even

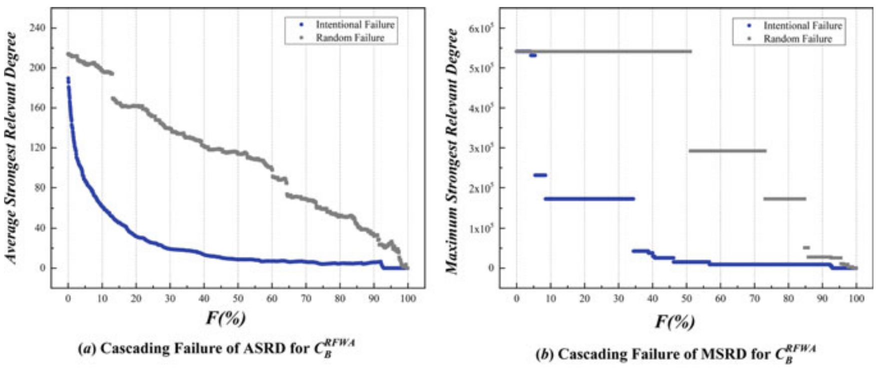


Fig. 4.10 Cascading failure analysis on the ASRD and MSRD of GIVCN-WIOD2016-2014

so, some industrial sectors, such as DEUS20, USAS10, USAS44, USAS27, and CHNS17, must be well guarded against risks and not allowed to become the Achilles' Heel of the world economy.

4.5 Pivotability of IO Relations

4.5.1 Heterogeneity of Pivotability

As mentioned above, it is the ICIO relations between industrial sectors, rather than the sectors themselves, that will firstly bear the brunt of international economic or political fluctuation. Hence, we assume that the pivotability at national or international level is determined by the overall domestic or inter-country C_E^{RFWA}. To be specific, in order to measure the importance of a given country or a pair of countries on the GVC, the C_E^{RFWA} of ICIO relations within every single Z^{sr} matrix need be combined, and a new Country-to-Country Pivotability Matrix can be formed, denoted by P. In the GIVCN model with m countries (u, v = 1, 2, ..., m), n sectors within each country, and totally N = m × n sectors (i, j = 1, 2, ..., N), the formula of P is:

$$P = \begin{pmatrix} P_{11} & \cdots & P_{1m} \\ \vdots & P_{uv} & \vdots \\ P_{m1} & \cdots & P_{mm} \end{pmatrix} \tag{4.14}$$

$$P_{uv} = \sum\nolimits_{i \in \tau(u)} \sum\nolimits_{j \in \tau(v)} C_E^{RFWA}{}_{ij}^{uv} \tag{4.15}$$

where, P_{uv} is the pivotability from country u to country v; $C_E^{RFWA}{}_{ij}^{uv}$ is that of ICIO relation from sector i of country u to sector j of country v; $\tau(u)$ is a set of numbers standing for the row sequence number of a certain country in the adjacent matrix Z^{uv}; $\tau(v)$ is a set of numbers standing for the column sequence number of a certain country in the adjacent matrix Z^{uv}. For instance, China is the 8th nation and the United States the 43rd in WIOD2016, so $\tau(8) = \{393, 394, \ldots, 448\}$ and $\tau(43) = \{2353, 2354, \ldots, 2408\}$ because each economy owns $n = 56$ sectors.

In order to observe the heterogeneity of pivotability at inter-country level, country-to-country pivotability matrices of 2000, 2005, 2010 and 2014 have been visualized in the following heat maps (see Fig. 4.11). Specifically, the top 10 country pairs by inter-country pivotability from 2000 to 2014 are listed in Table 4.4.

It can be seen from Fig. 4.11 and Table 4.4 that the pivotability at the international level differs significantly in different years, as expressed in the following two points:

Firstly, Germany-associated pivotability of various countries is notably high. Despite its lack of natural resources, Germany boasts sufficient funds and advanced technology, and has gradually shifted its industry towards the R&D and production of core technologies, making Germany at the top of the GVC and participating in

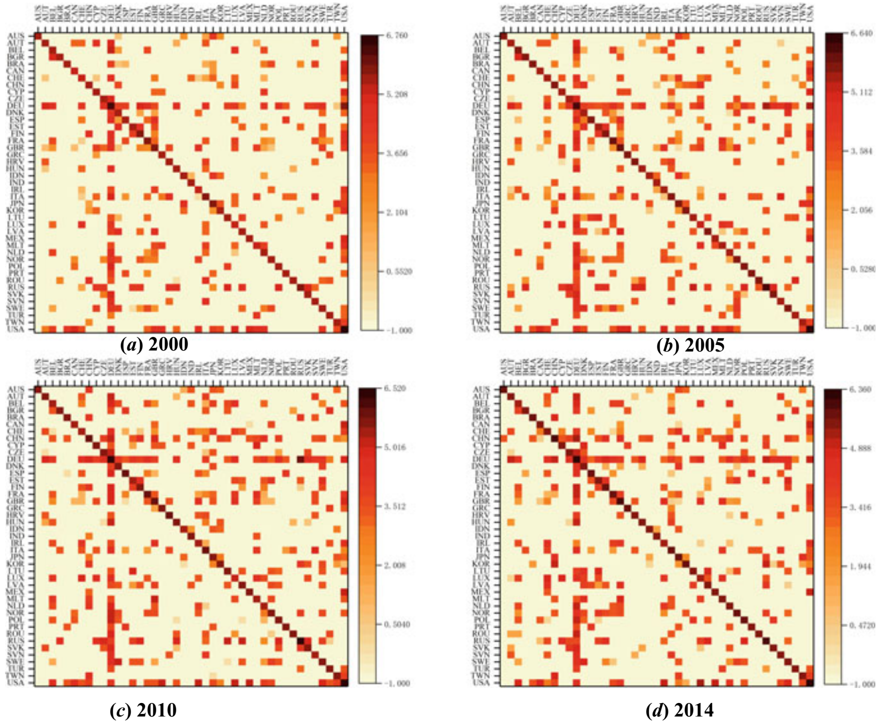


Fig. 4.11 Inter-country pivotability from 2000 to 2014. *Notes* Due to the strong heterogeneity of the pivotability value, we took the logarithm of the original data to enhance the visualization results

the global high-end specialization. Germany imports products from other countries, processes and upgrades those products, and then exports them at a profit.

Secondly, the top country pair is constantly changing, which is related to the relative economic development level and foreign trade situation of the countries in the world. First, in 2000, the world pattern featured one superpower (the United States) and multiple great powers (leading developed countries). The developed economies in the western world vigorously encouraged high-tech industries and transferred manufacturing industries to developing countries. As the world's largest trading body, the United States has always been Germany's largest trading partner outside the EU. The trade between Germany and the United States has facilitated the economic and trade development of both sides, leading to the significantly higher pivotability than that other country pairs. As can be seen from Table 4.4, the top 10 country pairs by pivotability are mainly distributed in the Europe and America. Second, after 2000, with Russia's rapid economic development and the soaring Russia-Germany trade volume, Germany became Russia's largest trading partner. Russia imports high-tech products from Germany, while Germany imports natural resources such as oil, natural gas and non-ferrous metals from Russia. The bilateral trade is characterized by good complementarity, resulting in the DEU → RUS pivotability ranking first in 2005

Table 4.4 Top 10 country pairs by inter-country pivotability from 2000 to 2014

Rank	2000		2005		2010		2014	
	Dyad	Num	Dyad	Num	Dyad	Num	Dyad	Num
1	DEU → USA	825,343	DEU → RUS	367,996	DEU → RUS	750,162	CHN → DEU	180,298
2	BEL → DEU	210,150	DEU → USA	307,598	RUS → LTU	175,820	USA → LUX	156,050
3	DEU → AUT	157,934	BEL → DEU	194,198	MLT → GBR	165,728	DEU → USA	128,063
4	USA → LUX	131,356	RUS → LTU	179,331	USA → LUX	163,426	DEU → CHN	128,010
5	USA → MEX	120,584	USA → LUX	149,605	POL → DEU	120,237	CZE → DEU	119,976
6	CAN → USA	120,121	USA → GRC	124,839	CZE → DEU	119,278	CAN → USA	117,709
7	SVK → DEU	120,049	MEX → USA	119,960	RUS → LVA	117,444	MEX → USA	113,397
8	BGR → BEL	116,569	CAN → USA	119,954	HUN → DEU	116,887	USA → MEX	110,946
9	AUT → DEU	114,074	HUN → DEU	119,339	CHN → DEU	116,608	KOR → CHN	109,969
10	RUS → SVK	110,674	POL → DEU	119,019	USA → MEX	116,280	AUT → DEU	108,434

and 2010. Third, after China's access to the WTO, its foreign trade volume increased rapidly, and the growth rate continued to remain at a relatively high level. The scale of bilateral trade between China and Germany continued to expand. With its industrial structure being dominated by manufacturing industries with low added value, China needs to import a large amount of advanced equipment and technology, which are exactly what Germany has been mainly exporting. The bilateral trade between China and Germany is highly complementary, so the CHN $\rightarrow$ DEU pivotability has jumped from the ninth place in 2010 to the first in 2014.

4.5.2 Domestic Pivotability

The diagonal elements of matrix P reflect the integral pivotability of all industrial sectors in a country and can be extracted to get a vector P^D, whose formula is:

$$P^D(u) = P_{uu} \tag{4.16}$$

where $P^D(u)$ is named the ***Domestic Pivotability*** of country u, and P_{uu} represents the element in the u-th row and u-th column of matrix P.

As is known to all, superpowers can hardly maintain their international status without a complete industrial system. The Domestic Pivotability reflects the relative completeness of a country's domestic industrial sectors. A complete domestic industrial sector can lead to a complete industrial chain, smooth inter-industry coordination, higher production efficiency, and the enriched product supply in the domestic market. This article first examines the changes in the influence of various countries' (excluding the ROW) domestic industrial sectors on the GVC at different times, as shown in Fig. 4.12.

From 2000 to 2014, the United States, Germany, and Russia, with their a relatively high degree of industrial completeness, have always been in an advantageous position on the GVC: (1) Except for 2010, the United States has long ranked first in terms of the domestic pivotability. The United States has experienced industrial model exploration and competitive advantage transformation for more than a century,

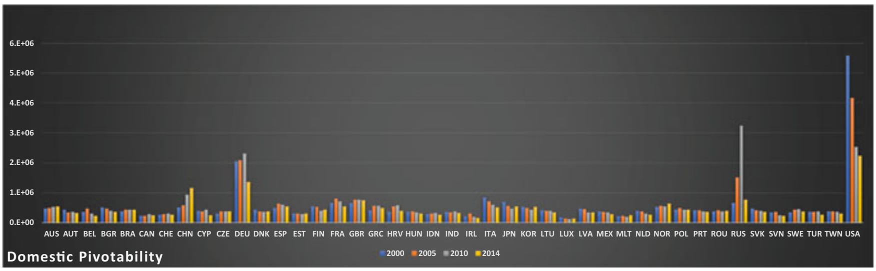


Fig. 4.12 Domestic pivotability of countries/regions from 2000 to 2014

with its development mode shifting from manufacturing industry leading, to service industry output and to division of labor model based on network platform industry. It thus formed an industrial structure led by financial service, high-tech, culture, and military, and firmly holds its commanding lead on the GVC by virtue of its advantages in technology and capital. In addition, the prosperity of its domestic trade is also inseparably related to the huge domestic consumer market. (2) The pivotability of Germany, second only to the United States, increased briefly in 2010. As one of the most developed industrial countries in the world, Germany digs down deep in the manufacturing industry. The advanced real economy is an important basis for Germany to revitalize the domestic industrial cycle and achieve a strong rebound in the economy after the subprime mortgage crisis. (3) In 2010, Russia leapfrogged the United States and Germany, coming first in the world. This reflects that despite a slow down after the outbreak of the financial crisis, emerging economies still enjoy faster an economic growth rate than that of developed economies, gradually becoming the engine of the global economic recovery.

In spite of the noteworthy steady rise, China's domestic pivotability has a certain gap in value compared with Germany and the United States. As the most populous country in the world, China boasts huge market demand and abundant human resources, which together inject resilience and potential to the economy. Besides, since the reform and opening up, China has gradually formed a complete industrial structure and is rapidly integrating into the global division of labor. However, China's manufacturing industry is mainly engaged in labor-intensive and resource-intensive ends on the GVC, which means the growth rate and its proportion of GDP are high, yet the added value of products is low. To boost economic growth and stop relying on high-end technology of developed countries, China proposed the Supply-side Reform in 2015 to further stimulate domestic consumer demand by providing high-quality commodities. This will vitalize China's economy and facilitate sustainable economic development.

To take a step back, countries' pivotability differences in terms of numerical value have gradually narrowed. Taking the year 2000 as an example, the pivotability of the United States was about 2.7 times that of the second place, Germany, and its domestic trade on the GVC had a commanding lead. But by 2014, its pivotability had dropped to about 1.6 times that of Germany. As economic globalization goes deep, countries participate in different levels of international division of labor and create more opportunities for domestic trade, thus gradually narrowing the gap on the GVC.

4.5.3 International Pivotability

Accordingly, the non-diagonal elements of matrix P represent the pivotability of countries pairs. Given the consistency of numeric value reflected by import and export trade, we sum up the off-diagonal elements in the rows and thus get a vector P^I:

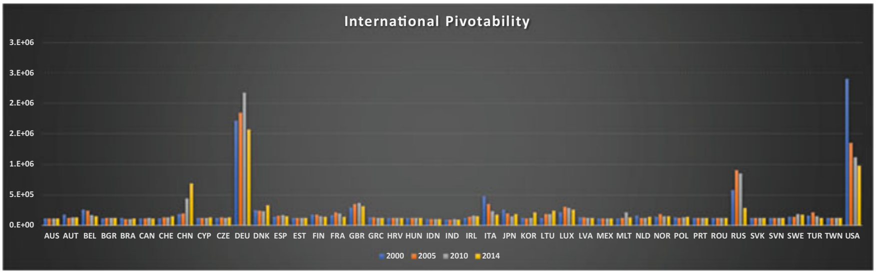


Fig. 4.13 International pivotability of countries/regions from 2000 to 2014

$$P^I(u) = \sum\nolimits_{u \neq v} P_{uv} \tag{4.17}$$

where $P^I(u)$ is named the International Pivotability of country u, and P_{uv} is the off-diagonal element in the u-th row of matrix P.

Countries' division of labor and rank variation on the GVC in terms of product export are observed, similarly with special choice of data of the year 2000, 2005, 2010, 2014. The result is shown in Fig. 4.13.

It is not difficult to notice from Fig. 4.13 that the outbound trade of Germany, the United States, Russia, and China still have a strong presence on the GVC.

To begin with, Germany's influence on the GVC through product exports has surpassed the United States since 2005 and continues to lead. Manufacturing industry dominates both Germany's domestic industry structure, but also its import and export trade. Within the EU, Germany's export accounts for one-fifth of intra-EU trade, far surpassing Britain, France, Spain, and other major European nations; globally, thanks to the reputation of "Made in Germany", Germany has maintained trade surplus ever since 1993 and played a pivotal role on the GVC.

To continue with, the United States is losing its ground once gained by its outbound trade; especially the five years from 2000 to 2005 witnessed a sharp decline. This reminds us of the two major crises that the United States experienced around 2000. First, since 1995, the emergence of the Internet set off an investment boom in the Nasdaq. In March 2000, the Nasdaq Composite index peaked and started to fall, marking the beginning of the burst of the Internet bubble, which made the United States economy severely suffer. Second, the United States, which was already in a period of economic slowdown, was again hit hard by the 9/11 attacks in 2001. After two crises, the United States economic environment was filled with uncertainty, which was obviously unconducive to its outbound trade.

Russia's high pivotability has benefited from abundant oil and mineral resources. For example, in 2010 after the financial crisis, driven by the rebound in international energy market demand and higher energy prices, Russia maintained the third place in the rankings of pivotability, and narrowed the gap with the United States; but in 2014, the price of crude oil plunged by more than 40%, resulting in the inevitable shrink of Russia's outbound trade. In terms of market factors, OPEC does not reduce production, and the United States shale oil and gas revolution has boosted its crude oil production, which has led to a bleak demand on the international crude oil market; for non-market factors, the U.S.-Europe and Russia were involved in the intensifying sanctions and anti-sanctions due to the Ukraine event, resulting in oil price plummet which was in the political interest of the United States to crack down on Russia.

In addition, Chinese product export began to have an increasing impact on the GVC after 2000 and has ranked third in 2014. Since its access to the WTO in 2001, China's foreign trade volume has increased substantially year after year, surpassing the United States and becoming the largest commodity trader of the world in 2013. In 2001, China's total exports amounted to US $266.1 billion, and by 2014 it had risen to US $234.3 billion[1] In addition, at this stage, China's export product mix has been gradually restructured, the competitiveness of new technology-intensive industries is enhanced, and the division of labor on the GVC improved.

In addition to the above-mentioned major countries on the GVC, the United Kingdom, Italy, and Luxembourg also have significant characteristics of international pivots. Among them, the United Kingdom has long been ranked among the top 10 exporting countries in the world by virtue of its geographical advantages and solid industrial foundation; Italy was one of countries with the world's largest trade surplus, but since the beginning of this century, increased domestic energy demand and high energy prices have led to trade deficit, making pivotability gradually decline over the past 15 years. Despite the limited territory area, Luxembourg is one of the most important financial centers in the world, which plays a vital role in Europe' economics and politics, resulting in its outstanding international pivotability.

4.5.4 Global Pivotability

Due to the heterogeneity of resource endowment and economic volume, the pivotability at domestic or international level might be different for various countries. To evaluate the synthetic importance at the domestic level, we introduce the definition of ***Global Pivotability*** denoted by P^G by combining P^D with P^I, namely:

$$P^G(u) = P^D(u) + P^I(u) = P_{uu} + \sum\nolimits_{u \neq v} P_{uv} = \sum P_{uv} \tag{4.18}$$

where $P^G(u)$ is the global pivotability of country u, consisting of both internal and external capabilities on transiting and processing intermediate goods on the GVC.

As can be seen from Fig. 4.14, the global pivotability, as a combination of domestic pivotability and international pivotability, shows a slightly different variation trend that with that of the two single pivotability.

Under the premise that both domestic pivotability and international pivotability are relatively high, the United States, Germany, and Russia are at the core of the

[1] The data is from the official website of China's National Bureau of Statistics, and web link is as follows: http://www.stats.gov.cn/.

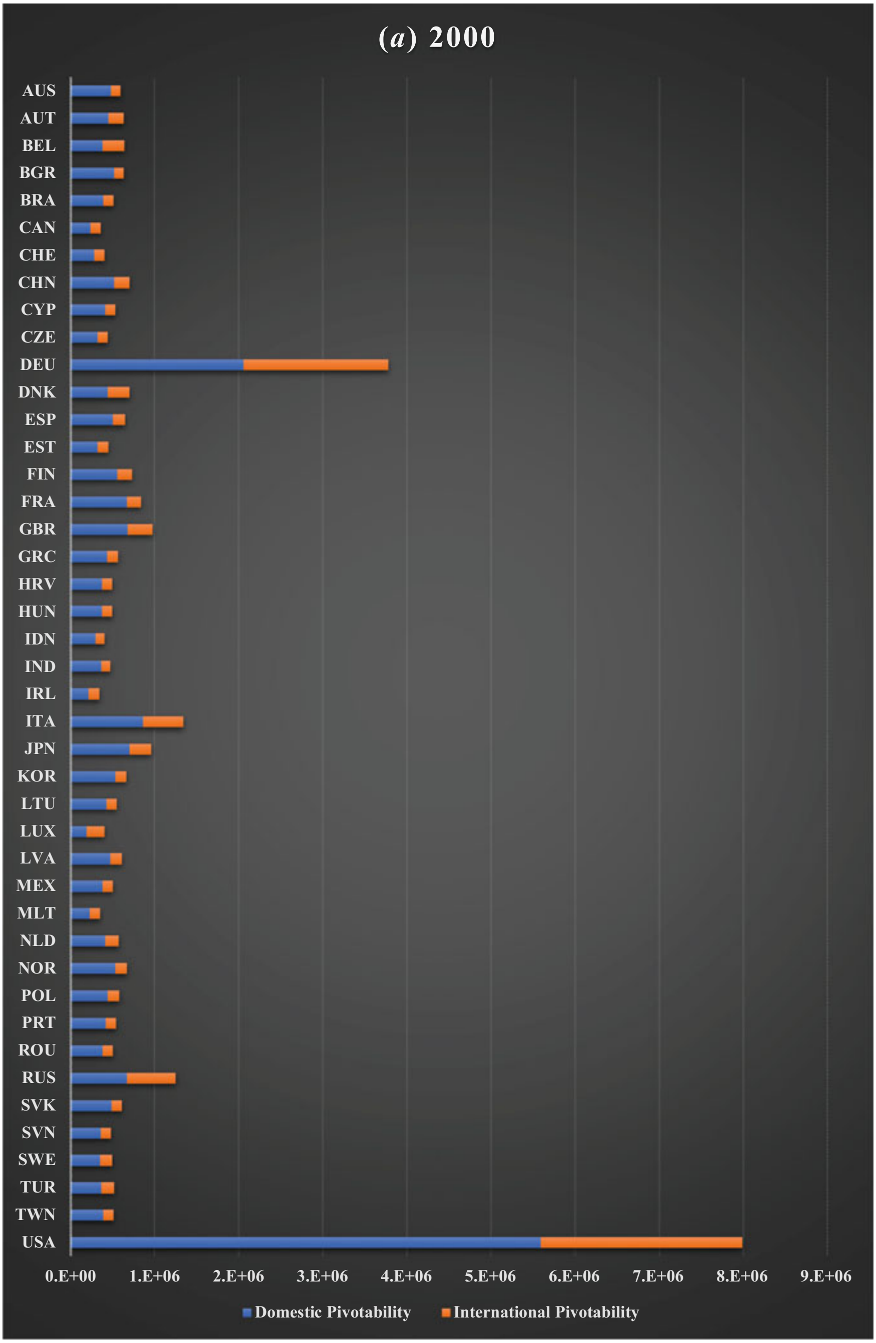


Fig. 4.14 Global pivotability of countries/regions from 2000 to 2014

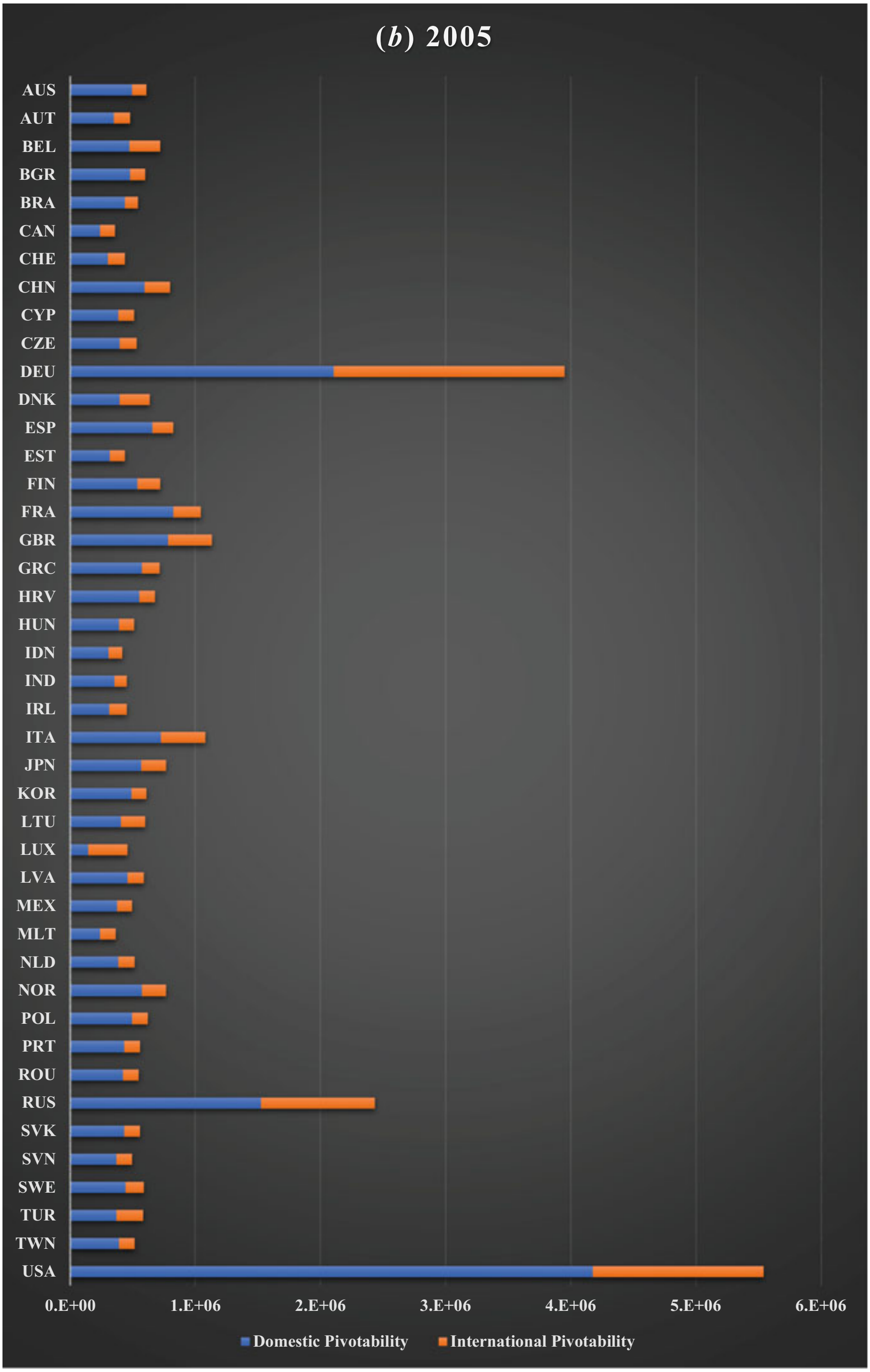
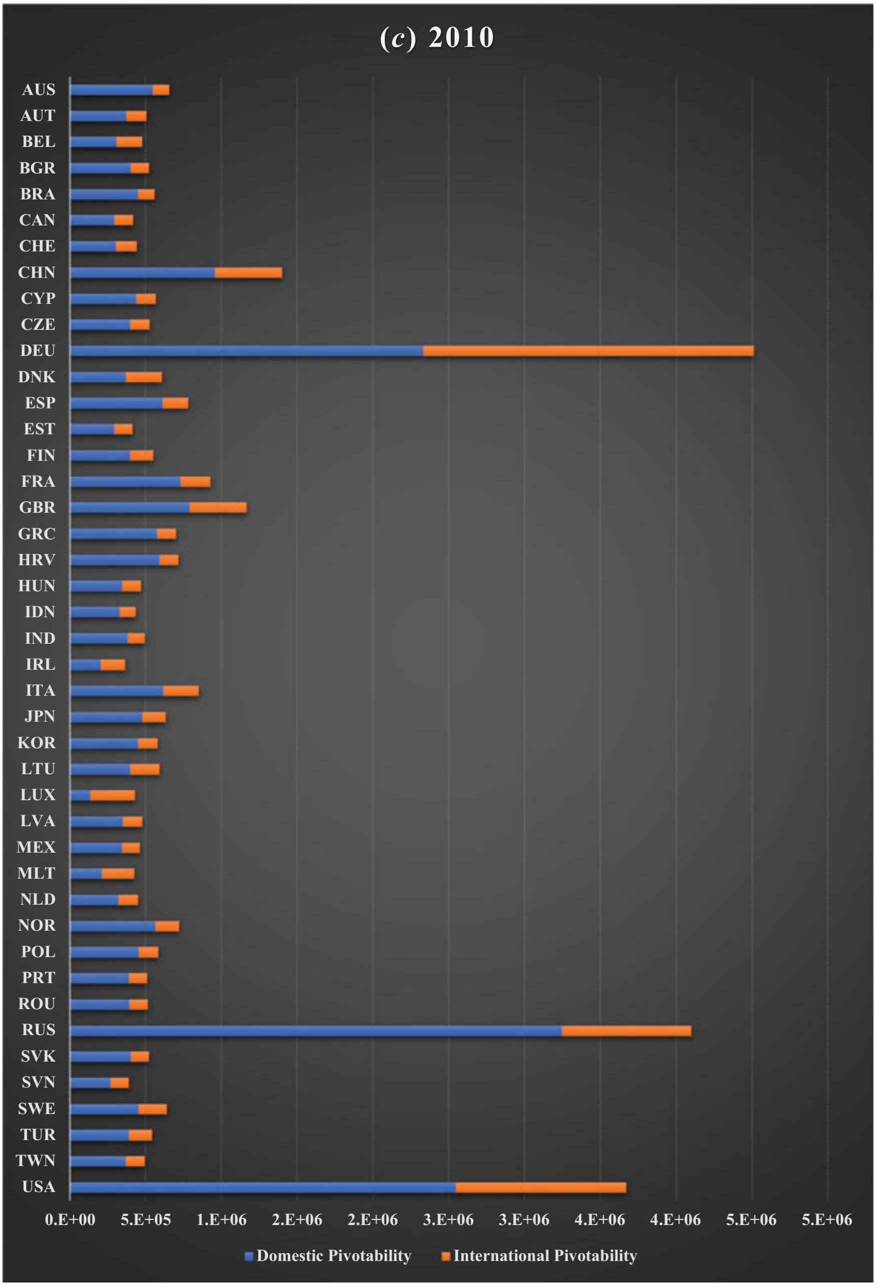


Fig. 4.14 (continued)



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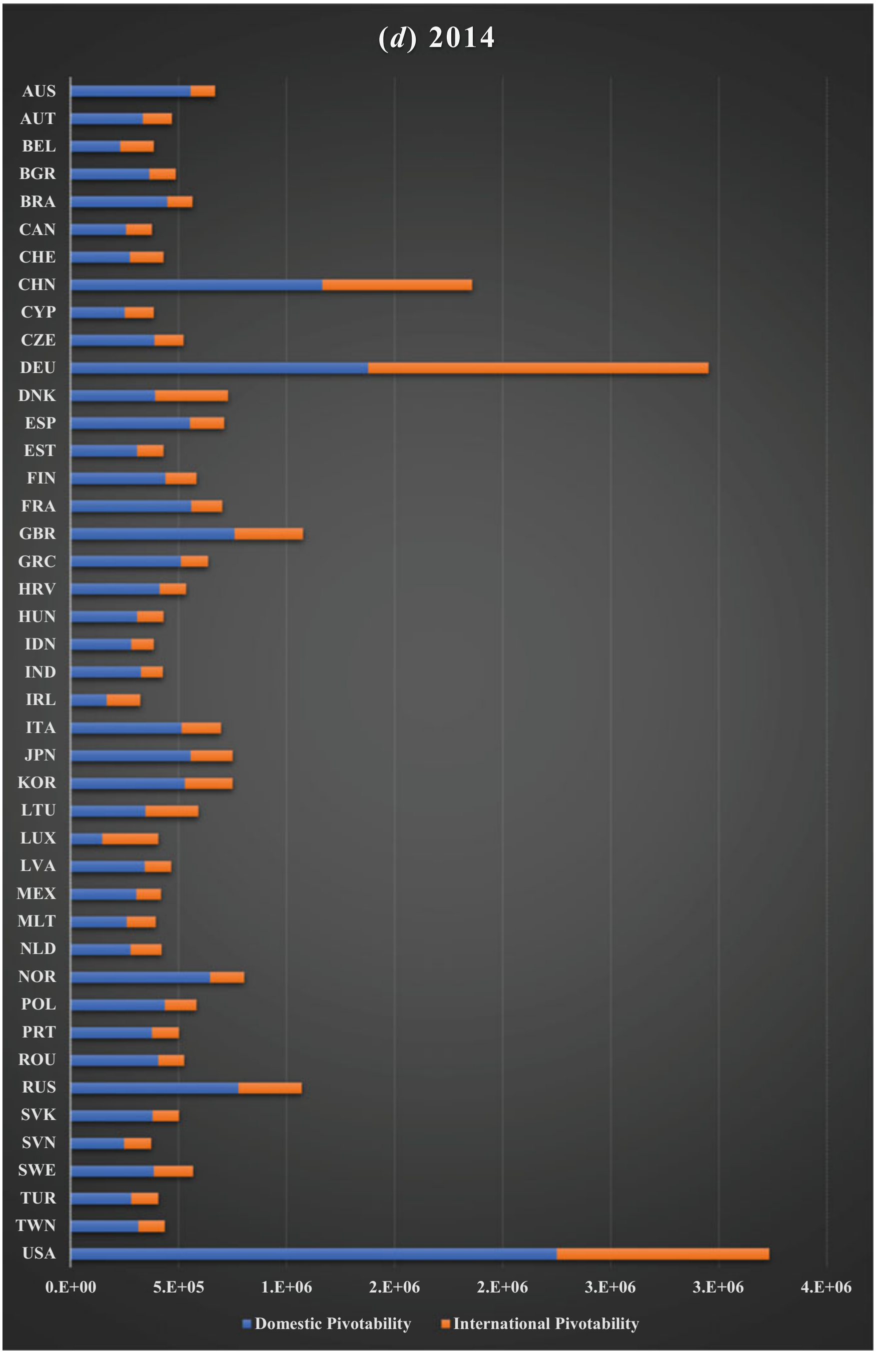

Fig. 4.14 (continued)

GVC. The difference is that domestic trades of the United States and Russia account for a significantly larger proportion than their outbound trade; however, Germany has basically the same proportion of domestic and outbound trade. The reason is that Germany has been dominating the European trade network. Germany imports industrial raw materials and intermediate products from other EU member states, and exports the reprocessed and manufactured products to EU countries or other countries in the world. Germany plays a dual role as a European trade center and a transit hub between Europe and the world. It is worth noting that, compared with 2010, Russia's Global Pivotability has shrunk severely in 2014. As mentioned in the previous section, under the pressure of declining energy prices and economic sanctions from Western countries, Russia encountered a new round of financial crisis in 2014, in which the sharp devaluation of the currency and sluggish economic activity put domestic investment, production, consumption and international trade under intense pressure.

In the past 15 years, China has become the rising star in the rankings of trade, with its pivotability on the GVC ranking the top in terms of growth speed and volume. However, seen from the numerical gap with the United States, Germany, and Russia, one can easily found that China is still facing the problem of being "big but not strong". Since the beginning of the new century, China has maintained its sound developing momentum and seized the opportunity of WTO accession, becoming the country with the most complete industrial chain in the world. However, during the outbreak of COIVD-19, the shortcomings in China's high-end medical equipment manufacturing have also been exposed, which will effectively fasten China's industrial upgrading.

Overall, countries' Global Pivotability is on the rise, and for most countries, domestic pivotability is higher than international pivotability. The upward trend reflects more intensive involvement of countries in the international division of labor. For example, South Korea has an increasing proportion of intermediate product export, and its trade volume continues to move to the upstream of GVC; on the other hand, the COVID-19 pandemic has brought tremendous impact on international trade for various countries. With countries' various prevention measures, the influence on the domestic market has gradually weakened, but overseas risks still restrict the export of products in many countries. Therefore, countries with well-developed domestic industrial chains have a stronger ability to withstand risks, while for countries that are oriented to international trade, this pandemic will be a severe challenge.

In general, domestic pivotability, international pivotability and global pivotability reflect the function and status of a country on the GVC from three different perspectives. Countries with high pivotability not only are more efficient in the transfer of intermediate products, but at the same time are more likely to have more advantageous resource control on the GVC, thereby gaining stronger competitiveness.

4.6 Coordinates of Industrial Sectors

According to the definition on $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$, if the backward or forward closeness of an industrial sector gets greater, there will be stronger compactness between certain sector and its upstream or downstream sectors, whereby reinforcing the ability to integrate upstream or downstream industrial resources and to connect the supply-side or demand-side along with increasing globalization and more elaborate international division of labor. Meanwhile, the industrial sector's value upgrading on the GVC division of labor will be gradually completed and its value-added capacity enhanced.

4.6.1 Overall Statistics

This section calculates the $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$ of 56 industrial sectors from 44 countries/regions in WIOD2016, and their distributions in GIVCN-WIOD2016-2014 in two sorts of coordinates are shown in Figs. 4.15 and 4.16.

For both of $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$, since the tail end distribution obeys a Pareto distribution, but the head end distribution prefers a Boltzmann–Gibbs distribution, we try to describe them with the features of Levy Stable distribution. That is, when $C_c^{RFWA-IN}$ or $C_c^{RFWA-OUT}$ is tending to zero, the probability does not quickly approach infinity, and we divide the trend range of two sorts of distributions with a certain value. In other words, a few (but not rare) nodes own very high values of $C_c^{RFWA-IN}$ or $C_c^{RFWA-OUT}$. From the perspective of an unbalanced industrial structure, this phenomenon shows that a small number of industrial sectors with higher backward or forward closeness have a prominent place in the international trade division network. Due to the heterogeneity in the factor endowment, geographic location, development stage and industrial structure, there is a great discrepancy between the

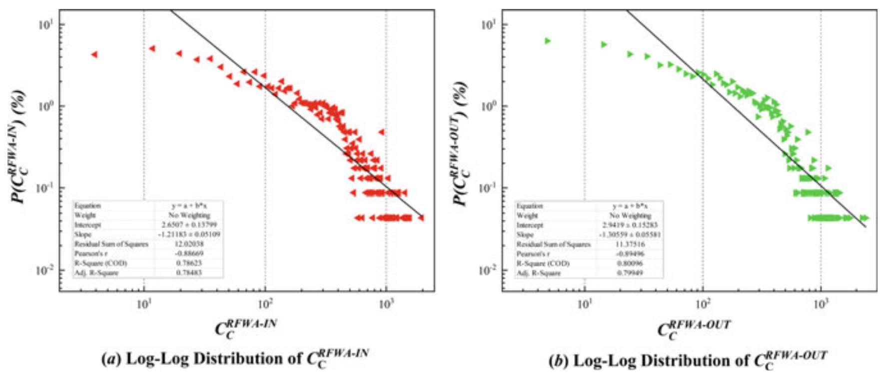

Fig. 4.15 Log–Log distribution of $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$ in GIVCN-WIOD2016-2014

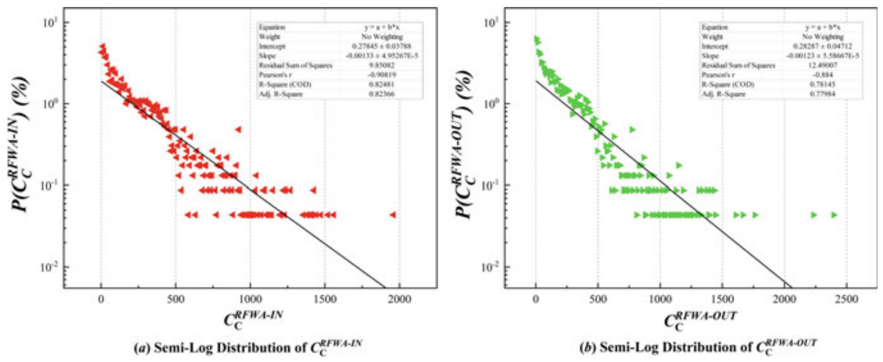

Fig. 4.16 Semi-Log distribution of $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$ in GIVCN-WIOD2016-2014

contributions of industrial sectors to the development of GVC, resulting in an uneven globalization.

The relation between $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$ in GIVCN-WIOD2016-2014 is shown by the scatter diagram and its fitting line in Fig. 4.17a. The Pearson correlation coefficient between them is 0.883 and $R^2 = 0.779$, indicating that they have a strong positive correlation. In our opinion, if an industrial sector has competitive advantage in backward or forward industrial relations, its competitive advantage will be eventually enhanced on the other side, just as the way synergy effect is described in the economic system. Figure 4.17b illustrates the distribution of RUI, which obeys the skewed distribution, and most of RUI values locate around 1 because of the strong positive correlation between sectors' backward closeness and forward closeness.

Table 4.5 illustrates the world's top 20 sectors of backward closeness and forward closeness in 2014. The results of backward closeness indicate that China's manufacturing sectors, among which the construction sector tops the list, predominate in the

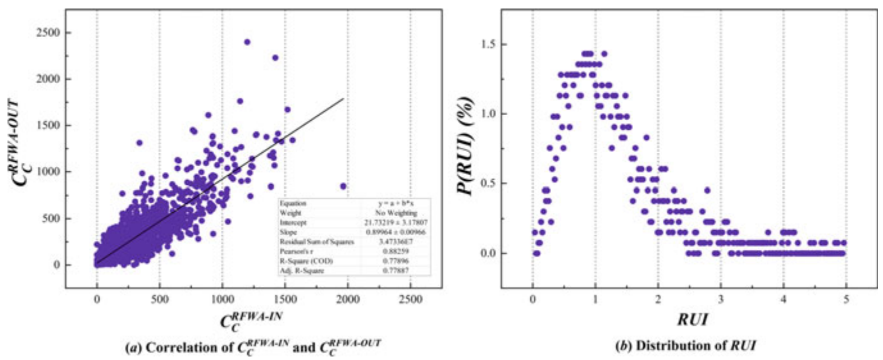

Fig. 4.17 Correlation of $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$ distribution of RUI in GIVCN-WIOD2016-2014

Table 4.5 Top 20 sectors of backward closeness and forward closeness in GIVCN-WIOD2016-2014

Rank	Sector	Backward closeness	Sector	Forward closeness
1	CHNS27	1963	ROWS4	2400
2	CHNS5	1559	ROWS24	2231
3	CHNS15	1520	CHNS4	1762
4	CHNS17	1471	CHNS15	1670
5	CHNS11	1443	ROWS19	1611
6	ROWS27	1427	ROWS45	1450
7	ROWS24	1422	ROWS15	1440
8	CHNS6	1415	ROWS41	1432
9	CHNS20	1409	CHNS11	1411
10	CHNS18	1405	CHNS24	1403
11	USAS51	1387	CHNS1	1396
12	CHNS19	1379	ROWS18	1383
13	CHNS10	1351	ROWS29	1378
14	CHNS24	1272	CHNS10	1375
15	CHNS1	1267	ROWS27	1341
16	CHNS16	1241	CHNS5	1340
17	USAS44	1236	CHNS17	1325
18	CHNS13	1230	RUSS4	1312
19	USAS53	1223	ROWS14	1308
20	USAS10	1218	ROWS31	1301

top 5. As the world factory, China has been undertaking large quantities of manufacture, and importing lots of intermediate goods from other countries' industrial sectors, which explains its stronger closeness with the supply-side. Besides, most of the sectors with the highest forward closeness in 2014 are manufacturing sectors of China, and other developing countries, who have long been providers of raw materials, energy and labor for developed countries. That's why China also has higher closeness with the demand-side.

The results show that, both the strongest backward closeness and forward closeness appear in manufacturing sectors, followed by services sectors; agriculture and mining sectors have relatively weak bidirectional closeness. It can thus be concluded that manufacturing sectors boast the strongest ability in integrating the resources of the upstream and downstream industrial sectors and connecting the supply-side and the demand-side.

4.6.2 Time-Series Analysis

The top 10 countries in the world GDP ranking in 2014 are selected for timing analysis and comparative analysis on the backward closeness and forward closeness of the four-sector categories as shown in Figs. 4.18, 4.19, 4.20, 4.21, 4.22, 4.23, 4.24 and 4.25.

The overall trend of two sorts of closeness have been growing in agriculture, mining, manufacturing, and services sectors of various countries from 2000 to 2014, notwithstanding a remarkable drop in 2009. This trend reflects that the economic scale and trade volume of countries are continuously on the rise, the compactness from a given sector to all its upstream and downstream sectors undergoes continuous

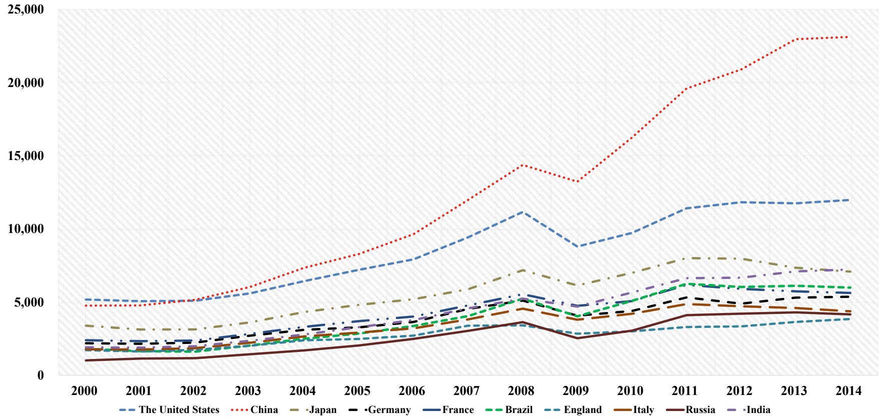

Fig. 4.18 Backward closeness of SC1 in GIVCN-WIOD2016SC4 models

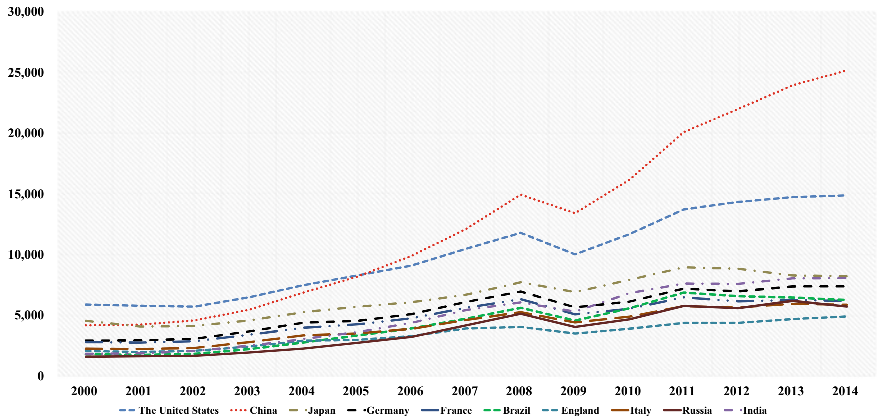

Fig. 4.19 Forward closeness of SC1 in GIVCN-WIOD2016SC4 models

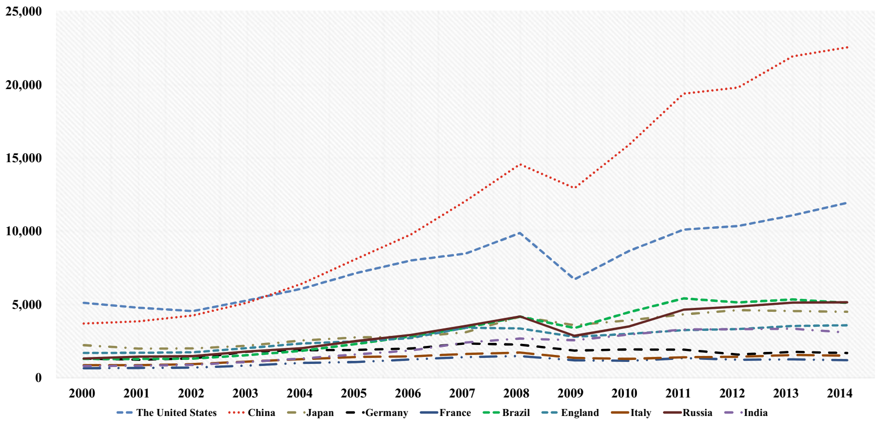

Fig. 4.20 Backward closeness of SC2 in GIVCN-WIOD2016SC4 models

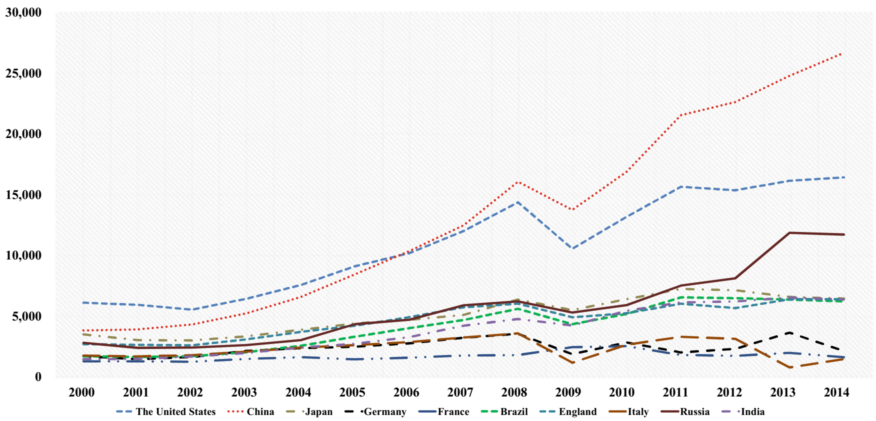

Fig. 4.21 Forward closeness of SC2 in GIVCN-WIOD2016SC4 models

increase, and that interdependence among industries continues to progress amidst the thriving international trade. In 2007, the economic tsunami caused by the subprime mortgage crisis impacted severely on the global trade network liquidity, therefore weakening the bidirectional closeness between most industrial sectors on the GVC, among which the manufacturing sectors experienced the largest average decrease in two ways. Suffice it to say that the manufacturing sectors are more vulnerable to external market shocks. In detail, several obvious results are as follows.

(1) The bidirectional closeness of China's agriculture, mining and manufacturing sectors are gradually surpassing those of the United States. At the same time, the gaps between China and other countries in two aspects are gradually widening. As we all know, the 2008 recession stroke manufacturing sectors in many countries, causing a brief decline in both ways of closeness. But why are those

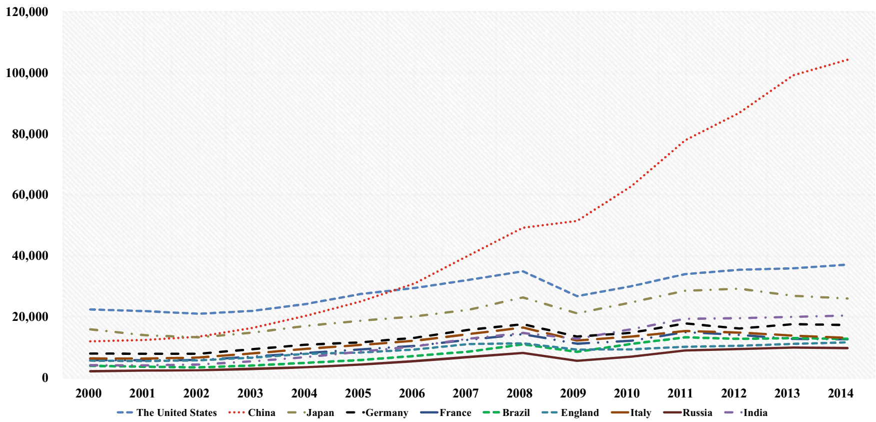

Fig. 4.22 Backward closeness of SC3 in GIVCN-WIOD2016SC4 models

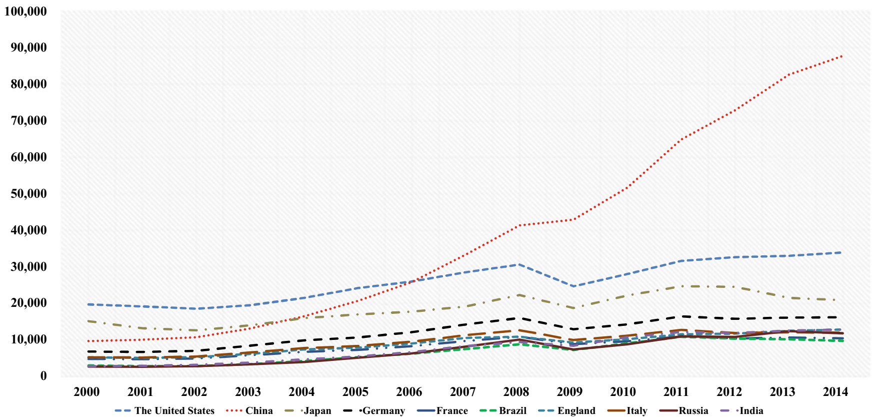

Fig. 4.23 Forward closeness of SC3 in GIVCN-WIOD2016SC4 models

of China still on the rise? In our opinion, it is the global economic crisis in 2008 that forced the transformation and upgrading of China's manufacturing sectors which drove the growth of China's infrastructure construction, real estate, and other real economies in turn.

(2) The bidirectional closeness of the United States' services sectors, however, have always topped the world ranking, significantly higher than those of other countries. This indicates the United States' services sectors are highly capable of connecting the supply-side and the demand-side. In reality, the United States is the world's largest service trader, with the share of service outsourcing accounting for about 60% of the world's total. Besides, the above conclusion also verifies its strong competitive advantage in information technology service.

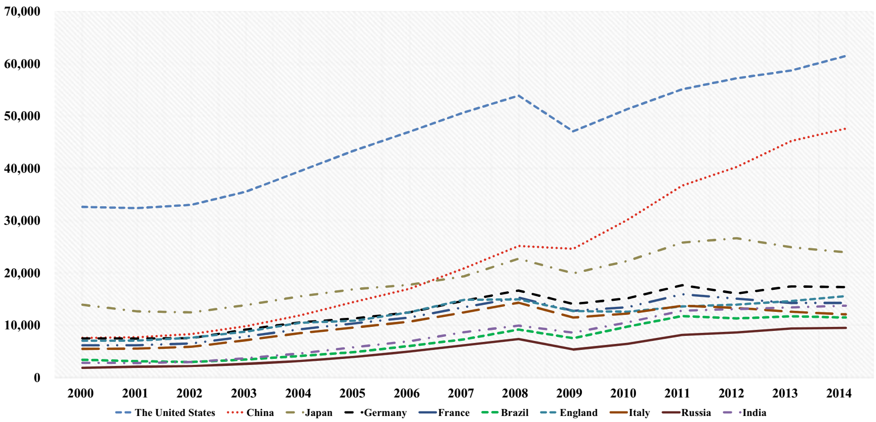

Fig. 4.24 Backward closeness of SC4 in GIVCN-WIOD2016SC4 models

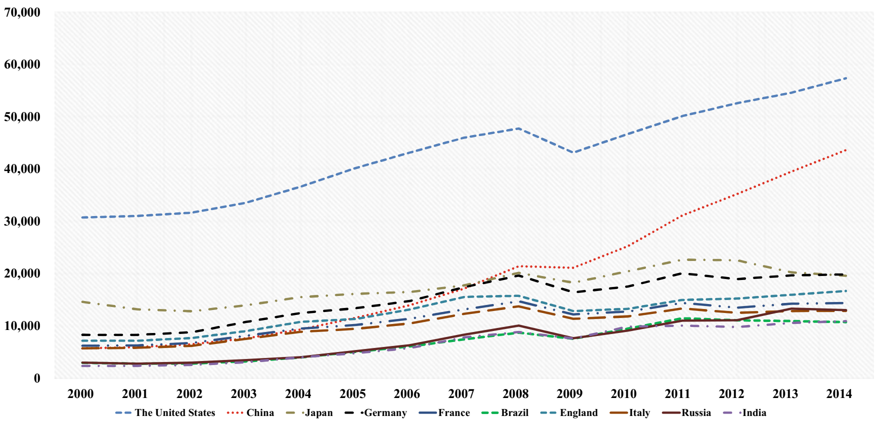

Fig. 4.25 Forward closeness of SC4 in GIVCN-WIOD2016SC4 models

(3) During the world economic crisis, China surpassed Japan to become the world's second in terms of the bidirectional closeness of services sectors and kept catching up to the United States. According to the statistics released by the World Trade Organization (WTO), China's import and export of services accounted for respectively 8.1% and 4.6% of the world's total in 2014, ranking at the second and fifth in the world. China has become the world's second-largest service trader and has been gradually narrowing the gap with the United States, which is quite identical with the results of the network analysis.

(4) Japan's earthquake and the Fukushima incident in 2011 caused cascading disasters and retarded the recovery of its manufacturing sectors, and meanwhile the "cost disease" caused by increasing production cost and sluggish productivity in the services sectors makes it plunged into the economic downturn. As a result,

the bidirectional closeness of Japan's manufacturing and services sectors experienced a downward trend from the year 2012 to 2014, clarifying its inferior position on the GVC.

(5) The manufacturing and services sectors of some BRICS countries (including China, Russia, India, and Brazil) grow faster, indicating a sharp increase of bidirectional closeness between their sectors and relevant upstream and downstream ones. Among the BRICS countries, India's rapid development in service trade benefits from the rapid growth of its service outsourcing, especially in the field of IT software.

4.6.3 Cross-Country Analysis

Significant heterogeneity exists between backward closeness and forward closeness among economies and sectors, especially between developed countries and developing countries. In this section, "Crop and animal production, hunting and related service activities" (S1), "Mining and quarrying activities" (S4), and "Manufacture of computer electronic and optical products" (S17), "Manufacture of motor vehicles, trailers and semi-trailers" (S20), "Retail trade, Except of motor vehicles and motorcycles" (S30) and "Financial service activities, except insurance and pension funding" (S41) are selected as the analysis subjects, whose bidirectional closeness in 44 countries/regions in WIOD2016 are calculated and compared. Due to the limited space, only top 10 sectors in 2000 and 2014 are listed in Tables 4.6 and 4.7. Also, conclusions are drawn in the following six aspects.

(1) China and the United States have higher S1 bidirectional closeness, although there is a reverse in their rankings, indicating that their agricultural production relies more on upstream suppliers and downstream customers and is more capable of connecting both the supply-side and demand-side simultaneously. Brazil's S1 has a rapid growth in forward closeness (faster than its backward closeness), while the United Kingdom experiences a sharp decline in this aspect. The reasons are the rapid export growth of the former's processed agricultural products and the latter's less agricultural exports caused by the global economic crisis and the European debt crisis in recent years.

(2) China, the United States, Canada, Australia, and Russia, whose S4 bidirectional closeness are higher than most other countries, not only have rich mineral resources and advanced processing and refining technology but also can pool together capital and mining technology and equipment from upstream suppliers, providing plenty of intermediate goods to other countries for industrial use. The exception here is Japan, whose backward closeness consistently ranks high from 2000 to 2014 but forward closeness drops a lot, because its excessive dependence on mineral resources and primary processed products imported from abroad makes the S4 very close to the upstream sectors which are usually located in mineral resource-rich countries; and Japan's recession,

Table 4.6 Backward and forward closeness of six sectors from different countries/regions in GIVCN-WIOD2016-2000

Rank	S1				S4				S17			
	Backward closeness		Forward closeness		Backward closeness		Forward closeness		Backward closeness		Forward closeness	
1	USA	370.248	USA	409.817	USA	340.205	ROW	553.242	USA	483.240	USA	389.371
2	ROW	300.904	ROW	341.479	ROW	295.946	USA	434.063	ROW	412.524	JPN	341.744
3	CHN	270.352	JPN	311.120	CHN	228.713	RUS	317.820	JPN	397.424	ROW	326.117
4	JPN	263.174	CHN	270.278	JPN	204.622	CAN	317.273	CHN	376.921	TWN	274.946
5	CAN	185.658	CAN	178.922	CAN	164.521	MEX	275.076	MEX	358.650	KOR	272.640
6	MEX	179.390	IND	164.836	AUS	153.427	AUS	270.406	TWN	356.316	CHN	254.480
7	DEU	179.205	GBR	162.187	MEX	153.132	CHN	269.413	KOR	332.497	MEX	237.073
8	KOR	170.682	DEU	153.598	GBR	124.643	JPN	263.230	CAN	274.387	DEU	225.383
9	IND	168.182	FRA	145.642	RUS	108.644	GBR	231.824	DEU	265.578	CAN	224.183
10	FRA	167.743	AUS	144.900	BRA	108.508	NOR	229.038	GBR	254.850	GBR	220.024
Rank	S20				S30				S41			
	Backward closeness		Forward closeness		Backward closeness		Forward closeness		Backward closeness		Forward closeness	
1	USA	495.880	JPN	348.811	USA	470.064	USA	391.964	USA	432.856	USA	485.821
2	JPN	388.471	USA	343.403	JPN	283.447	ROW	337.302	JPN	254.005	JPN	410.066
3	CAN	350.298	ROW	320.743	ROW	254.395	JPN	268.400	ROW	223.840	ROW	372.041
4	MEX	323.548	MEX	248.484	DEU	191.033	GBR	206.305	LUX	221.439	GBR	234.112
5	ROW	276.350	CAN	233.762	GBR	188.362	KOR	202.998	DEU	174.791	CHN	228.818
6	DEU	231.494	CHN	217.833	ITA	186.996	MEX	188.424	GBR	171.150	CAN	218.691
7	CHN	230.507	DEU	215.761	CAN	186.087	ITA	177.809	CAN	162.026	DEU	211.471
8	ESP	186.778	GBR	160.605	KOR	172.429	DEU	173.390	FRA	151.184	TWN	167.706
9	FRA	186.308	FRA	159.602	IND	169.208	CHN	170.031	CHN	143.804	KOR	164.877

(continued)

Table 4.6 (continued)

Rank	S20				S30				S41			
	Backward closeness		Forward closeness		Backward closeness		Forward closeness		Backward closeness		Forward closeness	
10	GBR	178.528	AUT	151.270	FRA	165.847	RUS	166.794	KOR	130.058	ITA	164.178

Table 4.7 Backward and forward closeness of six sectors from different countries/regions in GIVCN-WIOD2016-2014

Rank	S1				S4				S17			
	Backward closeness		Forward closeness		Backward closeness		Forward closeness		Backward closeness		Forward closeness	
1	CHN	1266.709	CHN	1395.544	ROW	1197.859	ROW	2400.322	CHN	1471.446	CHN	1325.120
2	ROW	958.108	ROW	1071.509	CHN	1140.975	CHN	1761.984	ROW	1086.150	ROW	1143.361
3	USA	918.930	USA	925.951	USA	806.235	RUS	1312.072	KOR	850.282	TWN	935.349
4	IND	571.324	BRA	704.024	JPN	667.664	USA	1097.531	TWN	801.318	KOR	920.019
5	JPN	505.628	JPN	523.635	CAN	435.108	CAN	927.523	USA	745.568	JPN	789.124
6	BRA	499.368	IDN	502.727	AUS	430.338	AUS	869.472	JPN	703.388	USA	777.023
7	MEX	444.547	IND	498.880	BRA	426.974	BRA	780.638	MEX	641.319	DEU	487.627
8	CAN	429.839	CAN	452.198	IDN	386.974	MEX	777.506	NLD	557.852	CHE	470.368
9	ESP	424.610	FRA	424.582	MEX	345.697	NOR	770.627	DEU	513.554	RUS	431.310
10	NLD	424.602	RUS	421.140	RUS	338.860	IDN	745.411	BRA	433.324	MEX	382.636
Rank	S20				S30				S41			
	Backward closeness		Forward closeness		Backward closeness		Forward closeness		Backward closeness		Forward closeness	
1	CHN	1409.013	ROW	1187.167	USA	1084.132	ROW	1046.559	CHN	925.758	ROW	1432.075
2	USA	998.729	CHN	1149.257	CHN	866.188	USA	921.460	USA	794.838	CHN	1150.541
3	ROW	907.385	JPN	685.959	ROW	748.938	CHN	817.177	ROW	777.743	USA	943.009
4	JPN	815.020	USA	671.098	JPN	695.903	RUS	685.005	LUX	623.512	JPN	649.245
5	CAN	743.958	DEU	666.386	IND	627.488	KOR	573.400	JPN	480.227	RUS	617.997
6	MEX	687.413	MEX	555.146	BRA	526.846	BRA	520.766	DEU	457.802	CAN	597.767
7	IND	648.433	CZE	500.505	DEU	457.966	IND	517.072	CAN	457.580	DEU	518.680
8	KOR	564.434	RUS	499.522	ESP	451.516	DEU	470.635	IND	358.217	GBR	510.741
9	DEU	548.400	HUN	483.784	CAN	444.276	JPN	461.261	FRA	352.522	AUS	505.593

(continued)

Table 4.7 (continued)

Rank	S20				S30				S41			
	Backward closeness		Forward closeness		Backward closeness		Forward closeness		Backward closeness		Forward closeness	
10	BRA	455.570	KOR	473.793	GBR	438.284	MEX	441.047	GBR	340.072	BRA	478.840

however, adversely affects its exports of processed mineral products, resulting in its worse relationship with the downstream sectors all over the world. Besides, Brazil's S4 has experienced rapid growth due to the huge demand for mineral resources from China in decades, and Vale of Brazil, as the world's largest producer and exporter of iron ore as well as the largest mining company in the Americas, contributes a lot to the integration of its mining industry chain.

(3) The United States, Japan, China, South Korea, and Taiwan province have played an important role in the division of GVC, especially in the aspect of S17. Over the past 15 years, the United States and Japan have gone backward in terms of the bidirectional closeness, while China, South Korea, and Taiwan province are catching up with them. The United States and Japan, with fewer manufacturers, have shifted their focus to R&D, product design and brand after-sales service in this field, while the segment of processing and manufacturing has been transferred to China, South Korea, and Taiwan province. This phenomenon is in conformity with the abovementioned tendency. Also, Netherlands' S17 backward closeness, thanks to its advanced semiconductor industry, moves up on the ranking and witnesses the rising compactness to the upstream intermediate products suppliers. The Netherlands ASML company, as the world's largest semiconductor lithography equipment and service provider with 60% of global market share, provides more than a quarter of the global semiconductor equipment; however, Netherland itself owns scarce domestic semiconductor materials and has to import them from other countries.

(4) Since the beginning of the new century, China's automobile industry has expanded rapidly, overtaking the United States to become the world's largest automobile producer and thus having the highest bidirectional closeness. The United States, Japan, Germany, and Canada as the major automobile manufacturing powers obtain higher value-added because they master core technologies and key components of automobile manufacturing, which also brings them the higher closeness on both supply-side and demand-side. Mexico as a member of NAFTA has great complementarity and interdependence with the United States and Canada in the automobile industry and has won a relatively higher competitive advantage through its low competitive cost and key strategic position.

(5) Among top 10 sectors with higher backward closeness or forward closeness, China and India are the best example to explain the new trends of today's retailing development. The S30 bidirectional closeness are relatively high in China and India with an obvious increase (China even did not show up in top 10 sectors in 2000). For China, its consumer market has tremendous potentials, and the rapid development of retail trade is closely related to the explosive growth of e-commerce retailers, such as Taobao, T-Mall, JD and other e-business platforms. And for India, the boom in retailing of this country is mainly due to strong domestic economic growth, deregulation of foreign direct investment, the consumption boom caused by younger consumer groups, and thriving e-commerce as well.

(6) Investment is one of the three main factors that drive a country's economic growth. If a certain country has higher S41 bidirectional closeness, we can therefore say it is successful and powerful in providing smooth and efficient communication platform to various industrial sectors at home and abroad. As a result, China, the United States, Japan, and Germany appears to be higher; but the ranking of some developed countries, including the three just mentioned, fell slightly from 2000 to 2014, while China's ranking continued rising. Besides, although Luxembourg is not top ranked in any category, the backward closeness of its S41 ranks fourth for this country is the world's second-largest investment trust center, second only to the United States. With advanced private banking and investment fund management, Luxembourg has attracted many global investment funds, with its securities trading volume accounting for 59% of global market share.

In conclusion, the backward closeness and forward closeness redefine the existent meaning of industrial sectors from a topological perspective and help understand the inner mechanism and base of forming competition force.

4.6.4 Cross-Sector Analysis

Drawn in Figs. 4.26, 4.27, 4.28 and 4.29 are the box plots of RUIs of 44 countries/regions based on the ICIO data from 2000 to 2016 in WIOD2016, which can

Fig. 4.26 Boxplot of SC1-RUI in GIVCN-WIOD2016SC4 models

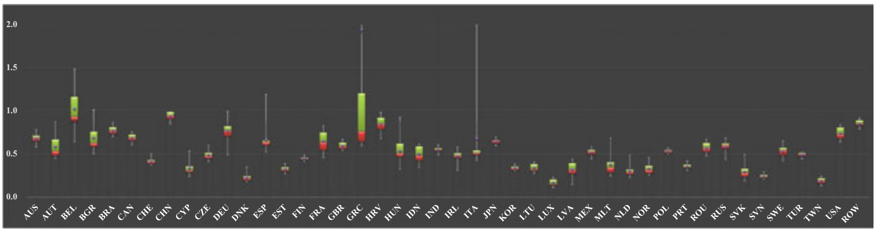

Fig. 4.27 Boxplot of SC2-RUI in GIVCN-WIOD2016SC4 models

Fig. 4.28 Boxplot of SC3-RUI in GIVCN-WIOD2016SC4 models

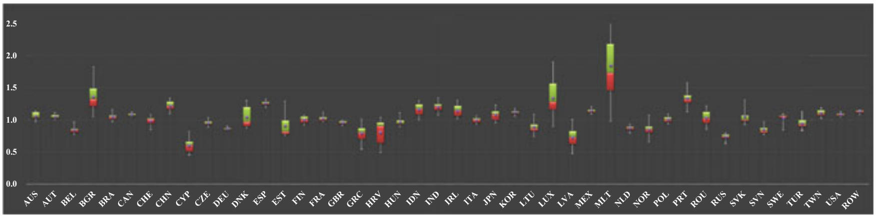

Fig. 4.29 Boxplot of SC4-RUI in GIVCN-WIOD2016SC4 models

be used to measure the relative position of each one of four-sector categories. If the RUI of certain sector is greater than 1, it is closer to the supply-side, otherwise to the demand-side.

Between 2000 and 2014, SC1-RUIs and SC2-RUIs in most countries are less than 1, indicating that they have closer relations with downstream sectors than upstream ones. Since the international division of labor become increasingly elaborated, there is growing demand for deep processing of agricultural and mineral products, which are more often used as the intermediate inputs to produce goods with higher value-added. Since IVCs are constantly extended, agriculture and mining sectors become closer to the downstream ones on the GVC.

However, in most countries, SC3-RUIs are greater than 1, indicating a higher closeness to the upstream sectors. The development of manufacturing sectors requires a lot of intermediate goods from all the upstream sectors on the supply-side. For example, automobile manufacturing requires a large amount of steel, aluminum, glass, petroleum products used to make plastics, rubber and specialty fibers, which means a majority of its industrial value-added is not created by the cooperation with demand-side sectors but supply-side ones.

The services sectors can be divided into the producer services sectors and the consumer services sectors. The former (e.g., financial services), mostly provide professional services for the manufacturing sector, enabling specialization and agile production, and their SC4-RUIs are thus less than 1 and closer to the demand-side. The latter (e.g., retail services), on the other hand, must handle multiple IVCs linked to them before delivering final products or semi-finished products to customers, so their SC4-RUIs are more likely to be greater than 1, i.e., closer to the supply-side.

Therefore, we can judge which type of services countries are more inclined to have based on SC4-RUIs.

4.7 Comparison with Similar Studies

In the end, we compare several similar network-based measures with the same purpose and figure out the essential difference to ours.

First, the mainstream studies in the field of world economics are based on the normalized amount of IO data, likely leading to the loss of many important and useful information, for instance, the heterogeneity of real economic systems. In other words, direct coefficients are good at depicting the structure of the global/regional economic system, but not how intermediate goods expand along the value chain.

Second, Mesa-Arango, et al. adopted a set of statistical network tools to measure the impact of international crises on the evolution of maritime transportation. Although the topological structure of their network models is identical to ours and the majority of network-based algorithms and indicators are subject to weights and directions, the betweenness centrality, indicating the importance of a given sector, is just obtained counting the number of times these elements are included in the shortest paths between every node duplet. As mentioned in the part of the methodology, geodesic-based centrality has lost its meaning in similarity-weight networks, let alone contributing to relevant economic analyses.

Third, Cingolani, et al. proposed three centrality measures for capturing the degree to which a given country plays a prevailing role in the upstream, midstream, and downstream stages of production in a given industry's GVC network. Among them, the midstreamness centrality can be taken as the counterpart of our betweenness centrality. The mainstreamness centrality is designed to capture the tendency of a country to import intermediate goods preferentially from countries with high upstreamness centrality and to export final products preferentially to countries with high downstreamness centrality. However, they only take neighbor countries of a given one into consideration when calculating certain sector's centrality, which means the measure is just for local optimization rather than global optimization.

Anyway, this chapter will be a useful experiment for understanding the function and position of industrial sectors on the GVC. If the inter-country import and export trades are ultimately to be built on the basis of comparative advantage as a basic common sense of economics, under the background of global economic integration, the function and position of the industrial sector on the GVC is not only the manifestation of comparative advantage, but also an important support for maintaining it.

4.8 Summary

Based on SRPL numerical matrix, ASRD and MSRD are introduced to evaluate the connectedness and compactness of economic system, and betweenness and closeness centralities to measure the pivotability and position of industrial sectors on the GVC. Contributions of this chapter are as follows:

(1) **Introduce the concept of connectedness and compactness for the GIVCN model**. In principle, the matrix formed by *SRPLs* between sectors is distinct from the Leontief inverse matrix or the Ghosh inverse matrix, but they own an identical purpose: to quantify both direct and indirect industrial relevance from the global perspective. Then, *ASRD* and *MSRD*, the average and maximum value of *SRPL*, respectively, are introduced to measure the connectedness and compactness of global, regional or national networks. *ASRD* serves as the measurement of the flow efficiency of intermediate goods, and its numerical results reflect the robustness of an economic system. *MSRD* measures the value chain owning the most significant spreading effect across industrial sectors. Under normal circumstances, random industrial fluctuation on a small scale is not supposed to shake the closest economic connection on the GVC. Normally, *ASRD* and *MSRD* will keep growing with the GDP increasing over time, but the systematic breakage of the world economy can make them decline temporarily.

(2) **Design the *SRPL*-based betweenness centrality of node to measure the pivotability of industrial sectors**. In a similarity-weight network, the issue of the optimal path should be reconsidered as the basis of all kinds of centralities. Now that such a path can be extracted from the GIVCN model based on RFWA, we use C_B^{RFWA} to measure the pivotability of globally industrial sectors, with the purpose to evaluate the level of the brokerage in the turnover of intermediate goods. If a certain sector in one country has a high centrality on the GVC, then it is at the core of the country's industrial structure, not only strongly promotes domestic economic development, but also occupies a large proportion in international trade as the main source of the country's trade surplus. Therefore, industrial sectors with high pivotability can be taken as media to demonstrate a country's competitive advantages to other countries.

(3) **Design the SPRL-based betweenness centrality of edge to measure the pivotability of inter-industry IO relations**. The pivotability of ICIO relations within and between them is believed to be much more useful and realistic for policymaking of industrial optimization and international trade. The economic environment changes, such as import and export restrictions under the COIVD-19 epidemic and the signing of RCEP, tend to inhibit or promote some input–output relationships, rather than exert an effect on a country or industry sector directly. But through the cascading effect, the impact will eventually be reflected in the changes on the importance of a country or industry sector.

We obtain a country-to-country pivotability matrix by merging the betweenness centralities of edges within each country, and then propose the domestic, international, and global pivotability to quantify the turnover efficiency of production system on the national level. From a local point of view, at any level, the United States, Germany, and Russia are always a force to be reckoned with, and China's pivotability on the GVC ranking the top in terms of growth speed and volume. Worth mentioning is their fluctuations of division and status in the network are in good agreement with their own economic trends and trade policy adjustments. From a global point of view, the gap of pivotability between countries is gradually narrowing, and the domestic pivotability is higher than the international pivotability in most countries, which is helpful to resist the impact of international economic risks.

(4) **Design *SRPL*-based closeness centralities to measure the position of industrial sectors**. Inspired by the concept of closeness centrality, $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$ are respectively defined as the backward closeness and forward closeness, to measure the interdependence of a given sector and all its upstream sectors or downstream sectors. Furthermore, RUI as the ratio of backward closeness to forward closeness is adopted to embody the relative position of industrial sectors on the GVC.

From the viewpoint of evolution, the most noticeable is that the bidirectional closeness of China's agriculture, mining and manufacturing sectors gradually surpass those of the United States as well as the gaps between China and other countries in two aspects are gradually widening; the United States' services sectors, however, have always topped the world ranking list of closeness, indicating they are highly capable of connecting the supply-side and the demand-side.

On the national level, the backward closeness and forward closeness redefine the existent meaning of industrial sectors from a topological perspective and help understand the inner mechanism and base of competition force.

On the sectoral level, SC1-RUIs and SC2-RUIs in most countries are less than 1, indicating that agriculture and mining sectors have closer relations with downstream sectors than upstream ones; SC3-RUIs tend to be greater than 1, which means the development of manufacturing sectors requires a lot of intermediate goods from all the upstream sectors on the supply-side; SC4-RUIs vary among countries, and we therefore can base our judgement on the type of services that countries are more inclined to have on the values of RUIs.

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Part III
Markov Process

Chapter 5
Measure the Global Impact of Industrial Sectors

5.1 Introduction

Considering the wide variety of mathematical properties of Markov chains, Leontief's IO model and Markov chains have naturally theoretical connections. However, only a few studies investigating the evolving world economic networks with Markov chain formalism. In the early studies, Blöchl, et al. adopted the ***Structural Analysis Database (STAN)*** of the ***Organization for Economic Co-operation and Development (OECD)*** to establish 37 countries' IO networks and derived two indicators for the weighted and directed network with self-loops, i.e., random walk centrality that reveals the most immediately affected nodes by a shock based on Freeman's closeness centrality, and counting betweenness to identify the most cumulatively affected nodes based on Newman' random walk betweenness [2]. Moosavi assessed different aspects of the evolving world economic network via various known properties of the Markov chains such as mixing time, Kemeny constant, steady-state probabilities and perturbation analysis of the transition matrices [3]. Xing, et al. analyzed the spreading effect of industrial sectors with biased random walk centrality, aiming at measuring their information superiority and intermediate interests [4]. Besides, random walk Markov chain approach can be used to detect the communities in the ICIO network, which highlights the deep international connections existing between production systems of different countries [5].

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5.2 Methodology

5.2.1 Features of Value Stream in Economic System

Black argued that the fundamental cause of the business cycle is the economic impact and its aftermath, which can be defined as the impacts of exogenous variables on the endogenous ones in industrial sectors. Specifically, market prices, advances in technology, profit distribution, government policies, and final demand are categorized as the exogenous variables; the material and capital flow between different sectors are categorized as the endogenous ones [6].

The economic impacts on the national economic system comprising of industrial sectors flow along the direction of intermediate inputs, and all of them converge into value stream just like a network. The target sectors, in the form of sink nodes in the network, are those whose final demands are met by the additional inputs at the end of this stochastic process of economic impact. Assuming that for some external reasons, such as government policies, additional productivity in the automotive industry becomes an impact on or disturbance to the entire economic system, which is to be absorbed by other industries. The abundance of extra production, on the one hand, is randomly distributed among other sectors, which can be traced from the IO table, and on the other hand, will bring about extra profits in the forms of extra manufacturing funds, labor remuneration and non-direct business taxes for the automotive industry. In this way, the external impacts given by the automotive industry will be transformed into inputs into other industries. This impact can then be shown as a ripple effect stirring additional economic flows in the economic system until it finally reaches a new stage of stability with all the impacts and disturbance absorbed by other industries.

5.2.2 Industrial Impact on the GVC

The GVC can be described as a cross-border system of supply chains within a globally integrated production network. From the perspective of industrial correlation, sectors have effects on both their upstream providers and downstream consumers in value-added trades. Within the GVC, each producer purchases intermediate inputs and then adds value through fabrication, which turns into outputs and enters the next stage of the value chain crossing international borders multiple times. It means that one sector in a certain country exerts direct and indirect impacts on others all around the world, even if the details of the whole process can be ignored. For example, in the massive explosions in China's Tianjin port in August 2015, thousands of imported vehicles stored there were burned causing a great loss to many auto manufacturers. The explosions also indirectly hurt many insurance companies; for instance, profits of the Zurich Insurance Group plunged in the third quarter of 2015. Nowadays, inter-industry butterfly effects which are prevalent on the GVC universally, even beyond the description of complicated international trade.

In the pioneering studies, due to the limited availability of the IO database, researchers spent a lot of effort to build up ICIO specifically for their models limited to single country's domestic IO table, to realize visualization when investigating vertical specialization. But the advent of ICIO simplifies this process, and more importantly, guarantees the accuracy, not considering those non-uniform import and export data. In that sense, the focus can be put on the topological structure of GVC and analyzing the interrelation between national industrial impact and its global economic status in GIVCN model.

It has been proven that industries with higher ***Random Walk Centrality***, denoted by C_{RC}, have more intensive industrial spreading effect to the industrial chains they stand in, because value stream transmission of sectors depends on how many products or services it can get from the other ones, and they are regarded as brokers with bigger information superiority and more intermediate interests [4]. The overall performance of sectors contributes to the competitive advantages of nations, so C_{RC} can be adopted to measure the national competitiveness on the GVC via expanding the research scale from inter-industry to inter-country.

In this section, the random walk centrality of each sector in 17 GIVCN-WIOD2013 models is calculated, including 40 countries and ROW. A coefficient is then proposed by summing total or partial random walk centrality within one sovereignty. Considering that a random walk process only reflects the topological characteristic of the network model, it contributes to eliminating abundant exogenous variables' disturbance, such as broad fiscal policies and changes in the global exchange rate.

5.2.3 Structural Holes Theory in Dynamic Network

In Burt's classic theory, holes come forth in social structures because weak ties exist in relations between groups on the connections of opportunities, capital, and information. Besides, these holes can also reinforce competitive advantages to the individuals in this relationship. As shown in Fig. 5.1a, A—C is referred to a structural hole, for there is no (or very weak) direct tie between A and C in the triangle network. If A, B, and C are in the state of resources competition, B will have information superiority and controlling advantage as an intermediate bridge because of the existence of a structural hole between A and C.

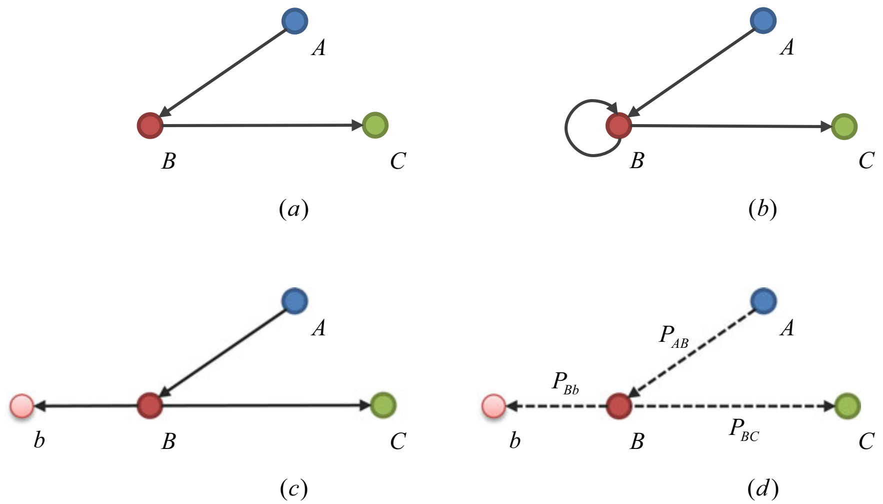

Fig. 5.1 Structural holes theory and its extension

However, its application in complex networks is limited because it leaves out weights, directions, dynamics, and self-loops. Overlooking such factors sabotages its ability to depict the infrastructures of economic systems, which are composed of industrial sectors and the quantitative relationships in between.

If B has a self-loop, as shown in Fig. 5.1b, it is assumed that there is a shadow node b, hence the self-loop can be replaced by a virtual edge B—b, as shown in Fig. 5.1c. Shadow nodes will only locate at the tail ends of the network, and there's no need to consider their out-degree or out-strength. In view of network flow, they can be regarded as sink nodes that merely receive from the original ones without any flow outwards.

Therefore, the index on the betweenness centrality should be modified when applied to studies that use the structural holes theory to investigate the dynamics of information transmission in networks. The practical value stream transmission in present industrial networks is a Markov process in the time-discrete state, taking into consideration the following factors. First, the direction of value stream, say B should have the provision of inflow and outflow of information simultaneously with probabilities of each transmission set respectively, for instance with $P(A,\ B)$ and $P(B,\ C)$ referring to the probabilities of existence of information transmission from A to B and B to C, but also the wastage and intra-industry consumption (outputs of the industrial sector itself). For instance, the industrial sector should first meet its own needs for products and services with the probability as $P(B,\ b)$.

5.3 Measurement

As one of the basic dynamic processes, the random walk process is closely related to network studies in many ways, and especially to the nature of the network topological structure. Three procedure parameters are generally involved in studying the random walk in complex networks. The first one is the ***First Passage Time (FPT)***. After a source node releases a walk signal, it will move to other adjacent nodes with equal probability or following certain transition probability, and the expected time to reach a pre-set sink node for the first time is the FPT. With FPT, the other two indices can be calculated. One is ***Mean First Passage Time (MFPT)***, i.e., the average of FPT of all nodes in the network; the other is ***Mean Absorption Time (MAT)***, which is the average of FPT from other nodes to a certain sink node [7].

Because of the progress of social networks in recent years, Freeman's ***Closeness Centrality*** has been widely applied, generally denoted by C_c. However, it restricts analyses on dense networks and merely takes self-loops into account. Therefore, Blöchl introduced random walk centrality, to describe how products and services flow within the economic system, considering the impacts of a certain industrial sector on its own [2].

5.3.1 Random Walk Centrality

As is known to all, the basic form of the IO table is material-type, but the widely used one is the value-type. WIOT adopted as the modeling data source belongs to the latter, so inter-industry relations are depicted by value stream flows. Borgatti gave an example: consider a specific dollar bill that moves within the economy, changing hands with each economic transaction. The dollar bill can easily move from A to B, B back to A, A to B again, then B to C, and so on. From a graph-theoretic point of view, the bill traverses the network via walks rather than trails. As a result, the money exchange process can be modeled as a Markov process, and the limiting probabilities of the nodes are proportional to degree [8]. In GIVCN model, however, the similar process is much more complex and need to be fully described by weights on edges, i.e., the ***Transition Probability Matrix*** of random walk, denoted by $M(i, j)$, which is subject to the impact of the importance of node j. In this book, M is defined as follows:

$$M = S_{diag}^{-1} W \tag{5.1}$$

where W is the weight set or the weighted adjacency matrix, and S_{diag} is the diagonal matrix consisting of nodes' out-strengths $S^{OUT}(i)$, say $S_{diag}(i, i) = S^{OUT}(i)$. For unweighted networks, S_{diag} can be substituted by diagonal matrix K_{diag} directly [9]. Transition probability matrix M describes possibilities when value stream transfers among sectors by selecting the next adjacent node as a path to continue, in the process of ***Absorption Random Walk (ARW)***. Hence $E(s, t)$ stands for MFPT, which is the expected number of steps when a random walk starts at source node s needs to reach sink node t for the first time. The formula is:

$$E(s, t) = \sum\nolimits_{r=1}^{\infty} r \prod\nolimits_{s \to t} (r) \tag{5.2}$$

where $\prod\limits_{s \to t} (r)$ is the probability of taking r steps starting from s reaching to t. When $s = t$, $\prod\limits_{s \to t} (r) = 0$ and $E(t, t) = 0$.

When considering an absorbing random walk, i.e., a random walk no longer leaves t after arriving at it, a modification is to be made transition matrix M by deleting its t-th row and column. The new $(n-1) \times (n-1)$ transition matrix is denoted by M_{-t}.

In unweighted networks, paths between any different nodes are more likely to be passed by central intermediate nodes with higher C_C values than those with lower C_C. Similarly, in a weighted network such as the GIVCN model, faster economic supply shocks tend to reach sensitive product sectors with higher C_{RC} values. Therefore, Blöchl defines random walk centrality as the inverse of the average MFPT by referring to Freeman's closeness centrality. The formula is:

$$C_{RC}(i) = \frac{N}{\sum_{j=1}^{N} E(i, j)} \tag{5.3}$$

From Eq. (5.3), it is clear that the shorter MFPT taken to reach i, the higher its C_{RC} value will be. In addition, from this indicator's derivation and calculation, it incorporates self-loops because they slow down the traffic between other nodes. Industrial sectors with bigger C_{RC} will create a much more spreading effect on the IVC where they locate, and their transfer capacity for value stream depends on how many products and services are acquired from the others. Thus, these sectors can be regarded as brokers owning information superiority and more intermediate benefits [10].

5.3.2 Global Industrial Impact Coefficient

To evaluate the national competitiveness on the GVC, ***Global Industrial Impact Coefficient (GIIC)*** is here introduced, which is derived from the sum of C_{RC} of all the sectors within each country:

$$GIIC(u) = 10^3 \times \sum_{i \in \tau(u)} C_{RC}(i) \tag{5.4}$$

Notes: due to the huge size of the GIVCN model, the value of C_{RC} is rather small, so the sum is timed by one thousand for convenience.

A country's relative competitive advantage derives from the macro performance of its inner industrial sectors. Based on the view of system science, the temporal variation of *GIIC* synchronously reflects the collapse of old steady-state and the formation of a new one. On the level of macroeconomic, moreover, the reconstruction of the international economic pattern and the alternation of new business forms embody the non-equilibrium and irreversibility of the global economic system.

However, the function of any system usually does not equal the simple integration of composition, i.e., there exist emergence phenomena widely. Therefore, the non-linear relation between inter-industry and inter-country structural measurements is worth considering.

5.4 Empirical Analysis: Macroeconomic Trend Forecast

In this section, we characterize the globalization with *GIIC* and analyze the development of GVC based on WIOD2013. The statistical result based on WIOD2016 is provided.

5.4.1 Comparative Analysis with Classic IO Theory

To illustrate the relation between the network-based topological feature and real economic development, GIVCN-WIOD2013-CHN model is built based on the NIOT in WIOD2013, which is the sub-network of GIVCN-WIOD2013 model. According to the assumption and formula on C_{RC}, each industrial sector's random walk centrality in GIVCN model is calculated. The time-varying candlestick of China is shown in Fig. 5.2.

We use C_{RC} to measure the short-term industrial spreading effect, and it depends on the industrial structure. Thus, its quantitative value of different years can be cross-contrast, which means variation trends of the industrial structure can be identified through timing analysis. As shown in Fig. 5.2, C_{RC} of some Chinese industrial sectors rises and some declines from 1995 to 2011, and most of them are associated with varying degrees of fluctuation. Then, sectoral analyses are also carried out.

Firstly, C_{RC} of "Agriculture, Hunting, Forestry and Fishing" (S1) in primary sectors and its downstream "Food, Beverages and Tobacco" (S3) declines drastically after 1997. When adopting China's IO data to establish a partial GIVCN model, more attention is paid to the domestic industrial structure of China without consideration of imported products. With the rapid growth of the import ratio of agricultural goods, China's agriculture sectors lost its crucial place on the IVC. In the meanwhile, capital flows to sectors with a higher rate of return on investment. Thus, primary sectors'

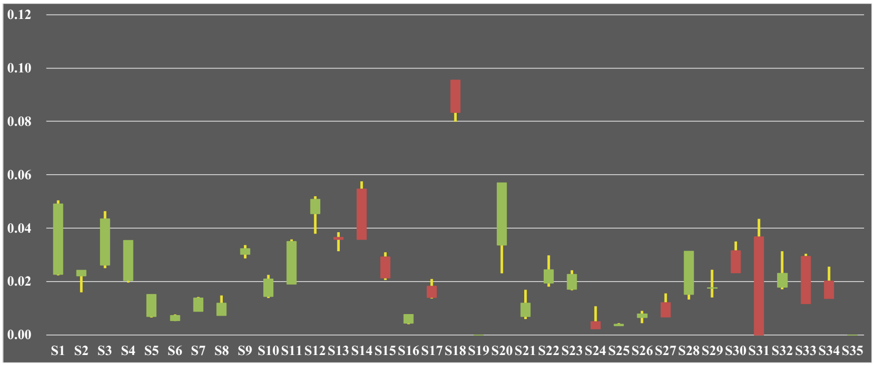

Fig. 5.2 Candlestick of C_{RC} of China in GIVCN-WIOD2013-CHN models

transmission function has been weakened due to both import price shock and financial capital transfer.

Secondly, C_{RC} of four sectors in secondary industries experiences large growth, including "Electrical and Optical Equipment" (S14), "Transport Equipment" (S15), "Electricity, Gas and Water Supply" (S17) and "Construction" (S18). The former two belong to typical modern manufacturing industries and their status enhancement in the industrial system benefited from higher participation in the vertical specialization. The latter two are closely bound up with China's urbanization, and especially construction. China's production value share of GDP is getting higher with a deepening impact on the industrial structure, for which Chinese authorities should be alert to all kinds of consequent economic and social issues, such as subprime lending crisis and over-capacity.

Thirdly, as the production and life pattern kept changing, as for the secular trend, traditional services sectors' impact gradually declines. According to the variation trends of C_{RC}, most of the circulation services sectors' short-term function of transferring value stream goes down, indicating that Chinese tertiary industries hit a bottleneck when transferring from labor-intensive ones to capital intensive and technology-intensive ones.

Similarly, ***Induction Coefficient*** (denoted by ***ISD***), and ***Influence Coefficient*** (denoted by ***IPD***) are also introduced for multiple regression with C_{RC}. *ISD* means in the national economy when all industries are adding a unit of final use, thereby subjects to the needs of an industry level sensors. *IPD* refers to a national increase of one unit of end-use industries, the right of the national economy resulting from the production needs of industry, affects the degree of the correlation coefficient. According to their definition, they respectively evaluate one sector's sensitivity and extraversion to the industrial structure, and the regression results will show which index determines the function of the short-term industrial spreading effect.

After the same estimation process, the fixed effect panel data model is used again. Since *IPD* has a negative effect, so the final panel data fixed effect model can be expressed as follows:

$$\begin{array}{l} C_{RC}(t) = -0.0000519 + 0.862493C_{RC}(t-1) + 0.003041ISD \\ (0.9589) \qquad\qquad\quad (0.0000) \qquad\qquad\quad (0.0044) \end{array} \tag{5.4}$$

Durbin-Watson stat is 1.76, according to D.W. Test table (1.58 < D.W. = 1.76 < 2.42), which means that the null hypothesis should be accepted, and the disturbance term does not have a first-order positive autocorrelation. Also, the higher R-squared means the goodness-of-fit of the model is very strong. Equation (5.4) displays that C_{RC} has a positive correlation with its first-order lag, which means every 1 unit in the last year will have a 0.862 unit of impact on this year.

In sum, exogenous and endogenous variables jointly influence the industrial structure and make it change slowly over time, Thus, C_F and C_{RC} are relevant with their last annual status. In addition, the industrial spreading effect is decided by capital in-flow and its sensitivity, not out-flow or extraversion. So, both the long-term and short-term value stream transmission depends on how many products and services sectors can get. If these sectors can get enough stuff in the economic system, with huge intermediate consumption, then they are to be regarded as brokers with information superiority and more intermediate interests according to the structural holes theory. This means their position and function are more important in the economic system than the others.

Industry analyses concentrate more on the dynamic swarm than the static individual. IO analysis, as an important research tool, focuses more on static analysis. However, the fundamental aim of industry analysis is to figure out how the interaction between different industries impacts on economic development, a dynamic process. Therefore, partial GIVCN models are established based on IO tables as a bridge between accurate static quantitative analysis and a comparable dynamic one.

Based on the revised structural holes theory, industries with higher flow betweenness or random walk centrality bring more intensive industrial spreading effect to the industrial chains. If they suffer from intentional failure, the connectedness of partial GIVCN model will decline rapidly. And according to the multiple regression results, value stream transmission of industrial sectors depends on how many products and services sectors they can get from others, and these sectors are regarded as brokers with information superiority and more intermediate interests.

Results from this section are, however, not enough for forecasting evolutionary trends of industrial structure. The reason is that IO data in the previous year are adopted to depict variation trends of two kinds of betweenness and centrality as well as the explain the dynamic mechanism of industrial effect spreading over the different temporal span. However, it is necessary to accurately estimate industrial development in consideration of multiple exogenous variables' effect, and the difference will be enormous when different exogenous variables act on different industrial sectors.

5.4.2 Robustness Analysis

GIVCN-WIOD2013-2011 is taken for example and some nodes are removed to observe what happens to the *ASRD* of this model. In detail, we intentionally removed specific nodes from those with higher C_{RC} to lower ones in one set of experiment, then we make random removal of nodes in another set of the experiment as reference. Figure 5.3 shows the results of implementing intentional and random failure for C_{RC}.

Finally, the flow efficiency of the value stream reduces compellingly by 50% when the ratio of nodes intentionally removed just reaches 4.114%, which covers the top 60 nodes released in descending order of $\mathrm{C_{RC}}$. In the meanwhile, reference sets are far from this level of damage, which is only 1.409%. Also, similar types of situations occur in the rest of GIVCN-WIOD2013 models, as shown in Fig. 5.4.

It is thus confirmed that in the regular industrial lifecycle, where exists no acute worldwide economic transformation, the GVC exhibits robustness even though most of the sectors' boom and bust. In contrast, if extremely small parts of crucial sectors lose their function, such as the ones with larger $\mathrm{C_{RC}}$, the global economic system will inevitably depict its fragility. Consequently, the results of robustness analyses inferred the inner structure of GVC changed cyclically. It can be noticed that the proportion of nodes intentionally removed to cut ASRD down to half of its function fluctuated over years, and this ratio is denoted by Half-Value Ratio (HVR), as shown in Fig. 5.5.

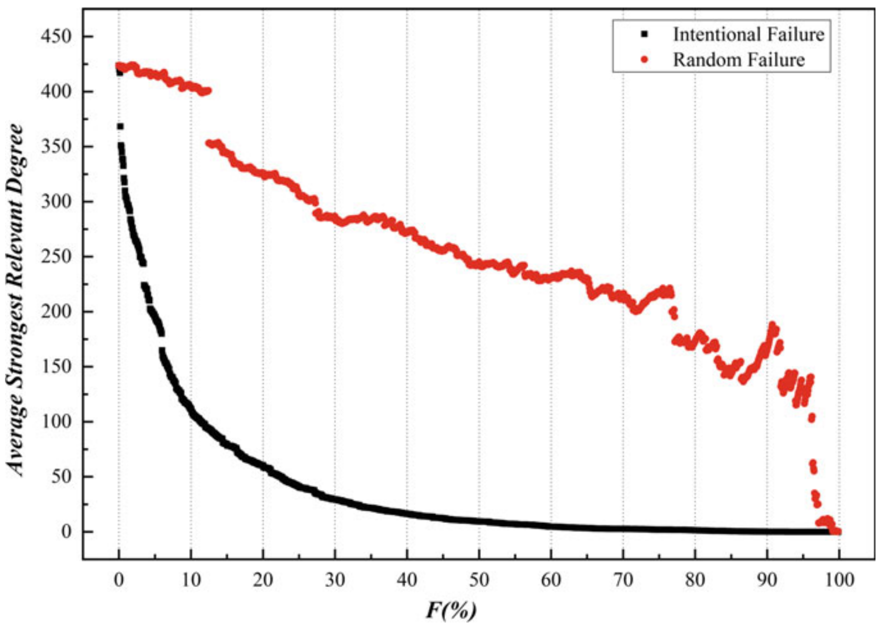

Fig. 5.3 Cascading failure analysis on the ASRD of GIVCN-WIOD2013-2011

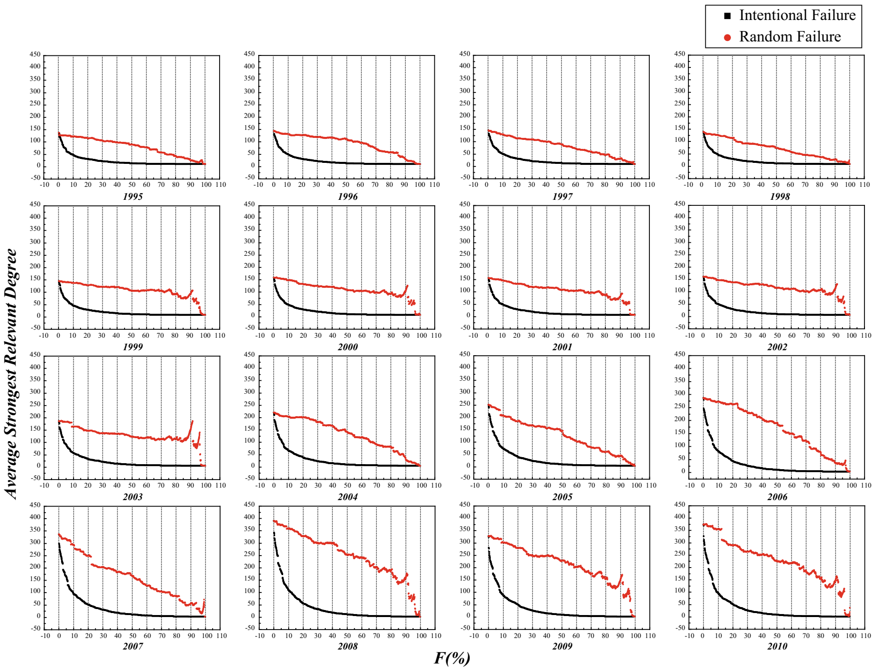

Fig. 5.4 Cascading failure analysis on the ASRDs of GIVCN-WIOD2013 models

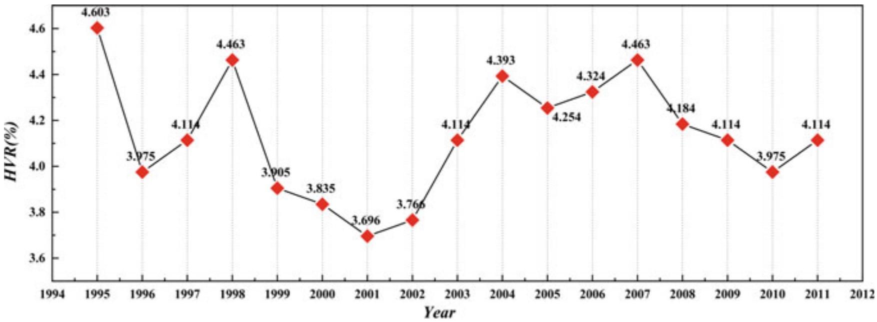

Fig. 5.5 Trend of HVR in GIVCN-WIOD2013 models

In Fig. 5.5, HVR displays the fluctuation over time, and we try to explain this phenomenon using the world business cycle. First, HVR sustained a downward trend from 1997 to 2002, during which the Asian financial crisis broke out and the dotcom bubble burst during this period. Then, HVR goes down again from 2007 to 2010, in coherence with the merge of the United States' subprime mortgage crisis, which intrigued a rapidly expanding global tsunami. To testify whether there is a correlation

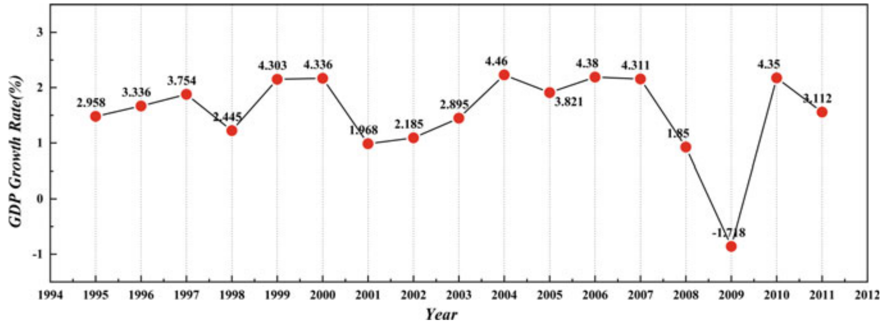

Fig. 5.6 Growth rate of global GDP from 1995 to 2011

between HVR and global macroeconomics, the GDP growth rate from 1995 to 2011 is taken as a reference object, as shown in Fig. 5.6.

By contrast, HVR and GDP growth rate share the same change pattern when the global economic system is relatively stable from 2000 to 2008. In the meanwhile, there is no significant association between them around 1998 and 2008. GIVCN model can be used to predict the basic trend of the world economy since they truly and directly reflect the inner topological characteristics of the global economic system. Nevertheless, one question remains: how to warn the systemic financial crisis? To answer the question, it is necessary to dig deeply into the industrial structure to find an economic incentive.

In GIVCN-WIOD2013-1998, the HVR involves 65 sectors mainly concentrates in the United States, Germany, Japan, the United Kingdom, France, and ROW. Although Thailand, Malaysia, Hongkong, and Indonesia heavily influenced by the Asian financial crisis belong to ROW, their total share of the economy is still small. Besides, there are few Japanese sectors and even no Chinese or Korean sectors in the HVR of 1998. Thus, HVR starts to decline after 1998 indicating the debilitating robustness of the global economic system. However, this trend does not make a system-wide impact on global economic development immediately. In GIVCN-WIOD2013-2008, most of the United States' sectors fall in the range of HVR when the subprime mortgage crisis just broke out in this country, and they largely weaken the connectedness of GVC, which in turn, led to the global economic crisis. In sum, HVR can be made full use of to measure the robustness of open-economy macroeconomics in the following research.

In GIVCN-WIOD2013-2011, the preceding 4.114% sectors play a leading role in the transmission of the value stream in the global economic system, which are shown in ascending order in Table 5.1. The top 60 sectors, except those in the ROW and Germany's "Transport Equipment", mainly concentrates in the United States and China.

Table 5.1 Top 60 sectors with the most important impact on the GVC in 2011

Rank	Country	Sector
1	The United States	Public Admin and Defence; Compulsory Social Security
2	Rest of World	Construction
3	Rest of World	Mining and Quarrying
4	China	Electrical and Optical Equipment
5	China	Construction
6	Rest of World	Food, Beverages and Tobacco
7	China	Basic Metals and Fabricated Metal
8	Rest of World	Public Admin and Defence; Compulsory Social Security
9	Rest of World	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
10	Rest of World	Renting of M&Eq and Other Business Activities
11	Rest of World	Agriculture, Hunting, Forestry and Fishing
12	United States	Renting of M&Eq and Other Business Activities
13	Rest of World	Inland Transport
14	United States	Health and Social Work
15	China	Machinery, Nec
16	Rest of World	Hotels and Restaurants
17	China	Chemicals and Chemical Products
18	Rest of World	Health and Social Work
19	China	Public Admin and Defence; Compulsory Social Security
20	China	Transport Equipment
21	United States	Hotels and Restaurants
22	China	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
23	United States	Financial Intermediation
24	China	Renting of M&Eq and Other Business Activities
25	United States	Construction
26	Rest of World	Electrical and Optical Equipment
27	United States	Other Community, Social and Personal Services
28	Rest of World	Transport Equipment
29	United States	Transport Equipment
30	China	Health and Social Work
31	United States	Real Estate Activities
32	China	Food, Beverages and Tobacco
33	United States	Food, Beverages and Tobacco
34	Rest of World	Other Community, Social and Personal Services
35	Rest of World	Education

(continued)

Table 5.1 (continued)

Rank	Country	Sector
36	United States	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods
37	Rest of World	Financial Intermediation
38	China	Agriculture, Hunting, Forestry and Fishing
39	China	Mining and Quarrying
40	China	Textiles and Textile Products
41	United States	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
42	Germany	Transport Equipment
43	China	Other Non-Metallic Mineral
44	China	Hotels and Restaurants
45	China	Other Community, Social and Personal Services
46	United States	Chemicals and Chemical Products
47	Rest of World	Real Estate Activities
48	China	Electricity, Gas and Water Supply
49	Rest of World	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods
50	Rest of World	Basic Metals and Fabricated Metal
51	China	Education
52	Rest of World	Electricity, Gas and Water Supply
53	China	Rubber and Plastics
54	United States	Post and Telecommunications
55	China	Inland Transport
56	China	Real Estate Activities
57	United States	Basic Metals and Fabricated Metal
58	Rest of World	Post and Telecommunications
59	United States	Coke, Refined Petroleum and Nuclear Fuel
60	China	Financial Intermediation

5.4.3 Statistics on Major Economies

To observe the overall performance of sectors with different C_{RC} in the level of country, GDP is here used to reflect the national competitiveness, and as shown in candlestick (Figs. 5.7, 5.8, 5.9, 5.10, 5.11, 5.12, 5.13, 5.14, 5.15 and 5.16), top 10 countries in 2011 are taken for example including the United States, China, Japan, Germany, France, Brazil, the United Kingdom, Italy, Russia, and India. When making the chart, four columns of results are calculated, with the initial value in 1995 and the final value in 2011, maximum and minimum value from 1995 to 2011. Red cylinders represent the initial value is smaller than the final value, in which under-cutting is

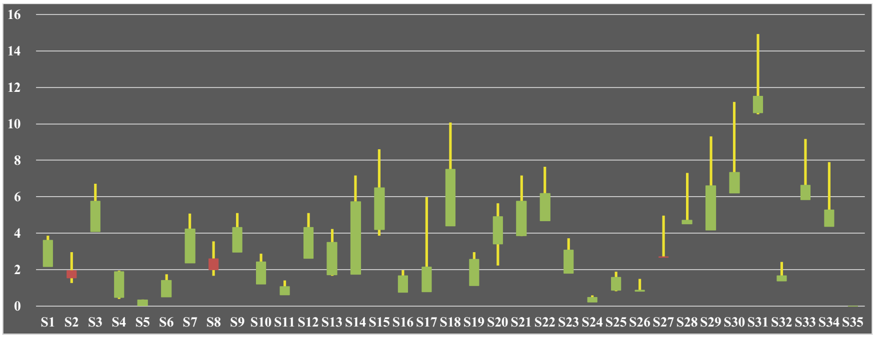

Fig. 5.7 Candlestick of C_{RC} of the United States on the sectoral level of GIVCN-WIOD2013 models

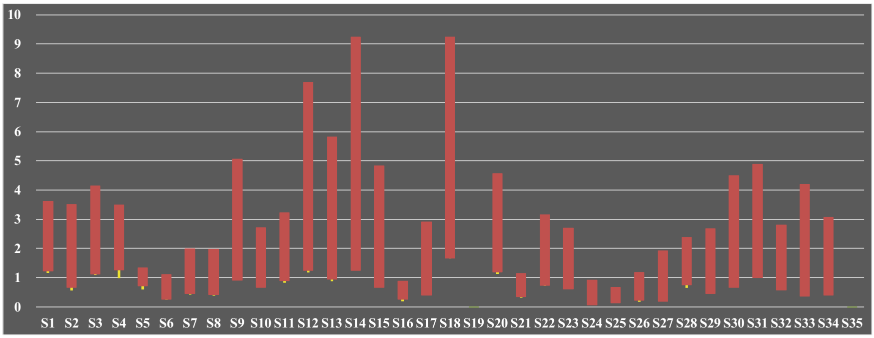

Fig. 5.8 Candlestick of C_{RC} of China on the sectoral level in GIVCN-WIOD2013 models

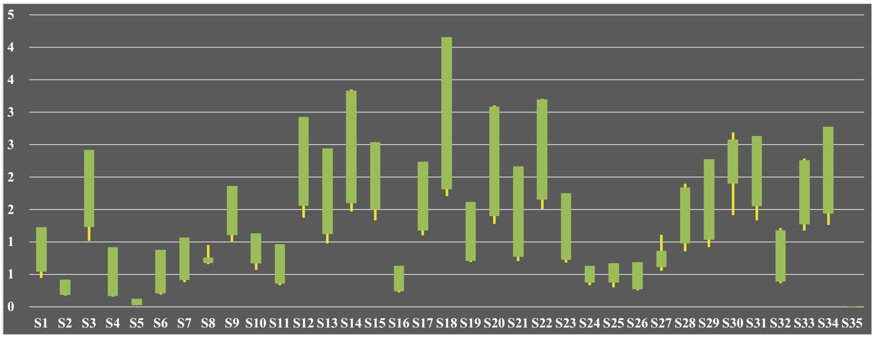

Fig. 5.9 Candlestick of C_{RC} of Japan on the sectoral level of GIVCN-WIOD2013 models

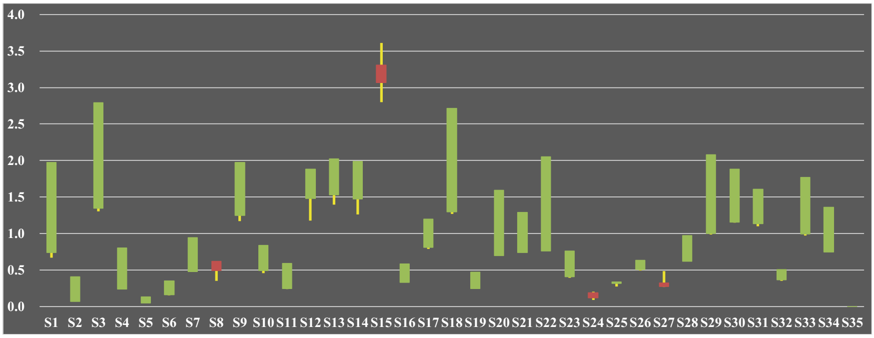

Fig. 5.10 Candlestick of C_{RC} of Germany on the sectoral level of GIVCN-WIOD2013 models

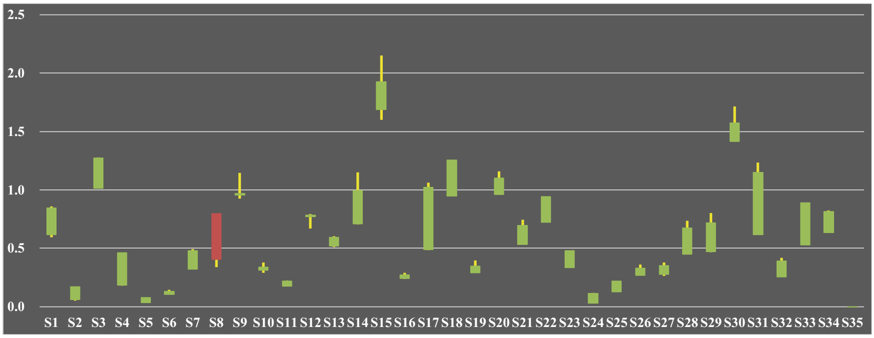

Fig. 5.11 Candlestick of C_{RC} of France on the sectoral level of GIVCN-WIOD2013 models

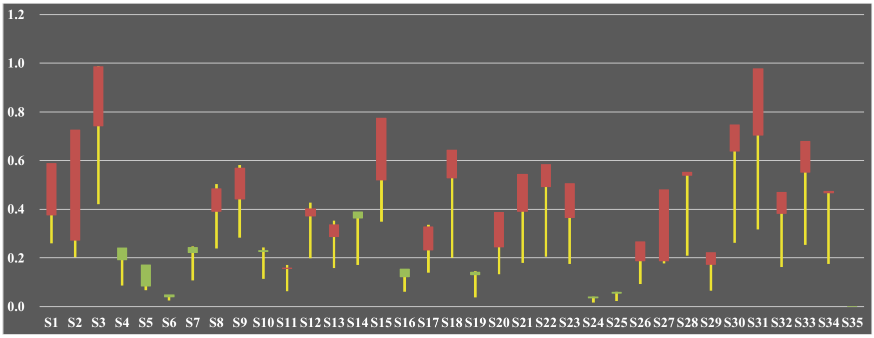

Fig. 5.12 Candlestick of C_{RC} of Brazil on the sectoral level of GIVCN-WIOD2013 models

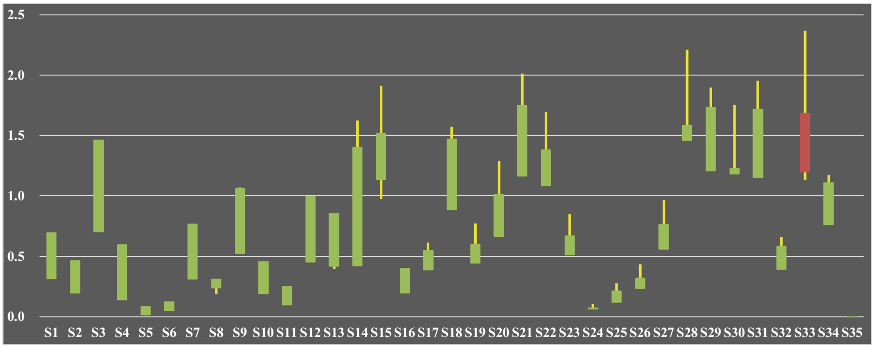

Fig. 5.13 Candlestick of C_{RC} of the United Kingdom on the sectoral level of GIVCN-WIOD2013 models

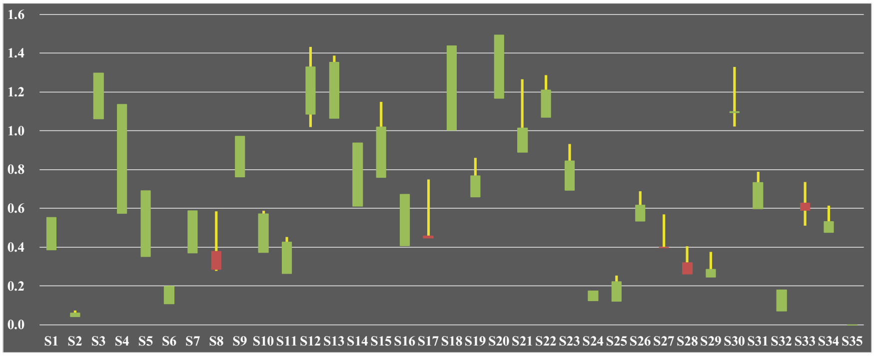

Fig. 5.14 Candlestick of C_{RC} of Italy on the sectoral level of GIVCN-WIOD2013 models

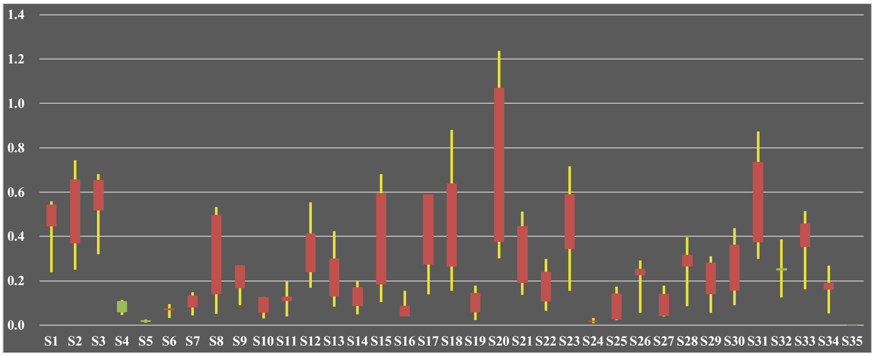

Fig. 5.15 Candlestick of C_{RC} of Russia on the sectoral level of GIVCN-WIOD2013 models

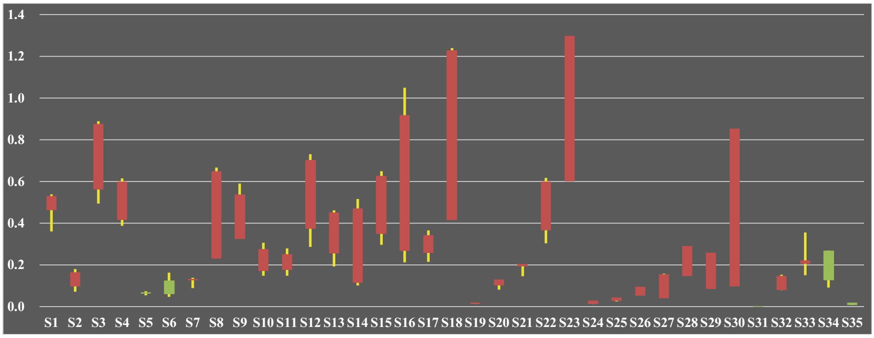

Fig. 5.16 Candlestick of C_{RC} of India on the sectoral level of GIVCN-WIOD2013 models

the initial value and upper-cutting the final value. On the contrary, green cylinders represent the initial value is bigger than the final value, in which under-cutting is the final value and upper-cutting is the initial value. Besides, the upper end of yellow fine lines is maximum value from 1995 to 2011, and the low end means minimum.

According to the trends of C_{RC} of sectors in these ten major economies in 17 years, some countries' information transmission capability on a global scale keeps going down to different degrees, including the United States, Japan, Germany, France, the United Kingdom, and Italy. In meanwhile, others, such as China, Brazil, and Russia, are undergoing a sharp rise. To certify the sectors' C_{RC} indeed impacts the relative status of countries in the global economic system, the countries are reviewed with their GDP ranks in 1995. At that time, the top 10 in order are the United States, Japan, Germany, France, the United Kingdom, Italy, Brazil, China, Spain, and Canada, besides Russia becomes the 13th and India the 15th. By comparison, we arrive at three conclusions.

(1) For countries with declining $\mathrm{C_{RC}}$ of most sectors, their GDP ranks are also in the declining trend, e.g., Japan (2nd to 3rd), Germany (3rd to 4th), France (4th to 5th), the United Kingdom (5th to 7th) and Italy (6th to 8th).
(2) For countries with ascending $\mathrm{C_{RC}}$ of most sectors, their GDP rankings are also improved, e.g., China (8th to 2nd), Brazil (7th to 6th), Russia (14th to 9th) and India (15th to 10th), which all belong to the emerging economies.
(3) With a large portion of sectors' $\mathrm{C_{RC}}$ falling sharply, the United States still ranks the first in GDP.

Thus, the overall trend of $\mathrm{C_{RC}}$ can be the gauge for forecasting a country's world-wide economic status. An overall rising trend of $\mathrm{C_{RC}}$ means an improving economy and an overall declining trend implicates a deteriorating one.

5.4.4 Geographical Distribution of GIIC

As the value of C_{RC} reflects the degree of economic information superiority, which is the industrial impact on the GVC, *GIIC* is used to evaluate this capacity on the level of country instead of industry. In other words, GIIC is introduced to measure the national/regional competitiveness of creating value-added on the GVC, which contributes to enhancing the economic status of the country.

According to the definitions and equations mentioned above, each country's *GIICs* from 1995 to 2011 are calculated, and the results are shown in the geographical distribution in Figs. 5.17 and 5.18.

The tendency is obvious that the United States' *GIIC* declines while China's ascends, with a turning point taking place around 2009. After the subprime mortgage crisis, China succeeded in readjusting the industrial structure with a package of policy regulations, itself the world's second-largest economy. China has become the so-called world factory, and its export-oriented industrialization has gradually formed, though most of its sectors are still in great need of the latest technologies and beyond profit margin.

GIIC and GDP from 1995 to 2011 is compared to testify the interrelationships between them, as shown in Fig. 5.19. There are 39 sets of comparison except Taiwan and ROW, because neither of them is counted as sovereignty.

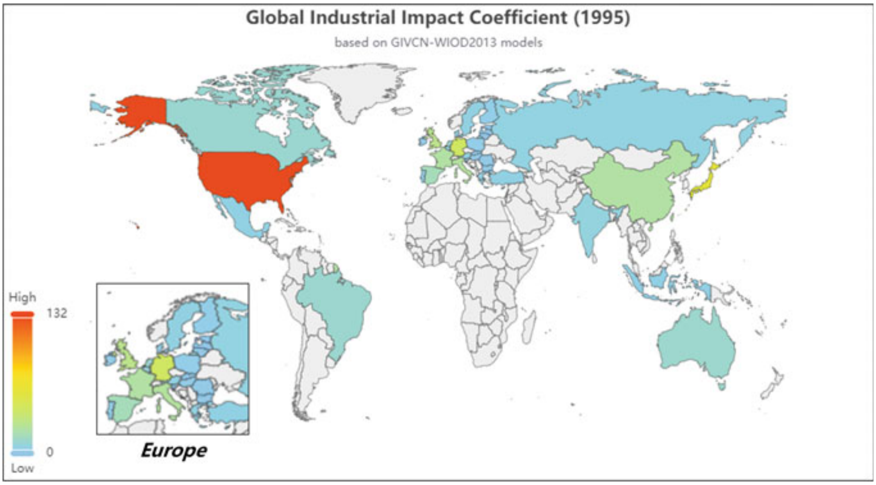

Fig. 5.17 Geographical distribution of GIIC in 1995

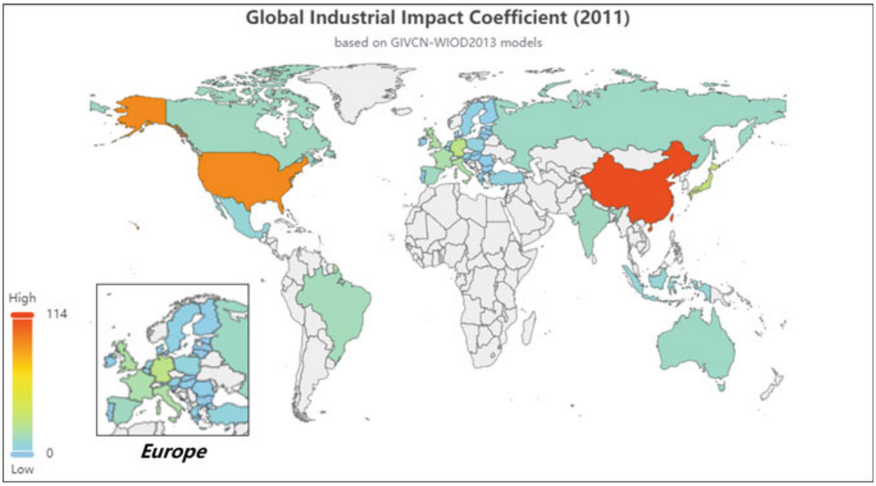

Fig. 5.18 Geographical distribution of GIIC in 2011

5.4.5 Correlation Analysis with GDP

For each sample that has experienced the same number of observations, the panel variables (countries) are strongly balanced, with the source data of 39 nations' GDP from 1995 to 2011. Table 5.2 lists the Hausman test results, showing that the fixed effects estimator is better than the random effects estimator.

Then, the fixed effects model is built, with results shown in Table 5.3.

This model exhibits a good fit with a large R^2 (0.838), and it conducts an F-test to determine whether the fixed effects model is better than pooled regression. As indicated by the results shown in Table 5.3, i.e., the *P*-value almost equals to zero, implying that different countries owned different intercepts. The ρ-value indicates that the composite disturbance is primarily from individual-specific effects.

The final fitted model is shown in Eq. (5.5):

$$GDP(i) = \alpha_i + 10.359 \times GIIC(i) \tag{5.5}$$

where, the first part to the right of the equation α_i denotes one country's domestic economy and $\overline{\alpha} = \sum \alpha_i/39 = 857.040$, while the second part $10.359 \times$ GIIC(i) denotes its global industrial impact. Considering that the overall average GDP of the 39 countries is 998.337 billion. That is to say, a country's GIIC has a positive correlation with its GDP at a level of 14.153% (1 − 857.040/998.337) on average. Thus, GDP is primarily derived from the domestic market, and segmentally from international trade on the GVC. Evaluating the competitive advantage of nations can't be only limited to whether they own larger trade surplus, more job opportunities or lower labor cost, but both the international industrial impact and the domestic market situation are equally important in assessing the economic status on the GVC.

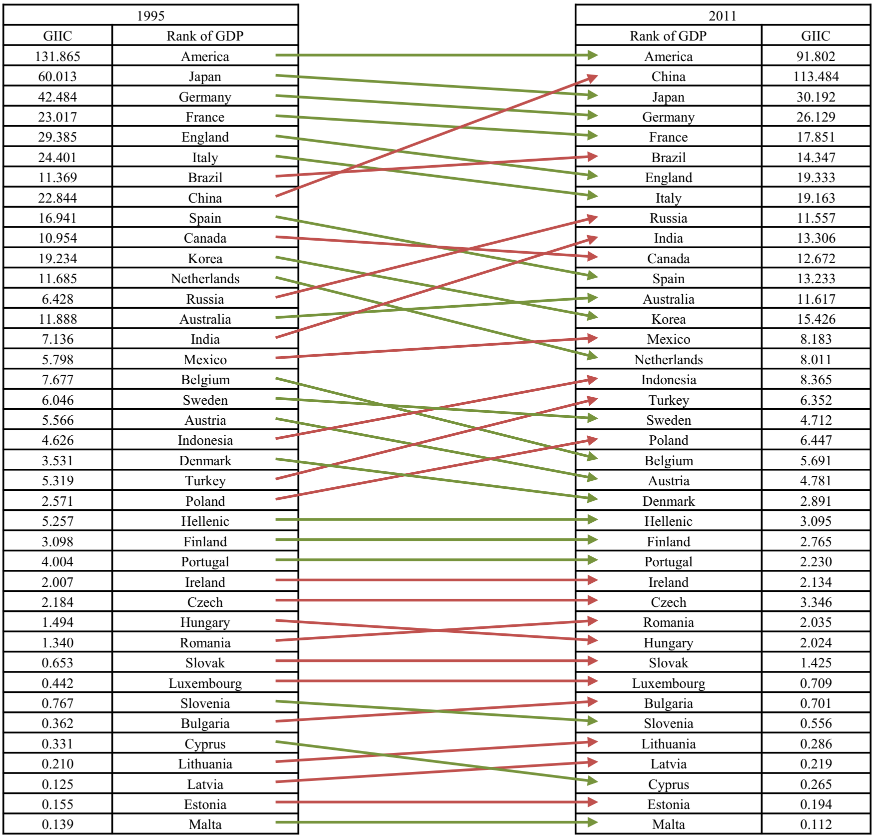

Fig. 5.19 Relationship between GIIC and GDP

Table 5.2 Results of the Hausman test

Hausman test	H0: difference in coefficients not systematic
chi2(2) = 189.88	$P = 0.0000$

Table 5.3 Results of regression between GDP and GIIC

Variables	Coeff.	Std. Err.	T	$P > \text{t}$
GIIC	10.359	3.687	2.810	0.005
cons	857.040	51.698	16.580	0.000
$R^2 = 0.838$			ρ= 0.898	
F (38, 623) = 17.130			P = 0.000	

In Fig. 5.19, the red lines represent that the initial value in 1995 of GIIC is smaller than the final value in 2011, while the green lines represent the opposite case with the arrow starting at the 1995 GDP ranking then pointing to the one in 2011 showing the chronological order. Thus, rising red lines and declining green lines mean that the trends of *GIIC* are in accordance with the corresponding GDP rankings, with the matching results indicating that *GIIC* and GDP have a positive correlation.

5.5 Summary

Contributions of this chapter are as follows:

(1) **Measure the globalization of industrial sectors based on Markov chain analysis**. Industrial sectors with bigger C_{RC} will create a much more spreading effect on the IVC where they locate, and their transfer capacity for value stream depends on how many products and services are acquired from the others. Thus, they can be regarded as brokers owning information superiority and more intermediate benefits. Also, the utilization of C_{RC} is extended from the sectoral level to the national level, i.e., *GIIC* is proposed as the summation of C_{RC} within each country/nation. Through geographical distribution and comparative analysis, *GIIC* is found to be feasible in depicting one country's global economic status from the perspective of industrial impact.

(2) **Adopt supplementary means to analyze the robustness of global production system**. In order to test the stability of GIVCN model, *ASRD* is adopted to be the gauge of the connectedness of GVC, and *HVR* to the robustness of the global economic system. Moreover, sectors with higher C_{RC} are found to be more capable of transferring value stream within the global economic system. Besides, the United States and China own those major sectors in the top 60 that play a fundamental part on the GVC.

(3) **Establish a quantitative relationship between network-based indicator and the level of macroeconomic development**. The positive correlation between *GIIC* and GDP indicates that a nation's global industrial impact can reveal its international competitive advantage, which specifically is constituted by industrial sustainable development and national economic welfare. Correspondingly, a higher *GIIC* often implies a greater GDP level.

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Chapter 6
Measure the Impact of Final Demands on the Global Production System

6.1 Introduction

Supply and demand are two fundamental terms to market mechanism theory in modern economics, and which of them dominates the market mechanism depends on the specific economic conditions in different historical periods. Nowadays, many economists believe stable economic growth needs three aspects of demands, which are consumption, investment, and export, the so-called *"**Three Carriages**"*. Therefore, we can assume that the final demands on goods or services, both at home and from abroad, have driven the value-added process of all industrial sectors on the GVC.

After reviewing the related macroeconomics models, we obtain two facts. On the one hand, influenced by many factors, such as labor, capital land, and technology, etc., the aggregate supply function reflects the, directly and indirectly, quantitative relation between the overall level of outputs and the general price. On the other hand, aggregate demand is formed based on the demand for goods, services, capital and money in the actual market. And here comes the question, how to quantitatively and qualitatively establish the scientific and reasonable functions between supply-side and demand-side? This is what economists are working on, but there is still room for putting forward more analytical perspectives, especially the perspective of econophysics. By doing this, more theoretical tools will be accessible to evaluate the structural risk resulting from industrial distribution and give policy proposals to promote supply-side reform of China.

L. Xing, *Complex Network-Based Global Value Chain Accounting System*,
https://doi.org/10.1007/978-981-16-9264-2_6

6.2 Measurement

6.2.1 Counting First Passage Betweenness

Based on Newman's random walk betweenness [2], Blöchl proposed ***Counting First Passage Betweenness***, denoted by C_{FP}, to track how often a given node is visited on the first-passage walks between all source-target pairs [3].

Given that, the element (s, i) of the matrix $((M_{-t})^r)_{si}$ gives the probability of a random walk starting at $s(s \neq t)$ and being at $i(i \neq t)$ in r steps; the probability of going from i to j is m_{ij}, and thus the probability of taking r steps and then choosing e_{ij} as next path is $((M_{-t})^r)_{si}m_{ij}$ hen we pay attention to all random walks in the whole network, the equation of calculating the frequency of taking e_{ij} as random walk path could be:

$$F_{ij}^{st} = \sum_{r=1}^{\infty} \left((M_{-t})^r\right)_{si} m_{ij} = m_{ij} \sum_{r=1}^{\infty} \left((M_{-t})^r\right)_{si} = m_{ij} \left((I - M_{-t})^{-1}\right)_{si} \tag{6.1}$$

If there is no path between i and j which means e_{ij} does not exist, the transition probability will be zero. Besides, the total number of times of paths going from i to j and then back to i is $F_{ij}^{st} + F_{ji}^{st}$. If adding i on any path from s to $(i \neq s, t)$, this node will be visited $\sum_{j=1, j \neq t}^{\infty} \left(F_{ij}^{st} + F_{ji}^{st}\right)/2$ times. That is to say, in the case, a random walk starts from s to t, the ***First Passage Frequency*** of node i is as follow:

$$F^{st}(i) = \sum_{j=1, j \neq t}^{\infty} \left(F_{ij}^{st} + F_{ji}^{st}\right)/2 \tag{6.2}$$

Due to the existence of self-loops, the random walk may take e_{ii} as a path, so i will be visited twice consecutively, which can be divided into two cases.

One is that when $i = s$, i.e., one extra visit happens at the end of source node s, so the equation needs to be revised as follow:

$$F^{st}(s) = \sum_{j=1, j \neq t}^{\infty} \left(F_{sj}^{st} + F_{ji}^{st}\right)/2 + 1 \tag{6.3}$$

Another is that when $i = t$, the random walk is just absorbed by sink node t. The equation here is:

$$F^{st}(t) = 1 \tag{6.4}$$

In consideration of all the above cases, Blöchl defined the first passage frequency of node i as the average of random walk quantity across all the source-target pairs in the network:

$$C_{FP}(i) = \frac{\sum_{s \in V} \sum_{t \in (V - \{s\})} F^{st}(i)}{N(N-1)} \tag{6.5}$$

According to the framework of GVC accounting system depicted in the ICIO table, $C_{FP}(i)$ measures the added processing amount of intermediate goods when a unit of globally final demand stimulates the production of all sectors on the GVC with equal possibility. The bigger C_{FP}, the more intermediate product inputs to sustain production to meet market demand, in which capital flows from material flows are used to pay for inputs of various factors of production. Furthermore, if the whole process occurs within a fixed time range, a sector with high C_{FP} will then be a drag on the velocity of intermediate goods.

6.2.2 Global Demand Dependence Index

The pulling effect of market demand on the economy can reflect the ability of economies' internal production system and external trade process to create value added. Studies in this area are mainly based on IOA. Soofi, et al. developed the final demand elasticity of exports and final-demand-weighted index of export elasticities in measuring the trade dependencies of the economies [4]. Duan, et al. proposed a modified ***Structural Decomposition Analysis (SDA)*** method, not only decomposing the technology coefficients into substitution effect and fabrication effect, but also evaluating the contribution of each region to the change of dependent variables [5]. In this section, we use the biased random walk process of intermediate goods on the GVC to reflect the dependence of the industrial sectors on global market demands, while C_{FP} measures the degree of dependency.

In GIVCN model, therefore, the sum of C_{FP} all the sectors within each country is defined as the ***Global Demand Dependence Index (GDDI)***. Compared with previous studies, this method can better and capture the instantaneous dynamic characteristics of value stream.

$$GDDI(u) = \sum_{i \in \tau(u)} C_{FP}(i) \tag{6.6}$$

In fact, *GDDI* reflects the cumulative effect of global market demands when directly and indirectly related sectors are involved in the global production system.

Thus, *GDDI* is here adopted to measure national sector's participation in worldwide synergic production, i.e., the bigger sector's *GDDI*, the higher the degree of globalization.

6.3 Empirical Analysis: Macroeconomic Trend Forecast

In this section, we are going to characterize the globalization with *GDDI* and analyze the development of GVC through statistics on the four-sector categories. Also, we have the statistical result of 56-sector version.

6.3.1 Robustness Analysis

According to the essence of *ASRD*, it reflects the overall robustness of the financial environment, i.e., the larger *ASRD*, the more stable macroeconomic architecture of GVC. Therefore, the dynamic relation between *ASRD* and C_{FP} must be clarified. Figure 6.1 shows the results of implementing intentional and random failure for C_{FP}.

It is obvious that intentional failure on sectors with large C_{FP} rapidly weakens the overall inter-industry connectedness, which is a typical cascading failure. In detail, flow efficiency of value stream reduces by 50% when the ratio of nodes intentionally removed just reaches 2.857%, which covers the top 5 nodes (corresponding to CHNSC3, ROWSC3, USASC4, USASC3, ROWSC4) releasing in descending

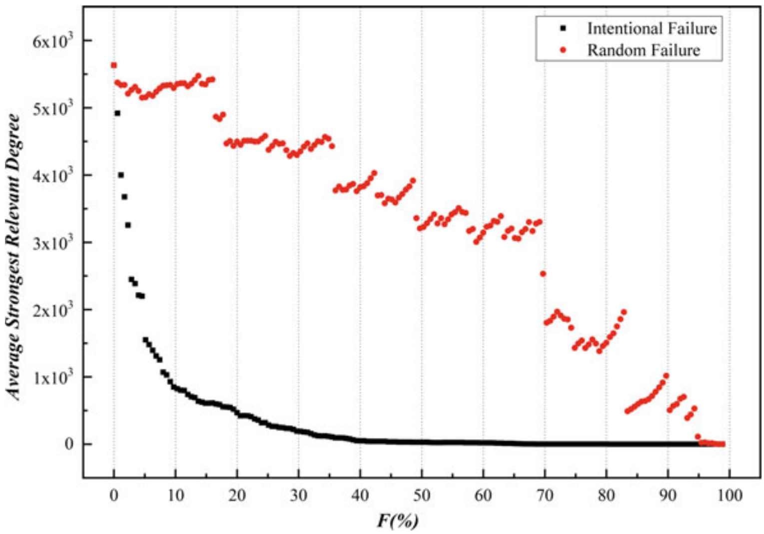


Fig. 6.1 Cascading failure analysis on the ASRD of GIVCN-WIOD2016SC4-2014

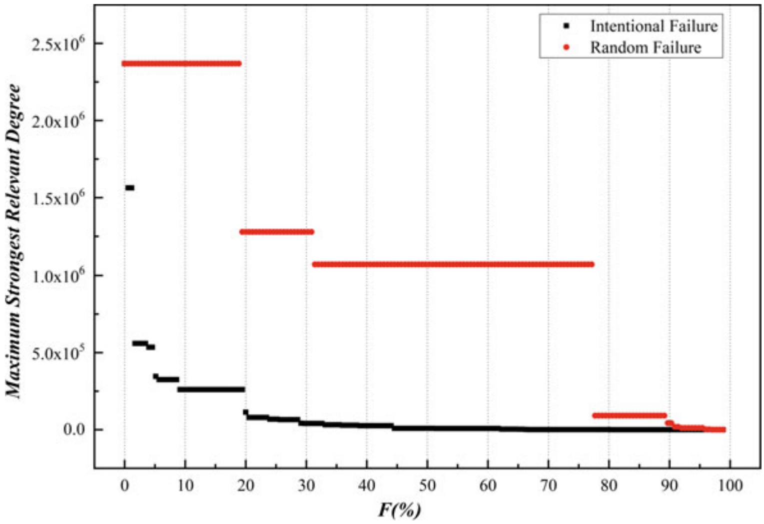


Fig. 6.2 Cascading failure analysis on the MSRD of GIVCN-WIOD2016SC4-2014

order of C_{FP}. In the meanwhile, reference sets are far from this level of damage. Correspondingly, similar types of situations also occur in the rest of GIVCN models.

It is also worth observing the relation between *MSRD* and C_{FP}, as shown in Fig. 6.2.

Analogously, the removal of nodes with large C_{FP} greatly brings down the value of *MSRD* of GIVCN-WIOD2016SC4, i.e., sectors corresponding to these nodes are crucial to the connectedness and robustness of GVC. If they suffered the negative impact of a rough economy, a system-wide financial crisis would arise with the inevitably increasing fragility shown on the GVC.

In sum, we prove C_{FP} feasible in measuring industrial sectors' financial position from the perspective of econophysics, which differs from the frameworks of both macroeconomics and microeconomics. We believe that *GDDI* can measure the degree of participation when countries, as well as their domestic sectors, are involved in the process of globalization. To testify this assumption, an econometric analysis is needed.

6.3.2 *The Econometric Analysis of Import/Export and GDDI*

In view of the integrity of statistics, both actual import and export volume of 42 countries (except Taiwan and the rest of the world) are taken as dependent variables, the *GDDIs* of four-sector categories as independent variables, while discussing whether network-based eigenvalues and macroeconomic performance are relational.

Table 6.1 Results of the mixture regression model

	Overall		Developing countries		Developed countries	
	Import	Export	Import	Export	Import	Export
SC1	−0.0817*	−0.335***	−0.332***	−0.664***	0.0228	0.0659
	(−2.09)	(−5.86)	(−4.35)	(−6.98)	−0.28	−0.72
SC2	−0.0921***	0.0278	0.0106	0.193***	−0.0939**	−0.017
	(−4.99)	−1.03	−0.27	−3.94	(−2.67)	(−0.42)
SC3	0.636***	0.970***	0.984***	1.541***	0.530***	0.629***
	−14.75	−15.36	−9.97	−12.51	−6.31	−6.57
SC4	0.314***	0.130**	−0.021	−0.458***	0.342***	0.0219
	−9.64	−2.72	(−0.23)	(−4.00)	−4.77	−0.27
_cons	−180.8***	−182.4***	0.22	−0.154	0.315	1.398***
	(−24.45)	(−16.87)	−1.15	(−0.65)	−1.17	−4.57
N	630	630	345	345	285	285
R^2	0.926	0.875	0.852	0.837	0.79	0.716
R^2_a	0.926	0.874	0.85	0.835	0.787	0.712

Notes * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

With 42 countries being divided into developed and developing ones, the first mixture regression model is built, and the results are presented in Table 6.1.

From the overall regression results, both of imports and exports are positively correlated with *SC3-GDDIs* and *SC4-GDDIs*, and manufacturing sectors are more positive than services sectors in correlations, which reflects the deep involvement of manufacturing sectors in the globalization.

From the perspective of different levels of economic development, on the one hand, developing countries are generally much more involved in globalization than developed ones. In detail, developing countries' imports and exports are strongly related to *SC3-GDDIs* and negatively correlated with *SC1-GDDIs*. The manufacturing sectors bring more value-added than agriculture sectors. On the other hand, *SC4-GDDIs* are negatively correlated with exports in developing countries but positively related to imports in developed countries. In other words, superior services sectors extend developed countries' influence on the GVC, and the lag of services sectors lay at the root of the unfavorable situation suffered by developing countries.

Furthermore, we investigate whether the correlation results vary with the year, and the fitting results are shown in Tables 6.2 and 6.3 Most significantly of all, *SC3-GDDIs* tend to be more and more positively related to both imports and exports, which means manufacturing sectors mainly embody the acceleration of global integration.

In sum, we believe *GDDI* can be soundly adopted to measure national sector's participation in worldwide synergic production.

Table 6.2 Correlation between imports and GDDIs

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
SC1	−0.198	−0.157	−0.0946	−0.0662	-0.018	0.0425	0.0458	0.0385	0.102	0.0709	0.108	0.0951	0.0407	−0.0125	−0.0332
	(−1.41)	(−1.13)	(−0.65)	(−0.44)	(−0.12)	−0.28	−0.29	−0.24	−0.69	−0.46	−0.75	−0.71	−0.28	(−0.09)	(−0.24)
SC2	−0.0205	−0.0418	−0.0855	−0.0893	−0.111	−0.133	−0.129	−0.126	−0.143*	−0.129	−0.130*	−0.130*	−0.139*	−0.133*	−0.116
	(−0.27)	(−0.55)	(−1.13)	(−1.18)	(−1.52)	(−1.83)	(−1.70)	(−1.65)	(−2.13)	(−1.93)	(−2.09)	(−2.24)	(−2.29)	(−2.25)	(−2.02)
SC3	0.497**	0.446*	0.443*	0.418*	0.460**	0.463*	0.506**	0.535**	0.519**	0.507**	0.531**	0.568***	0.655***	0.739***	0.741***
	−2.72	−2.44	−2.4	−2.33	−2.74	−2.7	−2.93	−3.23	−3.29	−3.09	−3.42	−3.97	−4.39	−5.25	−5.57
SC4	0.506**	0.537***	0.524***	0.529***	0.458***	0.429**	0.388**	0.355**	0.348**	0.366**	0.297*	0.264*	0.219*	0.166	0.158
	−3.42	−3.64	−3.63	−3.87	−3.66	−3.38	−3.05	−2.88	−2.93	−3.09	−2.65	−2.51	−2.05	−1.63	−1.68
_cons	−0.699*	−0.63	−0.571	−0.354	−0.0819	0.0266	0.199	0.414	0.6	0.235	0.519	0.704*	0.56	0.621	0.647*
	(−2.14)	(−1.94)	(−1.70)	(−1.04)	(−0.25)	−0.08	−0.56	−1.14	−1.71	−0.65	−1.55	−2.26	−1.68	−1.93	−2.08

Table 6.3 Correlation between exports and GDDIs

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
SC1	−0.540*	−0.525*	−0.470*	−0.429	−0.392	−0.301	−0.307	−0.34	−0.202	−0.117	−0.134	−0.0631	-0.12	−0.154	−0.188
	(−2.39)	(−2.43)	(−2.07)	(−1.82)	(−1.63)	(−1.21)	(−1.20)	(−1.34)	(−0.82)	(−0.46)	(−0.58)	(−0.29)	(−0.54)	(−0.76)	(−0.94)
SC2	0.187	0.155	0.0989	0.0947	0.0695	0.0367	0.0454	0.0363	−0.00908	−0.046	−0.0422	−0.0516	−0.0657	−0.0848	−0.0671
	−1.52	−1.33	−0.83	−0.8	−0.58	−0.31	−0.37	−0.3	(−0.08)	(−0.42)	(−0.42)	(−0.56)	(−0.72)	(−1.00)	(−0.81)
SC3	0.924**	0.938**	0.956**	0.909**	0.949**	0.874**	0.914**	0.973***	0.855**	0.789**	0.843**	0.799**	0.894***	0.977***	1.009***
	−3.14	−3.3	−3.3	−3.23	−3.46	−3.14	−3.29	−3.7	−3.22	−2.95	−3.37	−3.51	−3.98	−4.85	−5.28
SC4	0.196	0.202	0.203	0.224	0.169	0.196	0.174	0.155	0.222	0.224	0.151	0.126	0.0759	0.0348	0.0155
	−0.82	−0.88	−0.89	−1.05	−0.82	−0.95	−0.85	−0.79	−1.11	−1.16	−0.83	−0.75	−0.47	−0.24	−0.11
_cons	−0.864	−0.918	−1.003	−0.814	−0.601	−0.458	−0.389	−0.356	−0.143	−0.274	−0.0189	0.38	0.237	0.254	0.205
	(−1.64)	(−1.83)	(−1.90)	(−1.52)	(−1.13)	(−0.83)	(−0.68)	(−0.62)	(−0.24)	(−0.46)	(−0.03)	−0.77	−0.47	−0.55	−0.46

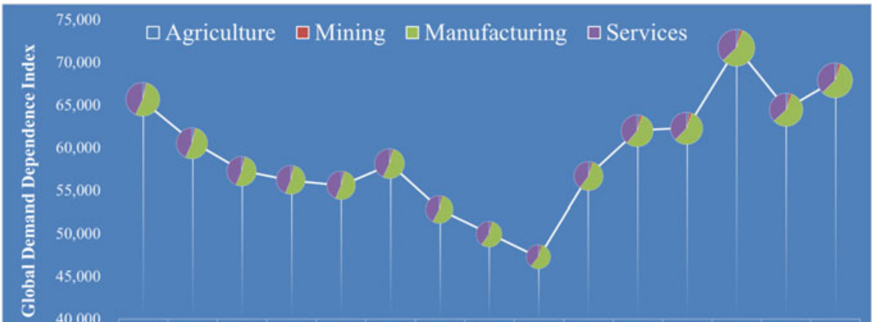
6.3.3 Statistics on the Global Level

According to our calculation, the degree of participation for the whole world increases slightly over time from 2000 to 2014 as shown in Fig. 6.3. During this period, the world's *GDDI* has gone through a long-term recession, and the 2008–2009 global financial crisis is naturally a disruption, but it rebounds rather quickly, and the world comes into the heyday of GVC expansion. Then, it slows down or reverses temporarily after the year 2012.

From the angle of the inner structure, the relative proportion of four-sector categories does not change dramatically, and the order from large to small is manufacturing, services, mining and agriculture (mining went beyond agriculture after the year 2011). Taking the top three countries in terms of GDP and ROW as an example, the more detailed *GDDI* ratios shown in Figs. 6.4 and 6.5 can provide us with useful information about globalization.

By comparison, it can be found that *SC1-GDDI* remains the same proportion; *SC2-GDDI* just goes up 2% for 15 years; *SC3-GDDI* has risen by about 4%; *SC4-GDDI* declines from 43 to 37%. This trend means barriers to trade in mining and manufacturing sectors are removed slowly, but those in services erect. In other words, the production process of mining and manufacturing sectors is becoming increasingly sensitive to the final demand in global markets; however, services sectors tend to serve the domestic market rather than foreign ones.

In detail, four sorts of *GDDIs* of both the United States and Japan declines between 2000 and 2014; in the meanwhile, that of China and ROW rise steeply. As we all know, China eclipsed Japan to become the world's second-largest economy in 2011, due to the deepening globalization on many industrial aspects. For ROW in addition to major economies, these developing countries have shown an increasingly higher degree of globalization in all aspects, especially in mining sectors (rising by 17 percentage points).



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Total	65,379	60,632	57,250	56,151	55,566	58,038	52,768	49,970	47,169	56,686	62,015	62,315	71,723	64,521	67,933

Fig. 6.3 Trend of GDDI in GIVCN-WIOD2016SC4 models

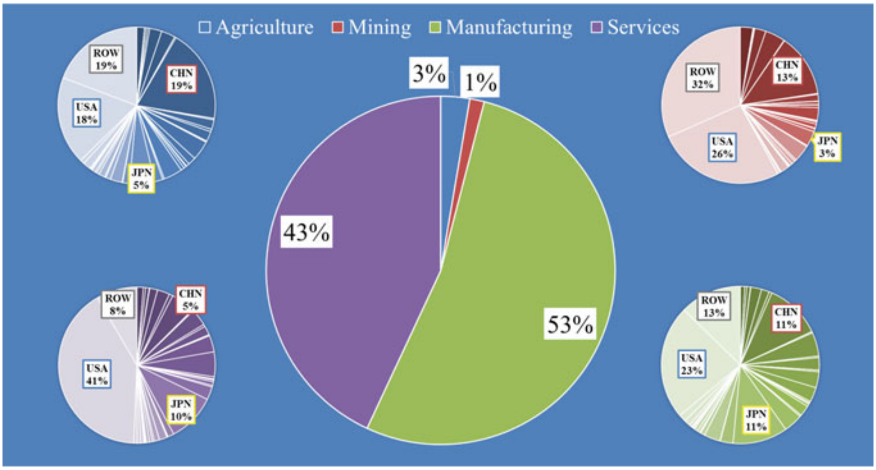


Fig. 6.4 Decomposition of GDDI in GIVCN-WIOD2016SC4-2000

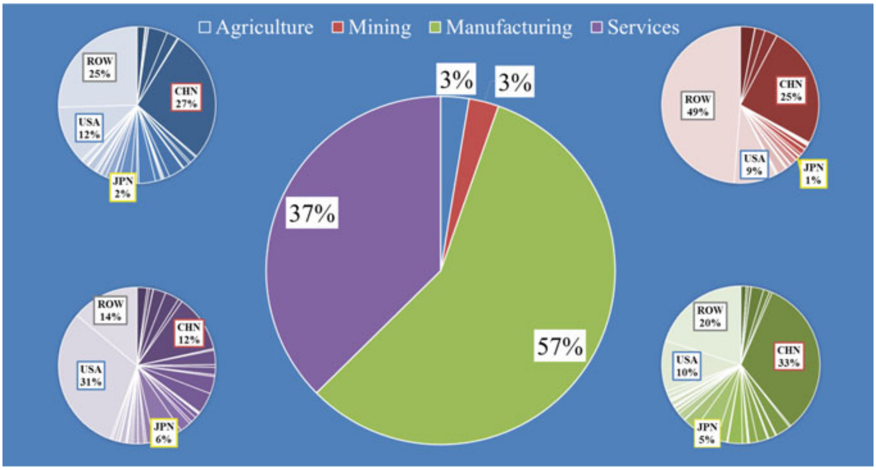


Fig. 6.5 Decomposition of GDDI in GIVCN-WIOD2016SC4-2014

6.3.4 Statistics on the Sectoral Level

To analyze the dynamic variation typically, the top 5 of each GDDI are taken as analysis objects, as shown in Figs. 6.6, 6.7, 6.8 and 6.9.

As shown in Fig. 6.6, China's agricultural sectors are closer to the global market than before, while the United States becomes weaker in this aspect. Notice that, the domestic market is also a crucial part of the global market, so we believe the size of the domestic population largely influences the SC1-GDDI. For instance, the first

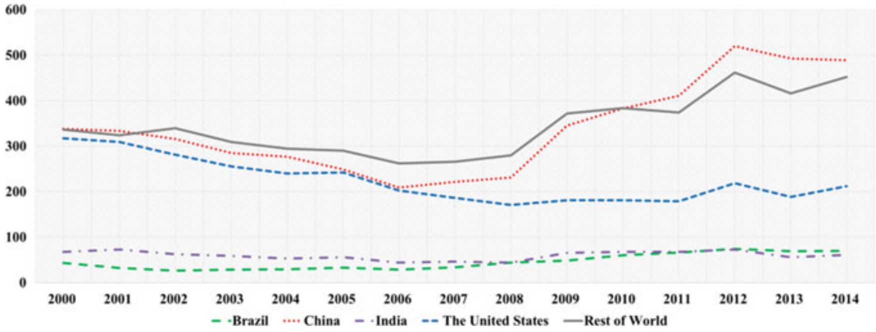


Fig. 6.6 Trend of SC1-GDDIs of major economies in GIVCN-WIOD2016SC4 models

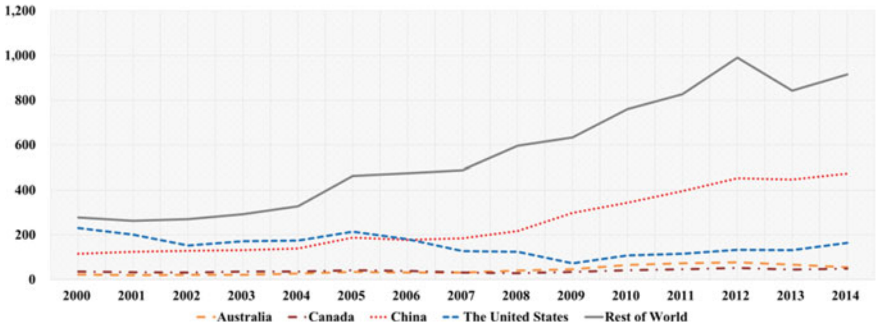


Fig. 6.7 Trend of SC2-GDDIs of major economies in GIVCN-WIOD2016SC4 models

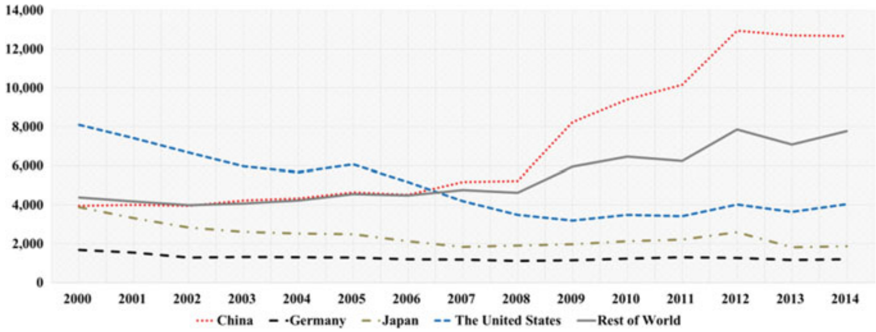


Fig. 6.8 Trend of SC3-GDDIs of major economies in GIVCN-WIOD2016SC4 models

few countries with higher SC1-GDDIs all boast huge population scale (China 1.3 billion, India 1.1 billion, the United States 130 million, Brazil 198 million in 2014), as well as ROW.

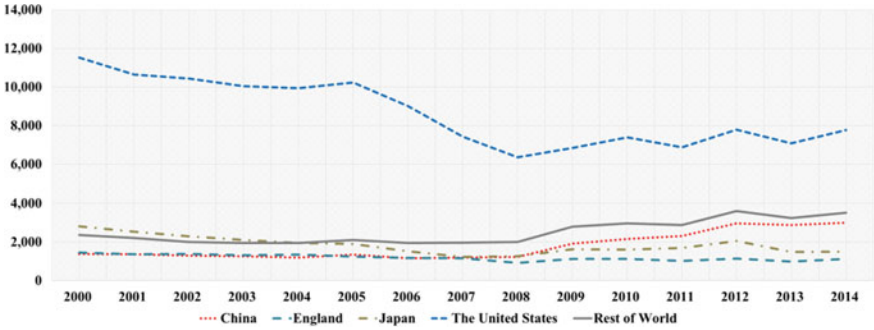


Fig. 6.9 Trend of SC4-GDDIs of major economies in GIVCN-WIOD2016SC4 models

However, we notice that the SC1-GDDIs of populous economies varies considerably. Thus, another determinant of the SC1-GDDI is grain exports. In 2015, the top 5 countries of grain exporting are the United States (140 billion), Brazil (75 billion), China (62 billion), Canada (49.5 billion) and India (38.4 billion).

China's 90% of the energy, more than 80% of industrial raw materials and more than 70% of agricultural production rely on mineral resources. The domestic demand already contributes a lot to the production of its mining sectors, let alone large quantities of minerals that China imports from around the world, such as iron ore from BHP Billiton of Australia and Vale of Brazil.

Let us take iron ore as an example. The world's four major iron ore giants are Vale of Brazil, Rio Tinto of England (its iron-ore-related business is mainly in Australia), BHP Billiton and FMG of Australia. In 2014, these four companies accounted for 47% of global production of iron ore, accounting for 65% of global trade. This partly explains the continuous growth of Australia' SC2-GDDIs (from 23.036 to 55.690) and Brazil (from 20.587 to 38.130) in recent years.

Historically, developing countries have tended to export unprocessed raw materials, suggesting that the jump to producing finished goods was difficult. Today, with the opportunities of integrating in specific parts of the value chain, many developing countries are exporting primarily manufactured goods, as a way to participate in global integration. Yet, only a small number of developing economies are deeply involved in globalization, China being the best example. As we all know, China now becomes the veritable world factory, whose manufacturing sectors on the GVC are more significant than ever before.

As for the developed countries, many are suffering a long-term recession due to various reasons, such as economic crisis, capital outflow, trade barrier, industrial transfer, etc. As a result, they are losing sensitiveness to global final goods demand and undergoing a low level of employment, especially the U.S. Department of Labor reported that 2.8 million manufacturing jobs in the United States had been axed from 2005 to 2009; although its manufacturing sectors achieved a steady recovery from 2010 to 2014, only 762,000 new jobs were created. As of the beginning of 2017, jobs in the manufacturing sectors are still 1.4 million less than that of 2007. According to the survey of Autor, et al., trade-related impact accounted for about 20% of all the factors leading to the reductions in manufacturing employment [6]. This view perfectly explains the United States' SC3-GDDI trends.

Besides, the international trade situation has reversed between China and the United States. Acemoglu, et al. argued that the United States had lost 0.6 to 1.25 million jobs from the rise in the import competition with China over the period from 1999 to 2011 [7].

From the overall situation of global trade development, trades in goods and services are highly correlated, both as important forms of participation in the international division. The huge gap in relevant trade data between trades in goods and services is still there to be bridged, which is reflected in the balance of international payments statistics. Services trade accounts for nearly 20% of the world's total, and if taking the existence of commercial services into account, this number may exceed or at least equal to the proportion of that of trade in goods. From the trade data of major countries, the stronger the competitive advantage of general manufacturing sectors is, the greater the competitive power of services trade is. Moreover, developed countries usually have a trade surplus with developing ones in this field. For instance, the United States has always been the largest services trade surplus country.

As the domestic consumption demand keeps growing, services consumption has become the main form of private consumption in the United States and other developed countries. In 2011, services consumption accounted for 67% of every American's consumption, nearly 2 times of that of commodity consumption. To stay ahead in the tourism and transportation infrastructure, both hardware and software, the successive the United States administrations have poured investment in infrastructure construction and R&D, making its public investment in services sectors rank first all over the world, especially in the field of applied information technology. In turn, the world's most advanced services infrastructure has become the most powerful support system for the United States' services trade's competitive advantage. For instance, thanks to the considerable investment in the "information superhighway", the United States' companies have gained a significant edge in services trade.

As shown in Fig. 6.9, though China's SC4-GDDIs gradually rose up after the subprime mortgage crisis in 2007, it still lags far behind that of the United States. With the comprehensive advantages in economic scale, manufacturing and processing, human resources, etc., China should follow the manufacturing-related services trade pattern, instead of duplicating the United States pattern.

6.4 Discussion

6.4.1 Economic Difference Between Static Metrics and Dynamic Metrics

In Chap. 3, the *SRPL*-based between and closeness centralities are proven to be much more economically meaningful than those only based on the topological structure of GVC, which is usually destroyed by misused dimensionality reduction techniques such as binarization. The Markov process-based ones, in fact, are empirically meaningful than SRPL-based. As is well known, ICIO tables are compiled based on annual trade data, and policymakers and scholars can propose various retrospective conclusion, explain the general process of globalization, or forecast the economic layout in the next few years. Nevertheless, what kind of guidance can ICIO analysis provide for the trading activities that take place whenever and wherever? For instance, if a cruise ship full of cargo is to depart from a port on the southeast coast of China, can we judge its destination based on the ICIO data of the most recent year? Obviously, it is impossible for us to divide it into several small boats and distribute the goods to countries located in various parts of the world according to the export trade ratio in the ICIO table (as described in Fig. 6.10).

Both of static and dynamic metrics of centrality supplement the mainstream GVC accounting system, however, in different angles. In our opinion, *GIIC* and *GDDI* are useful to disclose and guard against the financial risks on the GVC, since they focus on the fact that industrial sectors composed of thousands of enterprises are sensitive to the global demand. Although the SRPL-based centralities well quantify the importance of hub nodes in the GVC network, the random walk centrality and counting first passage betweenness give more detailed prediction of the impact on enterprises' strategic decision. In sum, the two sorts of metrics are complementary.

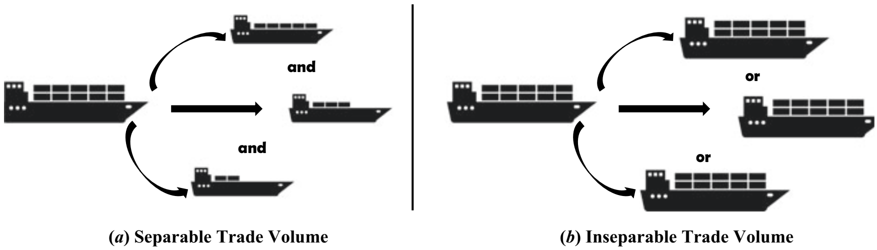


Fig. 6.10 Difference between separable and inseparable trade volume

6.4.2 *Intrinsic Relationship of Dynamic Metrics*

In this section, we use a ship-and-port metaphor to explain the economic meanings of dynamic metrics. Given that, there are four ships sailing across the ocean and four ports on their most possible navigation routes, as shown in Fig. 6.11.

We take Port B for example. Port B locates at the routes of all the four ships, which means it is the hubs node in consideration of uncertainty. In order to satisfy the global demand as soon as possible, ships carrying cargos will choose these routes with great possibility, and the summary results bring superiority to Port B in turn. Besides, we can see that Ship B and C select Port B as the first stop, in the meanwhile, Ship A and D select Port A and D respectively. Imagining that, if there was a sudden surge in demand on certain goods and all the ships were used to carry them, Port B will become the busiest one. By comparison, we believe industrial sectors (countries/regions) on the GVC paly their roles just like one port after another on the ocean, which can be measured by C_{RC} and C_{FP} (*GIIC* and *GDDI*). Of course, a busy port may also be a port on many important routes, and vice versa.

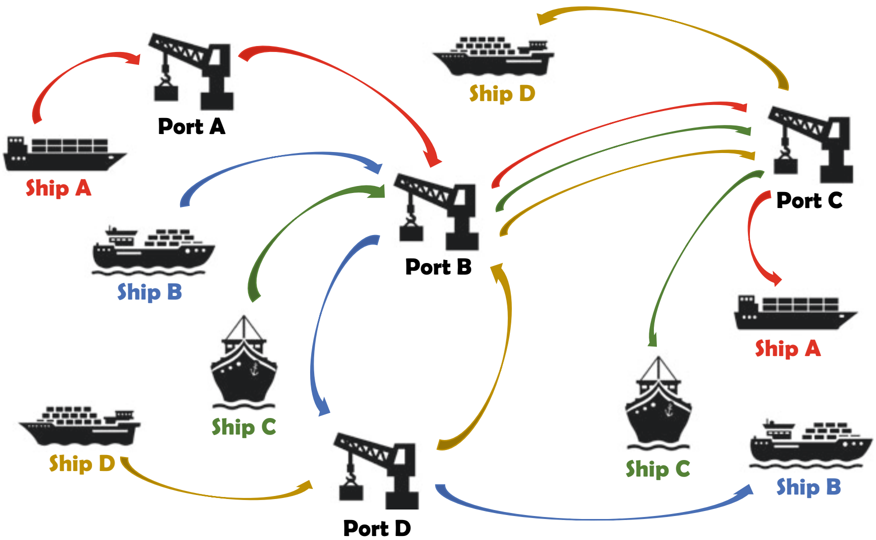


Fig. 6.11 A ship-and-port metaphor

6.4.3 Correlation Analysis Between Static Metrics and Dynamic Metrics

There may exist certain relations between C_{RC} and C_{FP} on the sectoral level, as well as *GIIC* and *GDDI* on the national level. Therefore, it is necessary to find the answer according to their distribution and correlation.

As shown in Fig. 6.12, the distributions of C_{RC} and C_{FP} are similar, both following the power-law distribution, which means the importance of nodes in the GIVCN model also shows strong heterogeneity under random walk conditions.

By observing the relation of *GIIC* and *GDDI* in different years, we find that there is a very significant positive correlation between them. In Chap. 2, we have discussed the role played by the industrial sector in the domestic and international economic circulations, and proven that the higher the proportion of imports of intermediate goods required by the NVC/RVC of country/region, the more its industrial sectors tend to export the domestically produced products and services—This is the meaning of global economic integration, i.e., it links the industrial sectors of various countries together, and jointly creates wealth to meet the needs of the global market. In the rapidly changing global production system, an industrial sector's sensitivity to the end market is closely related to its pivotal role on the GVC in a short period of time. In our opinion, *GDDI* can be regarded as the leading index of *GIIC* since the marketing

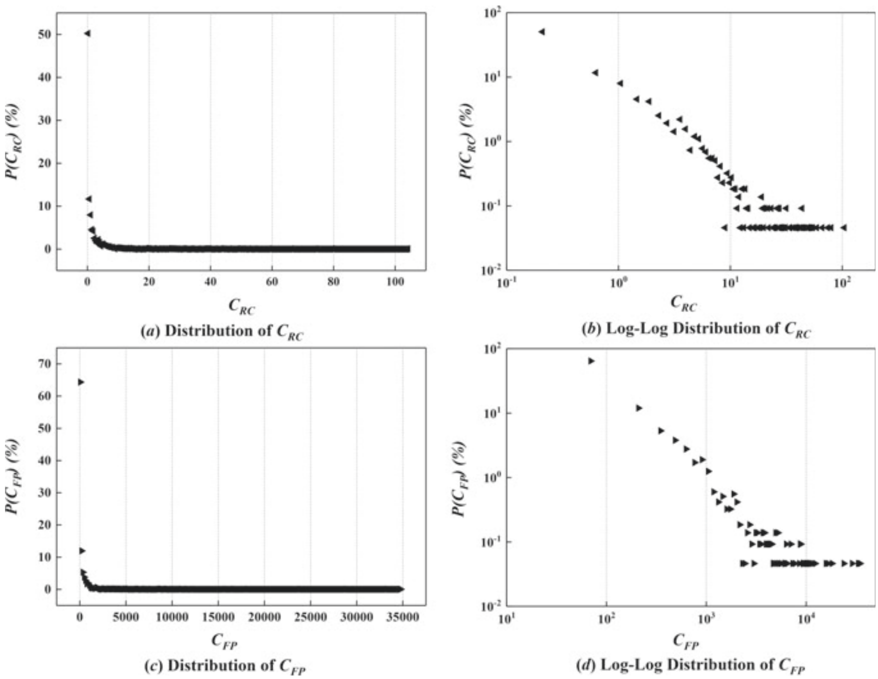


Fig. 6.12 Distribution of C_{RC} and C_{FP} in GIVCN-WIOD2016-2014

focus has shifted from a seller's market to a buyer's market. Anyway, whoever can seize the market opportunity will occupy the dominant position in the industry and exert a higher industrial influence. Of course, the premise is that the NVC/RVC of this country/region has been deeply embedded in the GVC.

We also find an interesting phenomenon: the top 10 nations in GDP are generally arranged along the upper right to the lower left of the fitted line, but China is an exception before 2010. China quickly became the "World Factory" after its accession to the WTO, which is the main reason for its rapid economic development in the first decade of the twenty-first century. Therefore, when China's *GIIC* and *GDDI* gradually catch up with the United States and join the first group, its GDP has also surpassed many developed countries. In Chap. 13, we will use the PLS-SEM model to analyze the causality of *GIIC/GDDI* and GDP in detail Fig. 6.13

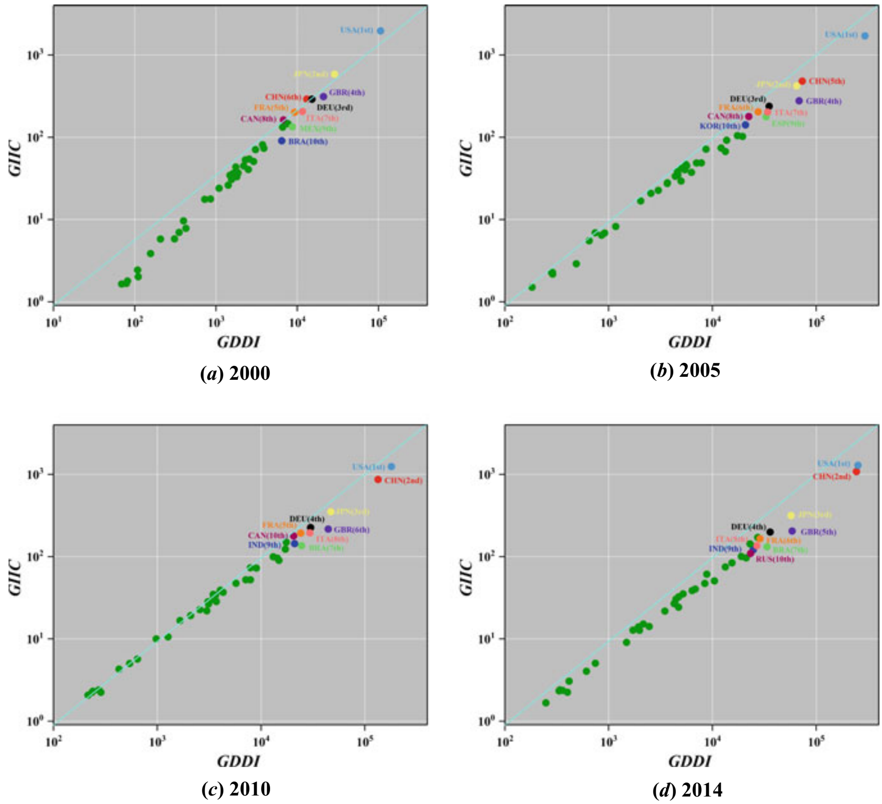


Fig. 6.13 Correlation of GIIC and GDDI in GIVCN-WIOD2016 models. *Notes* We use different colors to distinguish the top 10 nations in GDP in each year.

6.5 Summary

Contributions of this chapter are as follows:

(1) **Measure the globalization of industrial sectors based on Markov chain analysis**. According to the framework of GVC accounting system depicted in the ICIO table, C_{FP} measures the added processing amount of intermediate goods when a unit of global final demands stimulates the production of all sectors on the GVC with equal possibility. If the whole process occurs within a fixed time range, then a sector with high C_{FP} will be a drag on the velocity of intermediate goods. Therefore, as the economic explanation of C_{FP}, *GDDI* can be used to evaluate the national sector's participation in worldwide synergic production, i.e., the bigger a sector's *GDDI* is, the higher the degree of globalization will be.

(2) **Analyze the features of globalization on the sectoral level**. From the statistics on *GDDI*, the following conclusions can be made: over the time 2000 to 2014, barriers to trade in mining and manufacturing sectors are gradually removed, but those in services still erects; the population scale and the number of grain exports largely influence countries' *SC1-GDDI*; the domestic market demands contribute a lot to the production of its mining sectors; many developing countries are exporting primarily manufactured goods as a way of participating in global integration, and only a small number of them are deeply involved in the globalization; although services consumption has become the main form of private consumption in developed countries, the manufacturing-related services trade pattern is more suitable for China.

(3) **Discriminate the difference in design ideas between statistic and dynamic metrics of centrality, as well as the similarities and differences between the two types of dynamic ones**. On the one hand, *GIIC* and *GDDI* are more effective than *SRPL*-based centralities in the respect of disclosing and guarding against the financial risks on the GVC. On the other hand, although *GIIC* and *GDDI* are highly correlated, the latter can be regarded as the leading index of the former since the marketing focus has shifted from a seller's market to a buyer's market.

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Chapter 7
Industrially Economic Impacts of Trump Administration's Trade Policy Toward China

On July 6th, 2018, the United States proclaimed a 25% tariff on $34 billion worth of products from China and stated that further tariffs would be levied on $16 billion worth of products in accordance with the measures announced after the Section 301 Investigations. This move violated WTO rules and unleashed the most far-reaching trade war in economic history to date. Immediately afterwards, China responded with a 25% tariff on about $50 billion worth of imports from the United States. Then on July 11th, the U.S. declared another 10 % tariff on $200 billion worth of import products in light of China's countermeasures. The Trump administration's series of misjudgments about the U.S. economy and the world situation have not only caused serious damage to the world order, but also negatively affected the economic development of China and the United States. In particular, the global outbreak of the COVID-19 pandemic in 2020, the last year of the Trump administration, has complicated the game between the two countries and undermined the robustness of the import and export trade networks of both sides. Although the Biden-Harris administration has corrected some of the political problems left over from the Trump era in the past few months, no effective measures have been taken to repair United States trade policy, leaving Sino-US relation remaining bewildering. From a long-term perspective, the ***Thucydides Trap*** of the Sino-US relationship can hardly be removed, and the game between the two countries in the political and economic fields will be complicated. Hence, we need to further deconstruct industrial layout and the influencing mechanism of the international trade on the development of economies from the perspective of system theory, and thus review the Sino-U.S. co-opetition relationship in the arena of economy.

7.1 Bibliometrics on Sino-US Trade War

In this section, we carry out bibliometric analysis on the Sino-US trade war, taking the SCI and SSCI databases in Web of Science as data source. Note that, there are many keywords about this issue, such as "US-China Trade War", "US-China

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Trade frictions", "China-US trade conflict", "China-US trade", "U.S.-China Trade Disputes", etc. Through comprehensive consideration of recall rate and precision rate, the retrieval formula we chose is TS = ("U.S.-CHINA TRADE *") OR TS = ("US-CHINA TRADE *") OR TS = ("CHINA-US TRADE *") OR TS = ("CHINA-U.S. TRADE *") AND TS = ("ECONOMI*"). Finally, 114 key articles are left after removing irrelevant and low-quality ones as the retrieval date is July 20th, 2021. The visual analysis results by software Bibliometrix are as shown in Figs. 7.1, 7.2, 7.3, 7.4, 7.5 and 7.6 .

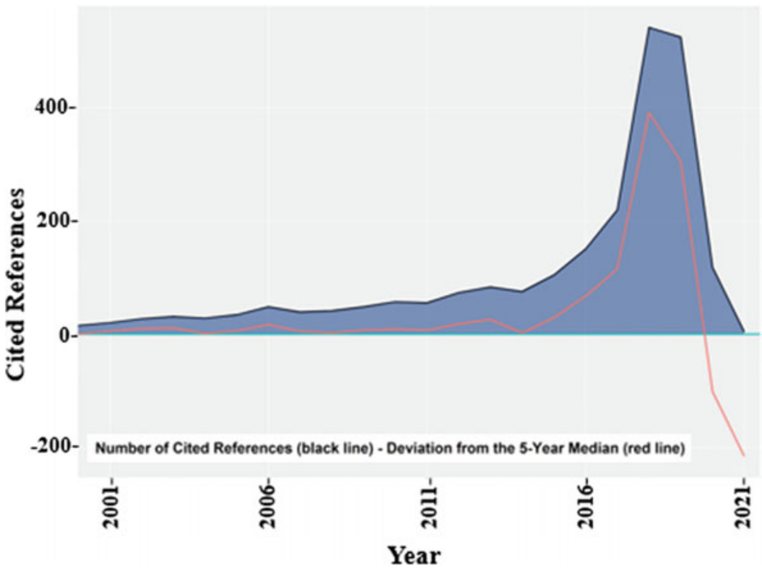


Fig. 7.1 Reference publication year spectroscopy

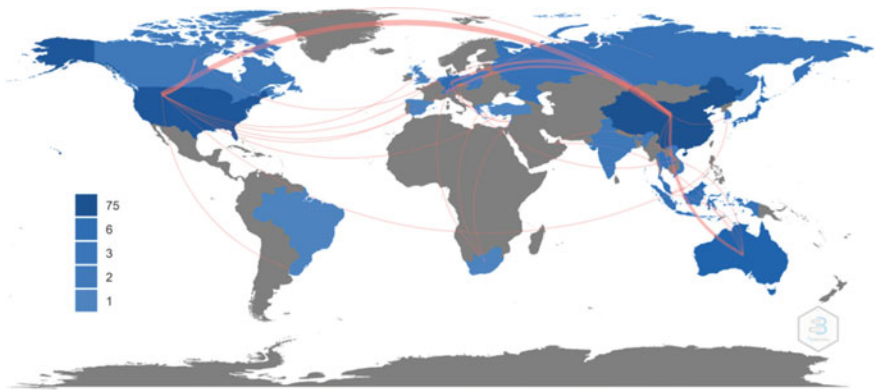


Fig. 7.2 International collaboration

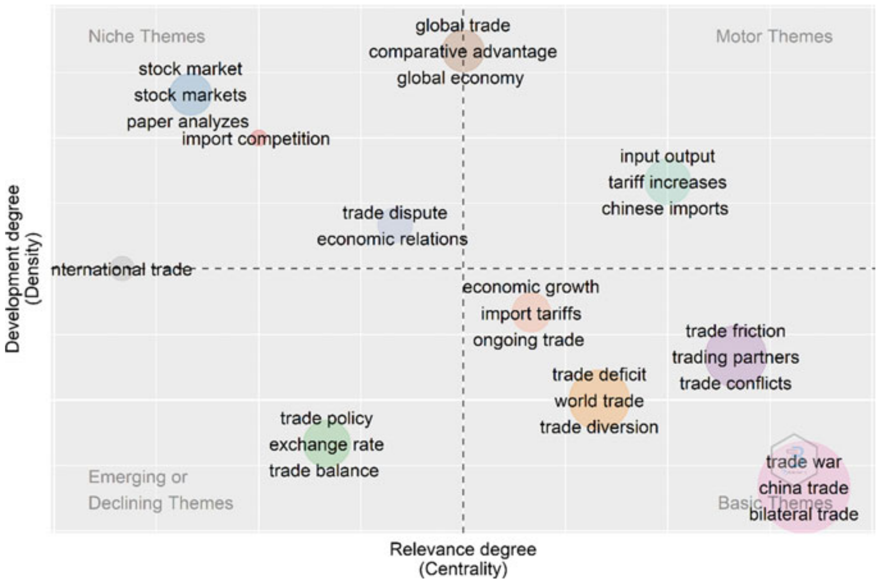


Fig. 7.3 Thematic map

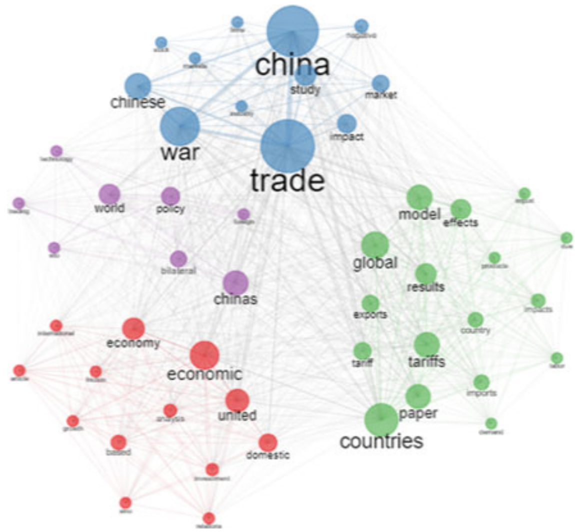


Fig. 7.4 Co-occurrence network

Fig. 7.5 Tree map

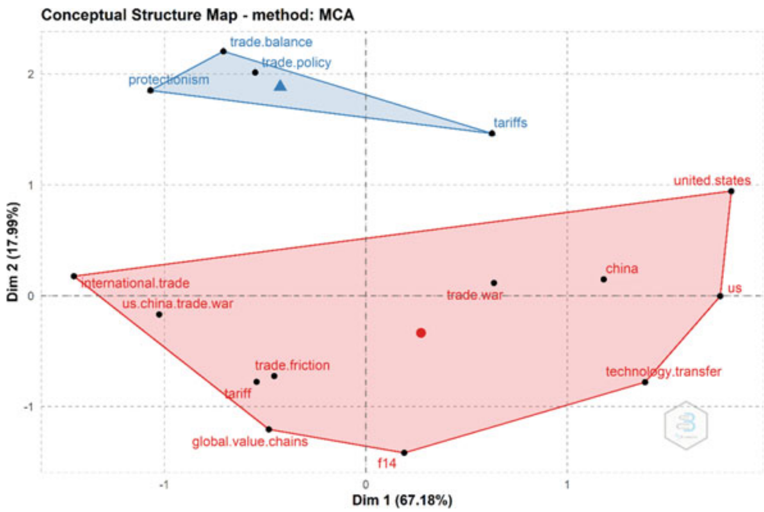


Fig. 7.6 Factorial analysis

In terms of publication time, there are related studies on the Sino-US trade war as early as 1998, but it did not arouse scholars' research interest. The first two articles were written by the same author, Yang J. W., who works at George Washington University. One of them reviewed some of the key issues in U.S.-China trade relations at that time and outlined the macro environment for trade between the two, including their economic ties with Hong Kong and Taiwan [5]. Another one argued that the prospects of growing trade between the United States and China represent enormous opportunities for Taiwanese firms, given the unique strengths that Taiwanese firms possess [6].

As shown in Fig. 7.1, academic attention to the Sino-US trade war varies in different periods, which can be roughly divided into three stages: from 2000 to 2018, the number of cited references gradually rose; between 2018 and 2019, it reached a peak at about 600 articles; since 2019, it started to decrease. This trend indicates that, first, China's accession to the WTO in 2000 has expanded its trade scale and strengthened its ties with the United States, leading to the increased attention of scholars to the bilateral trade. Then the outbreak of the Sino-US trade war in 2018 aroused even more focus, bringing about a significant increase in the number of references. And eventually, as bilateral trade relation has eased and a large number of scholars have added up to the related knowledge, the attention to this topic declined and the number of cited references decreased.

Figure 7.2 displays the number of domestic and international collaborative publications pertaining to the Sino-US trade war. It is clear that China and the United States are far more concerned about their trade and bilateral trade than other countries, seen from the number of both domestic and international collaborative publications. Following the two, Australia attaches great importance to this issue, with the number of publications ranking the third. This may be due to the fact that Australia is highly open in economy and strongly dependent on its trade with China [7], and therefore the intensified Sino-US trade war will be deemed inconducive to the healthy development of its economy.

To identify the focus points of the studies, the authors extracted the high-frequency words in the keywords and abstracts of the retrieved 114 papers, and classified them into basic themes, motor themes (well-developed), niche themes (very specialized), and emerging or declining themes according to their development and relevance. As is shown in Fig. 7.3, the basic themes are mostly related to trade, including "trade war", "trade conflict", "trade deficit", etc.; the motor themes include "input output, "tariff increases", and "Chinese imports", etc.; the niche themes include "stock market", "trade dispute", and "import competition", etc.; the emerging or declining themes are mostly linked to trade policies. This thus indicates that the related studies mainly focus on trade, economy, and tariffs.

Then, the authors used co-occurrence network to analyze the top 50 high-frequency words in the abstracts of the literature (see Fig. 7.4). The size of the nodes in the network is proportional to the frequency of co-occurrence of the term. In addition to such core words as "war", "trade" and "China", the high-frequency words include "tariffs", "economy/economic", "global" and "countries", most of which echo with the abovementioned basic themes. This indicates that influenced by the Sino-US trade war, countries have recently paid more attention to the intra-country economic development and inter-country trade.

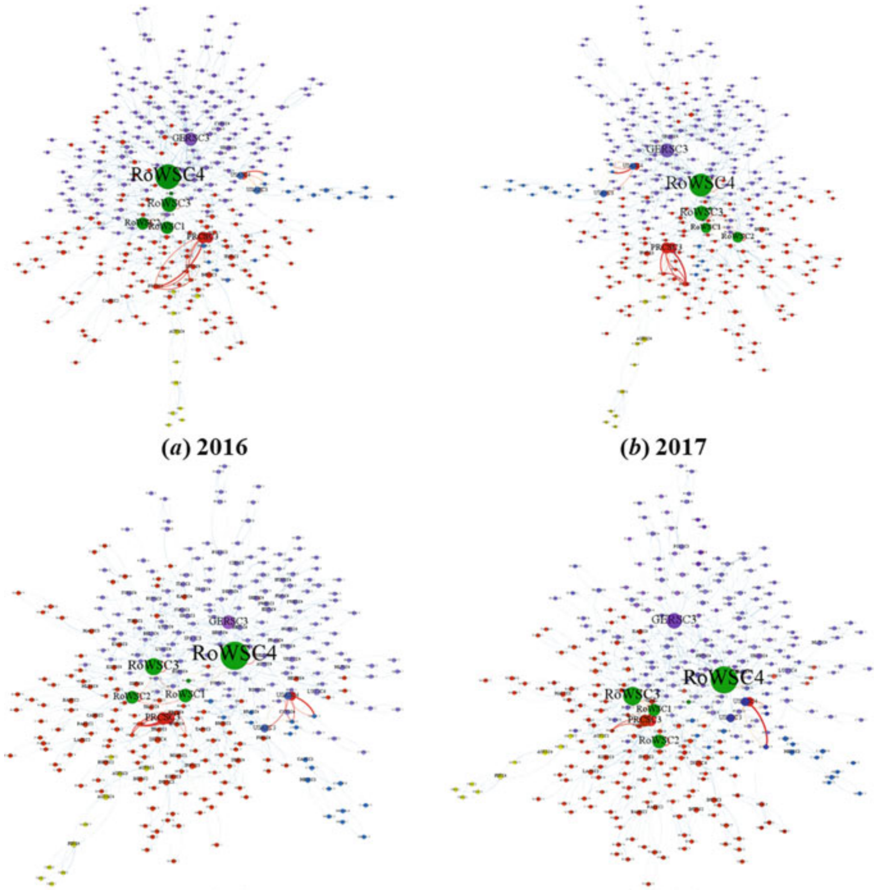
To examine the keywords of literature, a tree map is created (see Fig. 7.5). With a cumulative share of 36%, the top three keywords, i.e., "trade war", "China" and

"US-China trade war", not only confirm the basic themes, but also indicate that this topic remains to be the focal point of studies. In addition, other keywords, though accounting for lower percentages, indicate the gradual extension of the research focus to other fields, which is to become motor or emerging themes. Among them, some studies focus on the direct economic impact of trade wars on both countries, analyze the negative impact on enterprises in investment and production activities from the perspective of punitive tariffs and restricted technology transfer, and then extends to the market environment at large, which gives rise to keywords like "tariffs", "trade policy", and "trade (im)balance", etc. Besides, some studies focus on the indirect effects of trade wars on various countries around the world, the discussions of which thus involve keywords such as environmental pollution.

The authors mapped the conceptual structure of the related research areas by means of ***Multiple Correspondence Analysis (MCA)***, and identified two main dimensions after keywords clustering (see Fig. 7.6). Dim 1 revolves around "trade balance", "trade policy", "protectionism", and "tariffs", which basically represents the study of the causes of the trade war. Dim 2 covers "international trade", "global value chains", "trade friction", "technology transfer", etc., which involve the sanctions adopted by countries in trade wars and the trends of global value chains. Combined with the thematic map in Fig. 7.4, it can be seen that "input–output" is a hot topic, which can help scholars to analyze the competitive advantages of their own countries and identify the position of a certain industrial sector in the global value chain, so as to formulate reasonable trade policies.

Considering that the transmission of value stream within the global production system is a discrete Markov process, this chapter uses two types of dynamic meso-centrality indicators, i.e., *GIIC* (C_{RC}) and *GDDI* (C_{FP}) proposed in Chaps. 5 and 6, to measure the influence of industrial sectors and their sensitivity to global market demand respectively. Then, empirical evidence of the economic impact caused by the Trump administration's China policy is used to retrospectively analyze the shifts of the two countries' functions and positions on the GVC from 2016 to 2019. Finally, this chapter quantifies the additional impact of the pandemic on the economic development of the two countries through simulation.

In order to realize the research plan, we establish four GIVCN models based on the 2016–2019 ICIO data in the ADB2019, as shown in Fig. 7.7. Among them, GIVCN-ADB2019-2016 presents the initial state of the GVC network before the Trump administration came to power, and the other three models reflect the subsequent changes. International trade policy is essential in a country's economic development. It helps to change the industrial structure of export trade, and enhance the competitiveness of a country's industrial sectors in the global market, thus facilitating the transformation and upgrading of industrial structure [13] and the steady economic growth. Also, it helps build a diversified trade system and avoid trade frictions caused by excessive dependence on a few countries for export trade [14], which may spoil the national economic development. In view of this, this paper selects China and the United States as the objects of empirical research, with a focus on the far-reaching effects of the U.S.-China trade war during the Trump administration on the economic development and industrial policies of both sides.



(*a*) 2016 (*b*) 2017

(*c*) 2018 (*d*) 2019

Fig. 7.7 GIVCN-ADB2019 models. *Notes* In ADB-MRIO database, the abbreviation of China is "PRC"

7.2 Decomposition of GIIC

C_{RC} reflects the industrial influence of a sector on GVC, then the sum of C_{RC} of various sectors in a country or region to a certain extent reveals its relative competitiveness and economic status. Figure 7.8 shows the trend of global influence of five sectors and their sum in China and the United States from 2016 to 2019 in GIVCN-ADB2019 models.

As shown in Fig. 7.8, China's C_{RC} is higher than that of the United States in the P, LT, and HMT sectors, while the United States outperforms China in sectors such as BS and PWS. In short, the more influential sectors in China are mainly concentrated in manufacturing, while the United States in services.

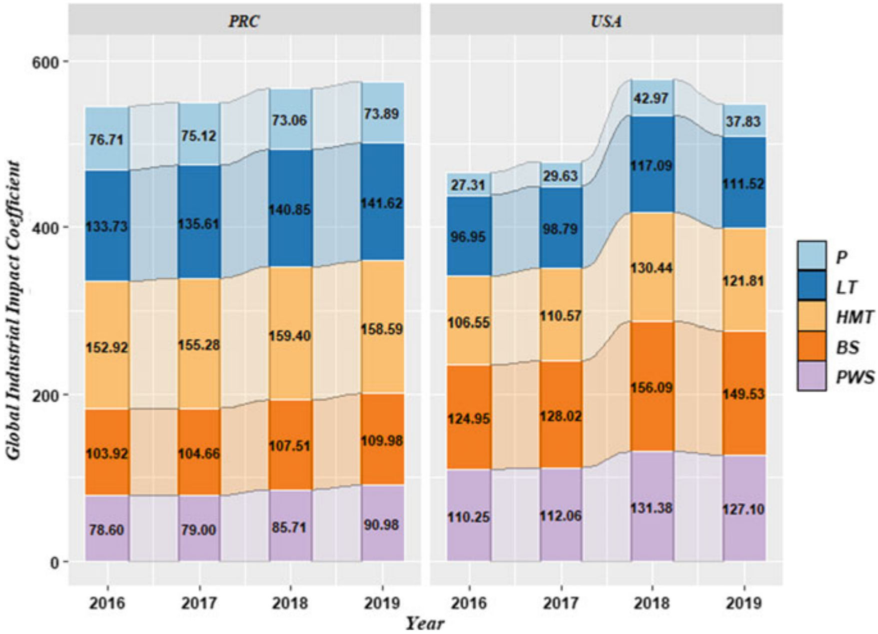


Fig. 7.8 Five-sector C_{RC} of China and the United States from 2016 to 2019 (E − 04). *Notes* In this chapter, the industrial sectors are aggregated into five categories according to ERDI Aggregation Level 2, which are Primary (P), Low Tech (LT), High and Medium Tech (HMT), Business Services (BS), and Public and Welfare Services (PWS)

The Sino-US trade war happens with close relation to the changes in the industrial structure layout in China and the United States Since its accession to the WTO, China's high-quality labor market and huge domestic consumer market have attracted developed countries such as the United States to move their low-end manufacturing industries to China. As a result, China's industrial sectors locate in the mid- and downstream of the GVC, while the U.S. HMT sectors and business sectors are in the upstream of the GVC. From this perspective, the industrial structure between China and the United States is supposed to be highly complementary.

As China's economy develops, the low-end industrial structure has seriously impeded its high-quality economic development and the expansion of global influence. In response, the Chinese government has taken proactive measures and proposed the "Made in China 2025" strategy, striving for a breakthrough transformation of the manufacturing industry from the midstream and downstream of the GVC to the upstream. Figure 7.8 shows that, in recent years, the C_{RC} of China's HMT sectors has outperformed that of the US, yet the C_{RC} of LT sectors still occupies a large proportion of all sectors in China. It is therefore an urgent need to achieve industrial transformation driven by HMT sectors and optimize the industrial layout [8].

Meanwhile, the industrial structure of the United States has also changed under the stimulus of the Trump administration's "Re-Industrialization" policy. The years 2017 and 2018 saw an upsurge in the C_{RC} of all sectors in the United States, and the overall C_{RC} exceeded that of China, showing a significant impact from the reshoring of manufacturing. However, this growth trend is unsustainable, mainly due to the lack of a well-developed industry chain in the United States and high labor costs. Consequently, the $\mathrm{C_{RC}}$ of all sectors in the United States declined in 2018 and 2019 and its overall C_{RC} is overtaken by China, highlighting that China is surpassing the United States in terms of global influence. Against this backdrop, the complementarity of the industrial structure between the two countries is gradually weakening, competition increasing, and trade frictions intensifying, eventually leading to the outbreak of a full-scale trade war.

Various phases of the Sino-US trade war show different impact on sectors of the two countries. In the short term, it is more favorable to the United States. The imposition of tariffs on imports by China and the United States has led to the reduced volume of exported products in both ways, and the products were thus transferred to their other trade partners, during which the product exports of the two countries have been continuously restructured. China has been establishing trade relations with many countries in the world, forming an all-round trade system, so products not exported to the United States can be diverted to other countries or to the domestic market. Meanwhile, the relative underdevelopment of the service industry makes China's various sectors less affected by the trade war. Yet on the other hand, the U.S. economy is service-oriented, and the reduction of imports from China forced the United States to look for alternatives to fill the supply gap, which has facilitated the manufacturing reshoring and the development of its own manufacturing industry as well as related services. In the long run, however, the trade war would be detrimental to both sides, with a greater impact on the United States. The trade war would have a large negative impact on relevant sectors in both countries, such as increased costs and reduced production. In addition, such economic shocks will flow along intermediate inputs and thus affect the relevant sectors, and the more important the sector on the GVC is, the more it will be affected. Thus, American BS sectors and PWS sectors will be more adversely affected than Chinese and this negative impact will continue to grow.

7.3 Decomposition of GDDI

C_{FP} reflects the degree to which a sector needs to depend on global market demand, and the sum of C_{FP} of each sector in a country measures its participation in globalization to some extent. Figure 7.9 shows the trend of global demand dependence of the five sectors and their sum in China and the United States from 2016 to 2019 in GIVCN-ADB2019 model.

As shown in Fig. 7.9, the C_{FP} of China's HMT sectors and LT sectors is significantly higher that of the rest sectors, accounting for almost 70% or more of the

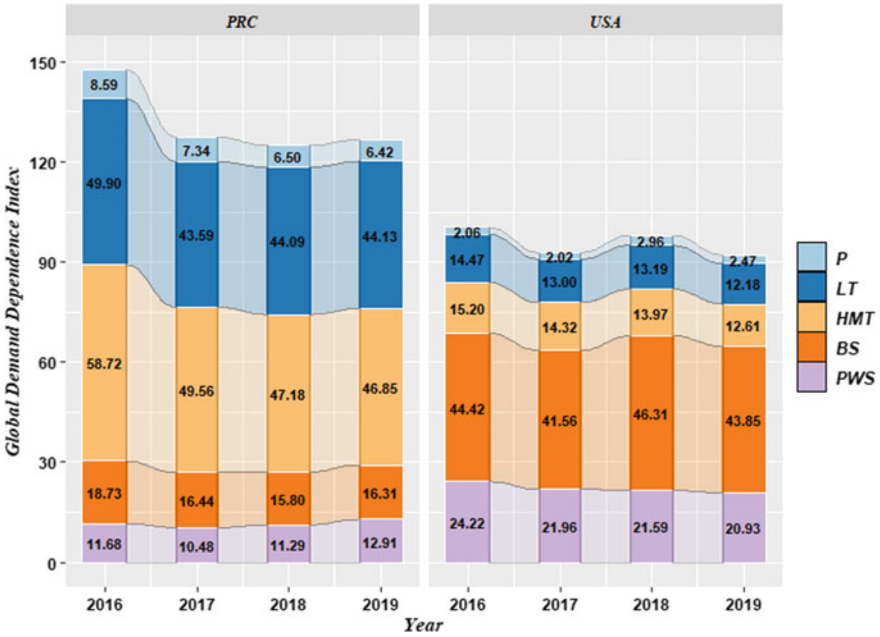


Fig. 7.9 Five-sector C_{FP} of China and the United States from 2016 to 2019 ($E + 02$)

overall. In contrast, the C_{FP} of BS sectors and the PWS sectors in the United States are remarkably higher than that of other sectors. It can be concluded that China and the United States will have different primary responses to global market shocks, with China mainly in manufacturing and the United States in services.

The sensitivity of China and the United States to the global market demand reflects the depth of their participation in the international division of labor. Since the bipolar world led by the U.S. and the U.S.S.R. has collapsed after the Cold War, the world political and economic landscape has evolved from being unipolar to multipolar, and the trend of global economic integration has driven the industrial sectors of countries to establish global production systems. China has become the "world factory" by virtue of its strong manufacturing capacity and established trade relations with the majority of countries in the world, forming a comprehensive trade system. Because China has challenged the U.S. leadership in the global advanced manufacturing industry, the political game between the two countries shows an increasingly obvious trend to fall into the Thucydides trap.

It is found that though being descendent during 2016–2018 and then picking up afterwards, the sum of C_{FP} of various sectors in China is consistently higher than that of the United States from 2016 to 2019, indicating that China is more involved in globalization than the United States. The sum of C_{FP} of the U.S. sectors did not change much over the time span, reflecting that China and the United States are not equally affected by fluctuations in the international economic environment. The root reason may be that China's manufacturing sector is oriented to the global market, and therefore it is struck not only by the sluggish world economic recovery, but a series of U.S. restraining tactics towards China's high-tech industries, such as the chip ban. As for the United States, its BS sectors have been dominating the world, and the PWS sectors as a non-tradable sector are mainly determined by the demand side from its domestic market, neither of which has been significantly affected by the Sino-US trade war.

In order to contain China's development, the Obama administration has promoted negotiations of the ***Trans-Pacific Partnership Agreement (TPP)*** and the ***Transatlantic Trade and Investment Partnership (TTIP)***, hoping to isolate China in the economic sphere. Meanwhile, China has launched the ***Belt and Road Initiative (BRI)*** and established the ***Asian Infrastructure Investment Bank (AIIB)*** as countermeasures. The U.S. goal of strengthening its global market penetration by engaging in the GVC cooperation has proven far less achievable than China's. After the presidential transition in early 2017, the Trump administration has pursued a series of trade protection policies, such as tax cuts and quantitative easing monetary policies domestically and withdrawal from the TPP and punitive tariffs on other countries internationally. These policies ostensibly preserve the U.S. position and curb China's expansion in the market, but in fact, they hinder the process of global economic integration and can only gain certain advantages for the United States in the short term. In the long run, such unilateral protective behavior is not only detrimental to GVC development, but also aggravates the trade deficit, intensifies trade frictions, weakens the United States own economic strength, and reduces the ability to meet market demand [9].

In order to improve the globalization of industrial sectors, China has adopted a "dual circulation" strategy oriented to both domestic and international market to adjust its participation in globalization [10]. For internal circulation, it proposes to "promote the deep integration of advanced manufacturing and modern service industries", and for external circulation, it establishes free trade zones with neighbors and other countries and strengthens economic and trade cooperation with Asia–Pacific countries through the Regional Comprehensive Economic Partnership Agreement (RCEP), actively building a global trading system [11].

7.4 Regression Analysis

In order to quantitatively analyze the indicative role of C_{RC} and C_{FP} on a country's overall development and economic development, we take the GDP of China and the United States from 2010 to 2019 as the dependent variable, and the C_{RC} and C_{FP} of the two countries in five sectors after min–max normalization as the independent variables, and adopts a regression model to analyze the quantitative relationship between GDP and C_{RC}, C_{FP} of the two countries.

Considering that the disturbances of the same country in different years are generally autocorrelated, we use the cluster-robust standard errors with the country as the cluster variable in fitting the independent and dependent variables. In the selection of regression models, we test the fitting effect under different models, including ***Ordinary Least Squares (OLS)***, ***Fixed Effects (FE)***, ***Random Effects (RE)***, and ***Least Squares Dummy Variables (LSDV)***, of which the OLS regression model performs best.

When using the OLS regression model, a strong multicollinearity is found between the independent variables (Mean VIF = 3619.83), and the value of SMC test are greater than 0.99, indicating a strong correlation between the independent variables; this would cause a large interference to the fitting results. Therefore, ***Principal Component Analysis (PCA)*** is firstly performed on the independent variables for the purpose of eliminating multicollinearity and reducing dimensionality. Table 7.1 shows the results after performing PCA on the independent variables.

In Table 7.1, the eigenvalues and proportion of Comp1 are much higher than those of the other principal components, indicating that it better explains GDP. Similarly, taking C_{RC} and C_{FP} of the five industrial sectors in two countries as independent variables, respectively, PCA shows that China's GDP fits better with comp1, comp2, and that of the United States fits better with comp2. The results of the OLS regression of the above principal components and GDP are shown in Tables 7.2 and 7.3.

In the regression models, China' goodness of fit values is 0.915 and the United States' is 0.685, indicating that the model fits well and that C_{RC} and C_{FP} for the five sectors in them can well explain their GDP. Combining the true meanings of the independent and dependent variables, the analytical equations of regression models are as shown in Eqs. (7.1) and (7.2).

$$\begin{aligned} GDP_{CHN} = 10^9 \times (&-5961.481 - 1771.50C_{RC}^{P} + 6135.73C_{RC}^{LT} + 4065.05C_{RC}^{HMT} \\ &+ 19718.35C_{RC}^{BS} + 18992.31C_{RC}^{PWS} - 1304.25C_{FP}^{P} - 6652.73C_{FP}^{LT} \\ &- 10174.74C_{FP}^{HMT} + 17020.90C_{FP}^{BS} + 6872.47C_{FP}^{PWS}) \end{aligned} \tag{7.1}$$

Table 7.1 PCA results of five-sector C_{RC} and C_{FP}

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	0.313	0.296	0.931	0.931
Comp2	0.017	0.013	0.051	0.982
Comp3	0.004	0.003	0.013	0.995
Comp4	0.001	0.001	0.003	0.998
Comp5	0.000	0.000	0.001	0.999
Comp6	0.000	0.000	0.001	1.000
Comp7	0.000	0.000	0.000	1.000
Comp8	0.000	0.000	0.000	1.000
Comp9	0.000	0.000	0.000	1.000
Comp10	0.000		0.000	1.000

Table 7.2 OLS regression results of China's GDP and Comp1, Comp2

Standardized GDP	Standardized Coeff.	Std. Err.	t-value	p-value	[95% Conf.	Interval]	Sig.
com1	−21,527.989	3767.532	−5.71	0.001	−30,436.786	−12,619.192	***
com2	28,815.035	3342.197	8.62	0	20,911.995	36,718.076	***
Constant	−5961.481	3079.359	−1.94	0.094	−13,243.009	1320.047	*
Mean dependent Var.		10,506.000		SD dependent Var.		2652.599	
R-squared		0.915		Number of Obs.		10.000	
F-test		37.758		Prob. > F		0.000	
Akaike Crit. (AIC)		166.320		Bayesian Crit. (BIC)		167.228	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7.3 OLS Regression Results of United States' GDP and Comp2

Standardized GDP	Standardized Coeff.	Sts. Err.	t-value	p-value	[95% Conf.	Interval]	Sig.
com2	12,896.601	3094.08	4.17	0.003	5761.64	20,031.562	***
Constant	252.091	4265.507	0.06	0.954	−9584.186	10,088.367	
Mean dependent Var.		17,951.620		SD dependent Var.		2142.909	
R-squared		0.685		Number of Obs.		10.000	
F-test		17.374		Prob > F		0.003	
Akaike crit. (AIC)		173.181		Bayesian Crit. (BIC)		173.786	

Equation (7.1) shows the impact of China's industrial sector development on its economy. First, C_{RC} and C_{FP} of the primary sectors have a negative impact on GDP, indicating that increasing the industrial influence and globalization (i.e., the degree of embeddedness on the GVC) of such sectors is detrimental to China's economic development. Second, C_{RC} of the manufacturing sectors (low-tech sectors and high-and-medium-tech sectors) has a positive impact on GDP, while its C_{FP} functions negatively. This implies that increasing the global industrial influence can help the sectors move upwards on the GVC and thus contribute to the country's economic development; however, increasing the degree of globalization will make them overly dependent on the sectors in other countries, leading to a "low-end lock-in" in manufacturing development [12], which negatively affects their ascent on the GVC. Third, both C_{RC} and C_{FP} of the services sectors (BS and PWS) positively affect GDP, in which C_{RC} has a more pronounced contribution than C_{FP}, suggesting that China's economic development will further benefit as these sectors become more embedded in GVCs. In conclusion, China's dominant position in GVC reconfiguration will be better secured by strengthening the GVC embeddedness of the service sector, weakening that of the manufacturing sector, and moving the two sectors both upwards on GVCs.

$$\begin{aligned} GDP_{USA} = 10^9 \times (&252.09 + 1779.73C_{RC}^{P} + 5029.67C_{RC}^{LT} + 4565.40C_{RC}^{HMT} \\ &+ 7351.06C_{RC}^{BS} + 6370.92C_{RC}^{PWS} + 206.35C_{FP}^{P} + 1599.18C_{FP}^{LT} \\ &+ 928.56C_{FP}^{HMT} + 4101.12C_{FP}^{BS} + 1418.63C_{FP}^{PWS}) \end{aligned} \tag{7.2}$$

Equation (7.2) shows the impact of industrial sector development in the United States on its economy. First, both C_{RC} and C_{FP} of both manufacturing and service sectors have a positive impact on GDP. This is due to the integration of its advanced manufacturing sector which is constantly being optimized and upgraded and its services sector which dominates the global value chain. Second, C_{FP} contributes more to GDP compared to C_{FP}, which suggests that for the United States increasing the industrial influence of each sector is more effective in promoting its economic development than enhancing globalization. Third, C_{RC} and C_{FP} of the manufacturing sector contribute more to its GDP than the service sector, suggesting that the United States needs to focus on its manufacturing sector and achieve balanced and synergistic progress in both sectors while increasing their global industrial influence and globalization.

7.5 Simulation on the Year of 2020

Just being eased in 2020, the trade relationship between China and the United States was again affected by the worldwide COVID-19 pandemic, leading to a plummet in trade volumes as well as more delicacy in the bilateral relationship. In order to quantitatively analyze the impact of the reduced trade volume between China and the United States on the industrial influence and demand dependence of the two countries, we reduce the two-way trade volume of each sector registered in 2019 on an equal proportional basis, of which the simulation results are shown in Figs. 7.10 and 7.11.

As shown in Fig. 7.10, the trend and the magnitude of the variation in each sector's industrial influence of the two countries mark difference when the bilateral trade volume decreases in equal proportion. China's influence in all sectors except the basic sector displays a modest decline, while that of the United States experience a sharp one, indicating that the two countries' industrial sectors differ in their abilities to withstand risks. The reason could be that China has formed a more complete industrialized production system and a reasonable industrial structure, which are developing towards optimization and upgrading. Besides, China's highly potential domestic market ensures that, in spite of the shrunk Sino-US trade volume, the products produced by each sector can be consumed domestically or exported to other countries. In contrast, although the U.S. service industry has a high industrial influence, most of its manufacturing industries have moved abroad, leaving its industrial structure seriously "hollowed out" and unbalanced, so changes in the external environment will severely affect its industrial influence.

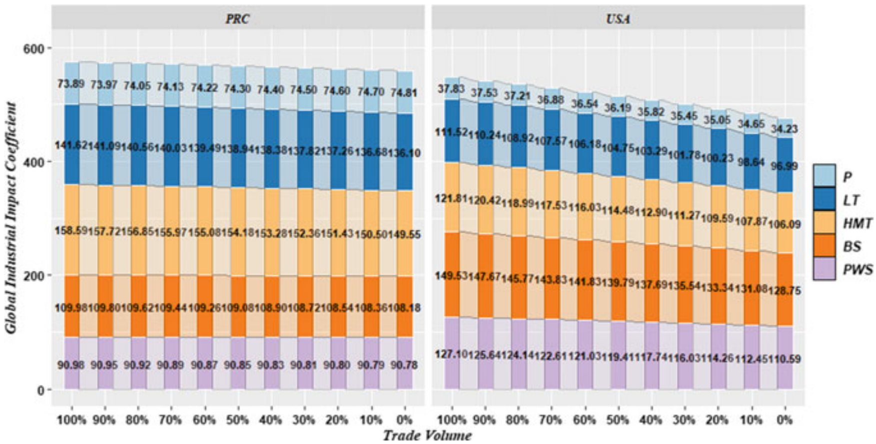


Fig. 7.10 Simulation on five-sector GIICs of China and the United States

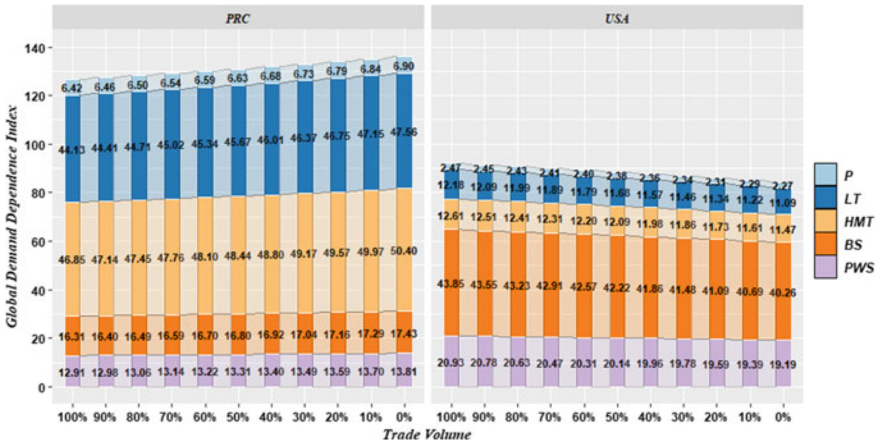


Fig. 7.11 Simulation on five-sector GDDIs of China and the United States

Unlike the industrial influence, when the trade volume between China and the United States decreases in equal proportion, the demand dependence of each sector in the two countries shows an opposite trend (see Fig. 7.11), which means the demand dependence of each sector in China increases while that of the United States decreases. While promoting the BRI and the RCEP agreement, China has basically built a comprehensive trade system and maintains a strong momentum in terms of foreign trade. Hence, the deterioration of trade relations between China and the United States has not exerted a substantial impact on China, but instead, has deepened its participation in globalization while strengthening trade relations with other countries. The United States, on the other hand, is obviously more dependent on imports from China, so a decrease in the volume of Sino-US trade not only directly

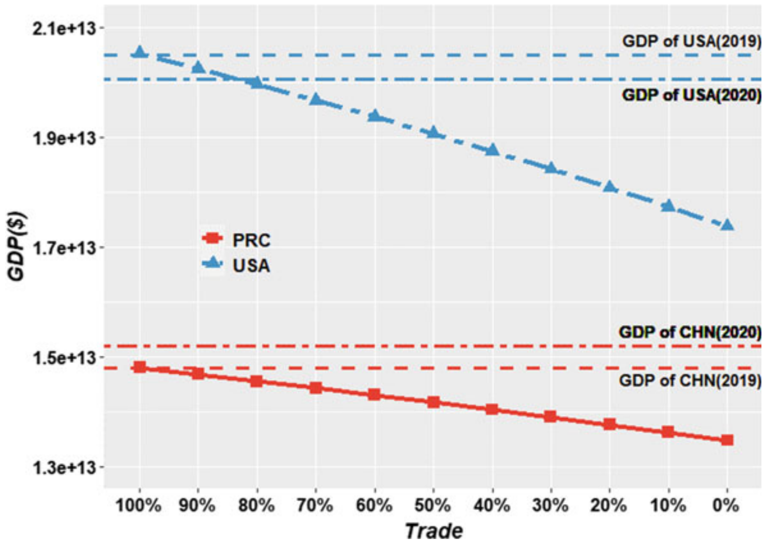


Fig. 7.12 Comparison of GDP and Simulation Results. *Notes* The horizontal dashed and dotted lines represent the actual GDP of China and the United States in 2019 and 2020, respectively. To accurately reflect the impact of declining trade volumes on the GDP of the two countries, we adjust the starting value of simulated GDP to the actual level in 2019

widens the trade deficit between the two countries, but also reduces the U.S. sectors' participation in globalization, thus hurting its economic development.

Based on the results of 2019 data and network indicator simulation, we predict the GDP trends of China and the United States in 2020 under the dual impact of the Sino-US trade war and the COVID-19 pandemic, and makes comparison analysis with the real situation (see Fig. 7.12). First, as the trade volume between China and the United States falls, both countries' GDP shrink, but China's GDP decreases less than that of the United States This suggests that China is better able to cope with global systemic risks than the United States, and is less influenced by the smaller trade volume caused by the pandemic. Second, it is noteworthy that when trade volumes fall to 80%, the U.S. real GDP in 2020 is essentially the same as simulated GDP, while that of China is much higher than simulated number. China's positive economic growth despite the adversity can be attributed to its elevated position on the GVC in recent years as well as the strong recovery after the pandemic control.

7.6 Conclusion

The existing GVC accounting system uses the whole year as a statistical window, reflecting the cumulative effect of value stream transfer over a longer time span. But in reality, economic shocks exert influence on individual countries or regions along the GVC in a shorter time. So, to make full use of the GVC topology information in the MRIO table in theory and practice, this paper proposes a complex network analysis model based on the biased random walk. Firstly, we take the intermediate goods circulation in the MRIO table directly as the adjacency matrix of an edge weight set, thus constructing a GIVCN model reflecting the operation mechanism of production links within the global economic system. Secondly, since the instantaneous value stream transfer on GVC is a discrete-time Markov chain with finite state space, i.e., biased random walking, we use the transfer probability matrix to describe the diffusion law of economic shocks. What's more, referring to the meso-centrality indicators in social network analysis, we design two types of dynamic network characteristics indicators, namely C_{RC} and C_{FP}—the former measures the pivotal function of the industrial sector in the value-added process of intermediate goods, and the latter the sensitivity of the industrial sector to the changes in market demand at the global level. Finally, based on the above analytical framework, this paper examines the global industrial influence and global demand dependence of China and the United States during the Trump administration, and retrospectively analyzes the changing trends in the functions and positions of the two countries on the GVC, as well as the delicacy relationship between the two types of indicators and the level of economic development. In terms of global industrial influence, considering China and the United States have roots in manufacturing and service sectors, respectively, a trade war would bring more benefits to the service-oriented economy in the United States in the short run, but ultimately adverse effects on both sides, especially on the Unite States due to the hollowing out of its industrial structure. As for global demand dependence, China's manufacturing sector faces economic shocks in the global market, sensitive to fluctuations in the international economic environment; the U.S. is globally dominant in the business services sector, with its public and welfare services being a non-trade sector, which save it from the influence of the trade war as an immediate outcome. In the long term, the systemic risks faced by the Chinese economy will be reduced due to the "dual-circulation" development pattern.

Based on the above results, this paper provides two policy advice. First, China should continue to deepen the supply-side structural reform, promote the deep integration of advanced manufacturing and modern service sectors in the domestic circulation. As for the external circulation, more active participation is expected in building a new global trading system with other countries. Specifically, China shall support the transformation and upgrading of strategic emerging industries, accelerate the rise of medium- and high-tech sectors to the middle and high end of the GVC, and reduce the negative effects of sanctions such as tariffs, disinvestment and technology embargo imposed by the United States; promote digital innovation on the supply side of services and digital consumption on the demand side, significantly increase the tradability of services, and expand international cooperation in service sectors such as R&D, finance, logistics, marketing, and branding through trade in service. We should promote the construction of BRI, RCEP, China-EU Comprehensive Agreement on Investment (CAI) and China-Japan-Korea free trade zone in an open and pragmatic manner, to reduce the dependence on the U.S. market. On the other hand, China and the United States should cease trade sanctions against each other, actively engage in economic and trade cooperation based on the principles of "mutual respect, peaceful coexistence, and win-win cooperation" proposed by President Xi Jinping, and jointly maintain the stability of the global industrial supply chain. Despite the differences between the two countries in the economic and trade fields, the complementary nature of the two countries' industrial structures remains true. The vicious competition between the two largest economies shall come to an end after frank and effective communication and dialogue. Both sides should play the role of responsible stakeholders in respect of international rules, and strive for the early resumption of the BIT negotiations to put the U.S.-China economic and trade relations back on track.

In the following part, the author will follow up on the reconfiguration trend of GVC in the post-pandemic era and the potential of economic cooperation between China and the United States in various industrial sectors.

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Part IV
Competition and Collaboration

Chapter 8
Quantify the Competitive Strength and Weakness of Economies

8.1 Introduction

The IO table is good at presenting sophisticated inter-industry dependencies from a global perspective, with which one can perceive how much production resources that sectors obtain from their upstream ones, as well as, how much productive capacities that sectors provide for their downstream ones. In other words, competition/collaboration occurs when sectors share the same providers/consumers because all sectors' products and services outputted to downstream ones are limited. Thus, inter-industry competition for inputs from upstream sectors, or collaboration on outputs to downstream sectors, may be quantified with IO matrix transformation.

The traditional IO analysis adopts the ***Direct Consumption Coefficient Matrix*** and ***Complete Consumption Coefficient Matrix*** to show the direct and indirect technical–economic relations among industrial sectors, before using ***Influence Coefficient*** and ***Reaction Coefficient*** to measure the pulling effect and demand intensity of one sector on the other. But no existing studies have examined the competitive/collaborative relations to the sectoral level, for there lies the difficulty of distinguishing the functional roles of any industry in outputting or consuming the intermediates. For this reason, we aim at consolidating the IO analysis and network-based approach to find out how industrial sectors compete for their production resources from the mutual providers and how they collaborate to facilitate the production of their mutual consumers.

Enlightened by the ***SWOT Analytical Framework***, which is a strategic planning method used to evaluate the ***Strengths***, ***Weaknesses***, ***Opportunities***, and ***Threats*** involved in a project or in a business venture, we try to identify the competitive and collaborative relations between industrial sectors and between economies they belong to. In this chapter and next chapter, we extract two sorts of network model out of the GIVCN model and design two indices for each of them, respectively. To verify the feasibility of our research plan on inter-industry and inter-country competition, we study the game relationship and the degree of influence between the TPP member states in the part of empirical analysis of this chapter.

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TPP, also known as the ***Trans-Pacific Strategic Economic Partnership Agreement (TPPA)*** and the ***Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP)*** for now, announced the conclusion of negotiations, reaching an agreement on October 5th, 2015, after five years of anticipation. As originally announced, this ***Free Trade Agreement (FTA)*** could exceed even the European Union, with the 12 members together encompassing around 40% of world GDP. The summary document of the TPP issued by the ***United States Trade Representative (USTR)*** declared that a high-standard, ambitious, comprehensive and balanced agreement had been reached and that TPP aims to promote economic growth, support the creation and retention of jobs, enhance innovation, raise living standards, reduce poverty, promote transparency, and enhance labor and environmental protections.

Nevertheless, on January 23rd, 2017, the new U.S. President Trump signed an executive order at the White House, officially announcing that the United States would withdraw from TPP. Although the original intention of TPP is to curb the rapid development of China's economy, in the final analysis it must be in line with the fundamental interests of the relevant countries, that is, the enhancement of its own industrial competitiveness. It is hence no surprise that some TPP member states expect China to join. So, are the United States and China beneficial or detrimental to the improvement of TPP's overall competitiveness? With this question in mind, we will analyze it through network models and measurement tools.

8.2 Methodology

8.2.1 Bipartite Graph

In a ***Bipartite Graph*** G the node set V is divided in two nonempty sets P and O with no intersection in between. Let $G = (P, \mathrm{O}, E)$ be a bipartite graph where E is the set of edges, $P = \{P_1, P_2, \cdots, P_n\}$ and $O = \{O_1, O_2, \cdots, O_m\}$ are the two sets of nodes. Of course, the intersection of P and O is empty. The nodes from the set P will be called ***Participants*** and those from the set O will be called ***Objects***. We take an example to describe its topological structure, where $n = 9$ and $m = 3$, as shown in Fig. 8.1.

In Fig. 8.1, the squares in the upper part are the objects (denoted by $O_1, O_2, \ldots, O_3$), while the circles below are the participants (denoted by $P_1, P_2, \ldots, P_9$), and the edges in black belong to the two-mode network. It is more than common to project a two-mode network onto one kind of nodes, and the resulting edges have been granted the property to re-flect certain relationship. As we can see, the edges in red coming from the projection of two black edges constitute a one-mode net-work, namely Complete Object Subgraph. Sometimes, there should be weights on the edges, which are gained through the defini-tion of co-occurrences and used to measure the potential relationship of two participants in the same object, or that of two objects in the same participant. For instance, it just likes the number

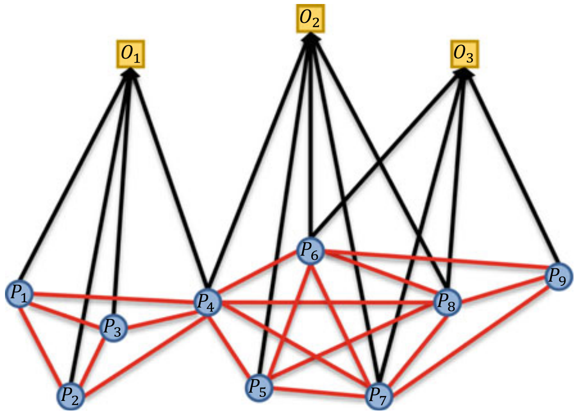


Fig. 8.1 A two-mode network and Its projection onto participants

of papers that two scientists (participants) wrote together, or the number of the same scientists that two papers (objects) have [2]. However, refined calculation on the weight of projected edge is very difficult, and we must use a specific method to solve a specific problem.

The bipartite graph has a wide application in complex network analysis, including cooper-ation and competition networks (mainly dealt with through affiliation networks), for either cooperation or competition is the common existence in social networks con-sisting of units of people. Padrón believed that this modeling process could bring dis-tinctive simulation on the potential coopera-tion or competition relation [3]. In the field of GVC-related studies, scholars and politicians all want to figure out the inter-country and inter-industry competition and collaboration for the purposes of academic research and policy-making. If limited industrial resources lead to competition among downstream sec-tors, then limited market demand leads to cooperation among upstream sectors. There-fore, with the purpose of extracting the in-ter-industry collaborative relations, the **Resource Allocation Process (RAP)** is also adopted in this paper as the algorithm of projection [4].

8.2.2 Resource Allocation Process

In order to minimize the information loss in the process of projection of two-mode networks, as well as take the scarcity of resources into consideration, the RAP approach is adopted in this Section (also the Sect. 9.2) as the algorithm of projection. The fundamental assumption of RAP is that participants' resources are limited, and not only does this scarcity limit the extent to which participants can contribute to the same objects, but also it makes an influence on the size of resources that participants gain from objects in turns. There is another suppressed premise that participants give objects the meaning of existence, otherwise these objects will become useless, e.g.,

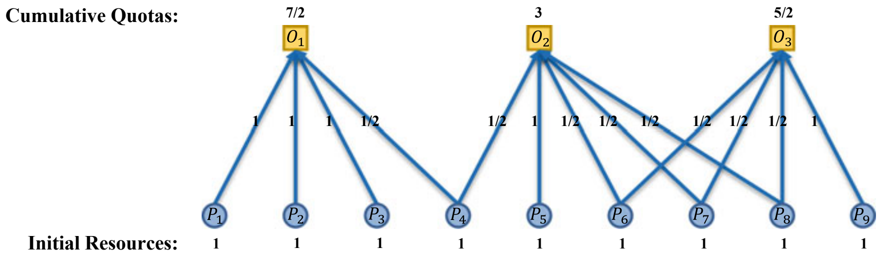


Fig. 8.2 Primary Distribution: Initial Resources from Participants are Equally Distributed to Objects. *Note* O_1 and relevant participants for an explanation are taken as example. For simplicity, we assume all participants here own an equal size of resources, i.e., $f(P_i) = 1$. P_1 only connects to O_1, so $K(P_1) = 1$, $a_{11} = 1$, $a_{12} = 0$, $a_{13} = 0$. The same thing happens in P_2 and P_3. However, P_4 connects to both O_1 and, O_2 so $K(P_4) = 2$, $a_{41} = 1$, $a_{42} = 1$, $a_{43} = 0$. Thus, $f(O_1) = 1 + 1 + 1 + \frac{1}{2} = \frac{7}{2}$. Similarly, $f(O_2) = 3$ and $f(O_3) = \frac{5}{2}$

papers without authors, patents without holders, goods without consumers, bus stops without routes, etc.

Let $f : O \bigcup P \to \mathbb{R}_+$ be a function such that $f(P_i) = 1$ for all $iin\{1, 2, \ldots, n\}$, which means the initial resource of each participant is the same. Firstly, we assume that the $P \to O$ primary distribution of initial resources is equal, as shown in Fig. 8.2.

The cumulative quota of the k-th node in O is:

$$f(O_k) = \sum\nolimits_{i=1}^{n} \frac{a_{ik} f(P_i)}{K(P_i)} \tag{8.1}$$

where, $K(P_i)$ is the degree of P_i, $\{a_{ik}\}$ is a $n \times m$ matrix:

$$a_{ik} = \begin{cases} 1 \ P_i O_k \in E \\ 0 \ otherwise \end{cases} \tag{8.2}$$

With all the demand signals flowing back to set P , the cumulative quotas from objects are satisfied by participants, as shown in Fig. 8.3. Note that, the assumption of equal distribution still holds for the secondary distribution.

The consumed resource of P_i is

$$f'(P_i) = \sum_{k=1}^{m} \frac{a_{ik} f(O_k)}{K(O_k)} = \sum_{k=1}^{m} \frac{a_{ik}}{K(O_k)} \sum_{j=1}^{n} \frac{a_{jk} f(P_j)}{K(P_j)} \tag{8.3}$$

$f'(P_i) \neq f(P_j)$ after implementing the RAP approach. This discrepancy stems from the nature of the resources themselves. That is, if objects could transfer resources without attenuation or loss, there will be no competition among relevant participants, e.g., papers and readers. But, if they could not, scarcity of resources will bring participants exclusive competition, e.g., banks and moneylenders. This kind of competitive

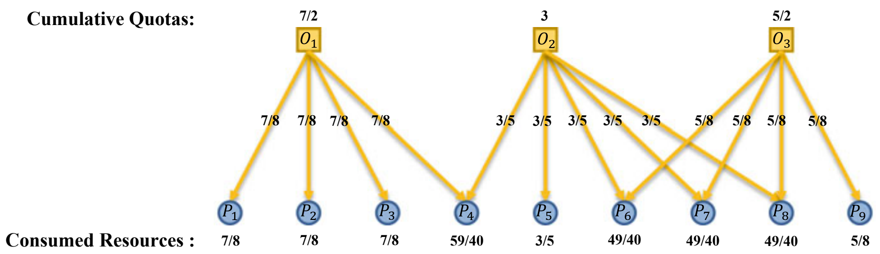


Fig. 8.3 Secondary Distribution: Cumulative Quotas from Objects are Equally Satisfied by Participants. *Note* When an object equally returns its cumulative quotas to relevant participants, the denominator is just the number of participants it owns. Thus, the consumed resource of participant is equal to the sum of quotas it gets from all objects, e.g., $f'(P_1) = \frac{f(O_1)}{k(O_1)} = \frac{7}{8}$ and $f'(P_4) = \frac{f(O_1)}{k(O_1)} + \frac{f(O_2)}{k(O_2)} = \frac{7}{8} + \frac{3}{5} = \frac{59}{40}$

relations among participants within Eq. (8.3) can be rewritten as:

$$f'(P_i) = \sum_{j=1}^{n} w_{ij}^{P} f\left(P_j\right) \tag{8.4}$$

where, w_{ij}^{P} is the relation strength produced in the two resource allocation processes between P_i and P_j, and describes how the other participants' occupation on resources affect P_i.

The w_{ij}^{P} in Eq. (8.4) could be written as:

$$w_{ij}^{P} = \frac{1}{K\left(P_j\right)} \sum_{k=1}^{m} \frac{a_{ik} a_{jk}}{K(O_k)} \tag{8.5}$$

Thus, we get the matrix $W^P = \left\{w_{ij}^{P}\right\}_{n \times n}$ as the weight set of complete object subgraph through RAP approach, as shown in Fig. 8.4.

As shown in Fig. 8.4a, the core of the RAP approach is to have resources distributed to each participant and object in the network, with w_{ij}^{P} represents the proportion of resources distributed to the participant j through the object from the participant i. Each participant equally distributes its initial resource to its objects, and then, each object redistributes cumulative quotas it received back to its participants equally through the edges of the bipartite graph. There lies, therefore, the fundamental difference between the RAP approach and traditional bipartite graph projection.

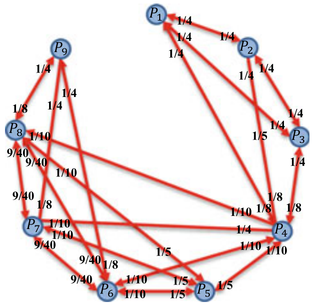
RAP approach shares the following three properties:

(1) The adjacency matrix W^P of the complete object subgraph is asymmetric, and $w_{ij}^{P}/K\left(P_j\right) = w_{ji}^{P}/K(P_i)$.
(2) As two participants take parts in the same object multiple times, their relation strength goes from intimacy to saturation rapidly.

$$\begin{bmatrix} f'(P_1) \\ f'(P_2) \\ f'(P_3) \\ f'(P_4) \\ f'(P_5) \\ f'(P_6) \\ f'(P_7) \\ f'(P_8) \\ f'(P_9) \end{bmatrix} = \begin{bmatrix} w_{11}^P & w_{12}^P & w_{13}^P & w_{14}^P & w_{15}^P & w_{16}^P & w_{17}^P & w_{18}^P & w_{19}^P \\ w_{21}^P & w_{22}^P & w_{23}^P & w_{24}^P & w_{25}^P & w_{26}^P & w_{27}^P & w_{28}^P & w_{29}^P \\ w_{31}^P & w_{32}^P & w_{33}^P & w_{34}^P & w_{35}^P & w_{36}^P & w_{37}^P & w_{38}^P & w_{39}^P \\ w_{41}^P & w_{42}^P & w_{43}^P & w_{44}^P & w_{45}^P & w_{46}^P & w_{47}^P & w_{48}^P & w_{49}^P \\ w_{51}^P & w_{52}^P & w_{53}^P & w_{54}^P & w_{55}^P & w_{56}^P & w_{57}^P & w_{58}^P & w_{59}^P \\ w_{61}^P & w_{62}^P & w_{63}^P & w_{64}^P & w_{65}^P & w_{66}^P & w_{67}^P & w_{68}^P & w_{69}^P \\ w_{71}^P & w_{72}^P & w_{73}^P & w_{74}^P & w_{75}^P & w_{76}^P & w_{77}^P & w_{78}^P & w_{79}^P \\ w_{81}^P & w_{82}^P & w_{83}^P & w_{84}^P & w_{85}^P & w_{86}^P & w_{87}^P & w_{88}^P & w_{89}^P \\ w_{91}^P & w_{92}^P & w_{93}^P & w_{94}^P & w_{95}^P & w_{96}^P & w_{97}^P & w_{98}^P & w_{99}^P \end{bmatrix} \begin{bmatrix} f(P_1) \\ f(P_2) \\ f(P_3) \\ f(P_4) \\ f(P_5) \\ f(P_6) \\ f(P_7) \\ f(P_8) \\ f(P_9) \end{bmatrix}$$

$$= \begin{bmatrix} 1/4 & 1/4 & 1/4 & 1/8 & 0 & 0 & 0 & 0 & 0 \\ 1/4 & 1/4 & 1/4 & 1/8 & 0 & 0 & 0 & 0 & 0 \\ 1/4 & 1/4 & 1/4 & 1/8 & 0 & 0 & 0 & 0 & 0 \\ 1/4 & 1/4 & 1/4 & 9/40 & 1/5 & 1/10 & 1/10 & 1/10 & 0 \\ 0 & 0 & 0 & 1/10 & 1/5 & 1/10 & 1/10 & 1/10 & 0 \\ 0 & 0 & 0 & 1/10 & 1/5 & 9/40 & 9/40 & 9/40 & 1/4 \\ 0 & 0 & 0 & 1/10 & 1/5 & 9/40 & 9/40 & 9/40 & 1/4 \\ 0 & 0 & 0 & 1/10 & 1/5 & 9/40 & 9/40 & 9/40 & 1/4 \\ 0 & 0 & 0 & 0 & 0 & 1/8 & 1/8 & 1/8 & 1/4 \end{bmatrix} \begin{bmatrix} f(P_1) \\ f(P_2) \\ f(P_3) \\ f(P_4) \\ f(P_5) \\ f(P_6) \\ f(P_7) \\ f(P_8) \\ f(P_9) \end{bmatrix}$$

(*a*) Matrix-Form Linear Relation



(*b*) Complete Object Subgraph

Fig.8.4 Competitive Relations Reflected by Complete Object Subgraph. *Note* In Fig. 8.4a, the matrix W^P represents the linear relation between each participant's consumed resource and initial resource, whose different values reflect their different status in the resource allocation process. Therefore, the weighted and directed graph in Fig. 8.4b embodies the unsymmetrically and unequally competitive relations among nine participants, while the values on the diagonal of matrix W^P are useless

(3) The relation strength between two participants is decided by not only the number of times they jointly take parts in the same object but also the number of participants at the same time of the very object.

Further extension of RAP approaches can also be made to the condition of weighted edges in bipartite graphs, when resources are no longer distributed equally, with the weight representing the degree of membership of participant's node to the object's one. The formula is:

$$w_{ij}^P = \frac{1}{S(P_j)} \sum_{k=1}^{m} \frac{w_{ik} w_{jk}}{S(O_k)} \tag{8.6}$$

where $S(P_j)$ is the weight of participant node P_j, $S(P_j) = \sum_{k=1}^{m} w_{jk}$; $S(O_k)$ is the weight of object node O_k, $S(O_k) = \sum_{i=1}^{n} w_{ik}$; w_{ik} and w_{jk} are the weights on edges connecting P_i and P_j with O_k, respectively.

In sum, the RAP approach reflects the scarcity of resources of network, and at the same time the limitation of resources taken by participant nodes from object nodes, enabling the complete object subgraph obtained through projection giving a clear indication on the competitive relations among participants.

8.3 Modeling

8.3.1 Database Selection

In order to fully restore the impact of the game relationship between TPP-related nations on GVC, we need to select the ICIO database with the widest coverage. Eora26 is thus chosen to build GIVCN-Eora26 models, which provides time-series data of 189 independent countries/regions from 1990 to 2015, covering all the 13 TPP-related nations.

8.3.2 Modeling Framework

IO table can well present the complicated interdependent relation among various industrial sectors from a global perspective, with a clear embodiment of the number of resources one sector may gain from its upstream sectors [5]. Studies on IO table mainly take advantage of its ability of depicting the topological structure of the economic system by measuring intermediate products as an indication of the inputs and outputs relation, so as to analyze the rules of value stream and industrial structural features [6]. Bipartite graphs on the rows indicate the supply from upper to downstream industrial sectors and columns indicate on the demand from lower to upper ones. And it is obvious that the IO table is proficient in showing the cooperation or competition relation among different industrial sectors. However, there is no such relation among industrial sectors being reflected through direct structural measurement on the IO network, with adequate matrix transformations to be introduced for this goal.

If there exists more than one supplier or consumer for one single industrial sector, cooperation or competition will show up, for the scarcity of resources limits the flow of intermediate from upstream to downstream sectors. Traditional IO theory uses direct consumption coefficient and complete consumption coefficient to present this scarcity, with influence and reaction coefficients presenting the relations between one industrial sector and its environment. Yet it still bears the shortcoming that its focuses are restricted to the linear technical–economic relations among different industrial sectors and between the gross outputs and final usage, neglecting the scarcity of productive resources as constraints on cooperation and competition relations. This chapter contributes to set up modeling analysis with bipartite graph theory on the IO data, aiming at restoring the competition relation between downstream industrial sectors from the perspective of econophysics. The modeling framework is shown in Fig. 8.5.

Industrial sectors' economic relations can be vividly depicted in the form of complex networks based on IO/ICIO data, as shown in Fig. 8.5a, b. The sector's self-consumption on its own intermediate outputs is usually indicated by self-loop.

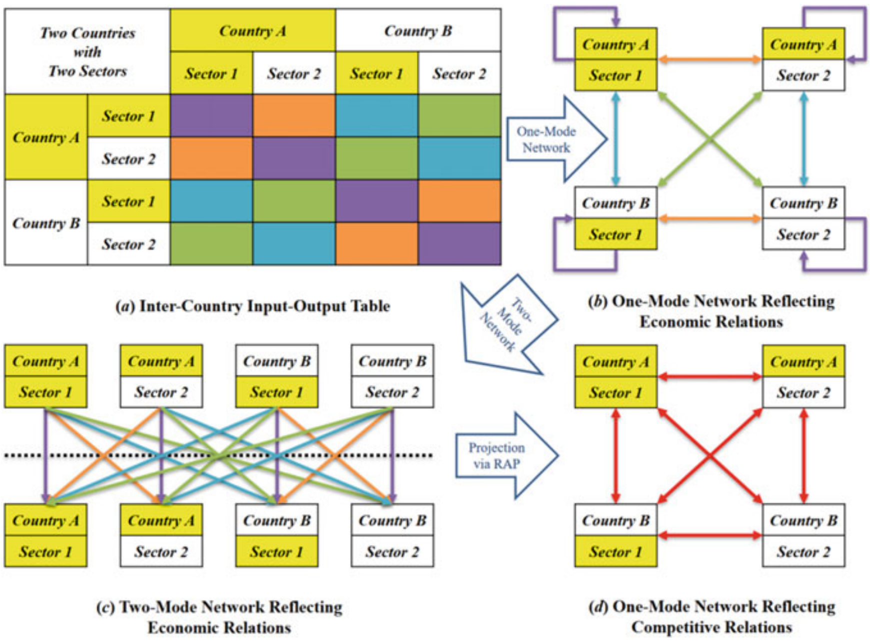


Fig. 8.5 Modeling framework for reflecting inter-industry competitive relations in consideration of the scarcity of productive resources. *Notes* The flows in bipartite graphs direct from the participant nodes to the object nodes in common, but the IO/ICIO networks flow in the opposite direction from the upper stream sectors to the lower ones at the mercy of the transfer of the intermediate goods along the GVC, as shown in Fig. 8.5c. Besides, we indicate different relations by colors, e.g., orange for domestic industrial IO trade, purple for domestic industrial self-consumption, green for international inter-industry trade, blue for international intra-industry trade and red for worldwide competition among industrial sectors

If we want to dig more information from IO/ICIO data, such as competitive status, it is necessary to reexamine IO/ICIO networks from another angle.

We need to change the one-mode network into a two-mode network, in order to separate the inner identity of each sector and prepare for the projection. In Fig. 8.5c, the same sector distributes on the two sides of the dotted line, which means it belongs to both the upper stream and the lower stream. In other words, the upper stream sector in the IO/ICIO table could be referred to as the object nodes in the bipartite graph, while the lower one as the participant nodes. Now, self-loop becomes a common edge between the two identities of this sector.

Then, we adopt RAP mentioned above to extract competitive relations hidden in the IO/ICIO relations, as shown in Fig. 8.5d. If any industrial sector enjoys with any other sector more than one upper stream industrial sector as production resources provider, there will be edges in the complete object subgraph depicting the competitive relations.

8.3.3 GIVCNBG Model

With its data structure enclosing the competitive relations among industrial sectors, the GIVCN model reveals the mechanism of creation, distribution, transfer, and value-addition of value on the GVC. Furthermore, a two-mode network is introduced to open the lid of the hidden competitive relations in this one-mode network, either direct or indirect, with the following assumptions:

(1) All the upstream industrial sectors contribute to the set of object nodes O, the downstream industrial sectors constitute to the set of nodes of participant nodes P, for the industrial sectors in IO tables show up in the status of both upper and downstream simultaneously. In consequence, one sector will appear twice in different identities.
(2) Edges are directed from the upstream industrial sectors to the downstream ones, making known to the flowing directions of the intermediates. Edges between two sorts of node constitute set E. The self-loop of each node reflects the industrial sector's consumption of the part of its own outputs as inputs, which is also incorporated in set E.
(3) The set of weights between the upper and lower industrial sectors are W. Among $N - 1$ other competitors and itself as a consumer, the downstream industrial sector i obtains the amount of w_{li} intermediates from its upstream industrial sector l, and $l = i$ indicates the upper- and lower-stream industrial sectors are practically the same one.

Based on the above assumptions, the GIVCN model is turned from a simple graph $G = (V, E, W)$ to a bipartite graph $G = (O, P, E, W)$, which is named ***GIVCNBG*** model (BG stands for the form of the bipartite graph). Serving two empirical analyses, we create the topology maps of GIVCNBG-Eora26-2015-TPP13 as shown in Fig. 8.6.

Although the number of nodes doubled in GIVCNBG-Eora26 model, the nature of economic relations reflected by the network architecture is the same as that of GIVCN-Eora26 model. Based on the transformation of the network, however, we can distinguish the dual function of industrial sectors and carry out further data mining about inter-country/inter-industry competition.

8.3.4 GIRCN Model

With the global economic system under explanation by GIVCNBG model, the downstream industrial sectors consume the limited outputs produced by the upstream ones, proving the scarcity of production resources. When several downstream industrial sectors share an upstream sector as the feeder of production resources, the scarcity will be translated into competition relations among the downstream industrial sectors. With the help of projection algorithm RAP, the competitive relations implied in GIVCN model can be shown by its complete object subgraph, and the formula of

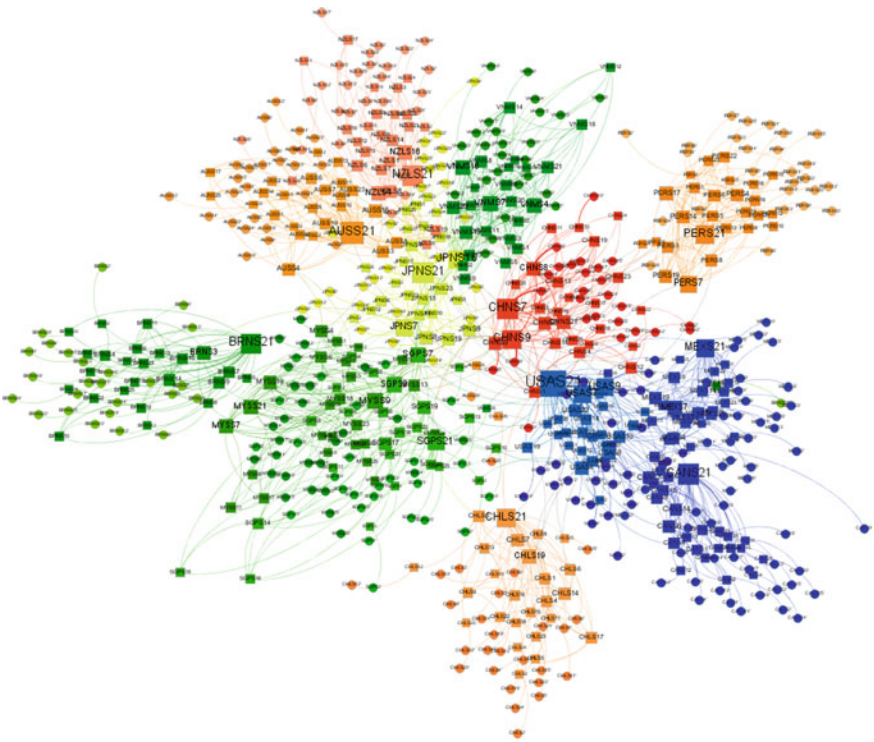


Fig. 8.6 GIVCNBG-Eora26-2015-TPP13. *Notes* Labels of nodes can be categorized into the abbreviations of the economic entities and serial numbers of the industrial sector. Nodes of the same color indicate that they are different industrial sectors belonging to the same economic entity. In detail, ***Association of Southeast Asian Nations (ASEAN)*** member states are labeled with green nodes, NAFTA blue, China red, Japan yellow and the others orange. Besides, the square nodes reflect the set of object nodes O composed of upstream industrial sectors, and circle one the set of object nodes P of the lower-steam sectors. In addition, edges only exist between two sorts of node in GIVCNBG-Eora26 model

projection is as follow:

$$w_{ij}^{P} = \begin{cases} \frac{1}{\underset{j}{\overleftarrow{w}}} \sum_{k=1}^{N} \frac{w_{ki} w_{kj}}{\vec{w}_k}, & i \neq j \\ 0, & i = j \end{cases} \tag{8.7}$$

where, $w_{ki}(w_{kj})$ is the k-th row and i-th (j-th) column element of the adjacency matrix of GIVCN model, representing the upstream sector k and downstream sector i (j) respectively; $\vec{w}_k$ is the gross outputs of upstream sector k, and it is numerically equal to the out-degree strength of node k in GIVCN model, say $\vec{w}_k = S^{OUT}(k) = \sum_{i=1}^{N} w_{ki}$; $\underset{j}{\overleftarrow{w}}$ is the gross inputs of downstream sector j, i.e., $\underset{j}{\overleftarrow{w}} = S^{IN}(j) = \sum_{k=1}^{N} w_{kj}$; w_{ij}^{P}

measures the ***Competitive Pressure*** of the sector i against j; downstream sectors i and j are connected by an edge denoted by e_{ij}^P in the complete object subgraph.

Until now, the edge set $E^P = \left\{ e_{ij}^P \right\}$ and weight set $W^P = \left\{ w_{ij}^P \right\}$ reflect all the competitive relations among sectors in the global economic system. We named the graph $G = \left(V, E^P, W^P \right)$ as the ***Global Industrial Resource Competition Network (GIRCN)*** hereafter, which is a sort of weighted and directed one-mode network without any self-loop of any node.

Figure 8.7 shows the topological structure of GIRCN-Eora26-2015-TPP13.

Agglomerations in GIRCN model can be easily located and competitions mainly exist within a certain nation or certain regional FTA. Moreover, although all the

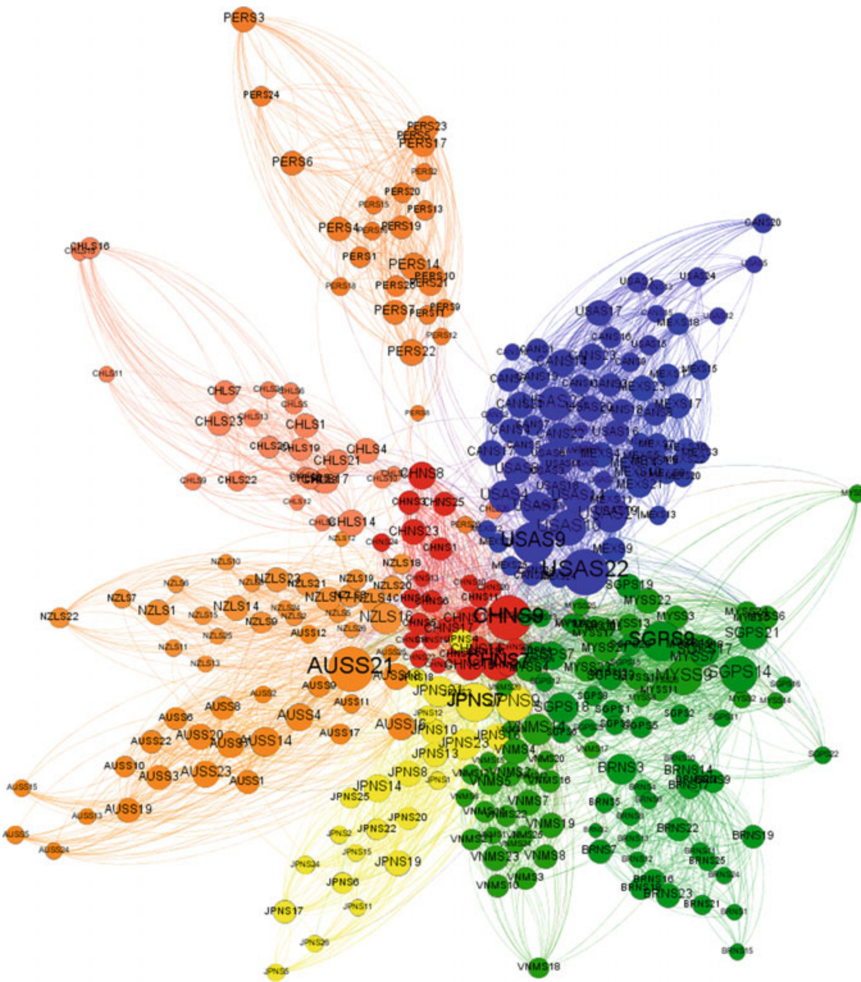


Fig. 8.7 GIRCN-Eora26-2015-TPP13

shadow nodes belong to the set of participant nodes, no connecting edge exists for these nodes after the projection. The connecting edges between shadow nodes and original ones are ignored, and thus there are no shadow nodes in GIRCN model. For one thing, our emphasis is the competitive relations among industrial sectors; for another, we want to eliminate the influence of one industrial sector's consumption of its own outputs upon its own benefit.

8.4 Measurement

According to our study on the application of the complex network theory [7, 8], network-based algorithms and indices have great potential to enhance the understanding of the industrial sector's position and function, given the network-form architecture of GVC. The inter-industry competitive status has been embodied in the GIRCN model, and out-strength and in-strength as simple yet important tools are hence introduced to quantify industrial sectors' competitive strength and weakness on the GVC, based on which we further carry out econometric, static timing and simulation analyses.

8.4.1 Sector-Level Indices

The weight set W^P of GIRCN indicates the direct and indirect competitive relations among industrial sectors. It is noteworthy that this competitive relation is directed, which means w_{ij}^P is the competitive strength of the industrial sector i against j, while w_{ji}^P is that of the opposite. Hence, the summation of the competitive pressure that an industrial sector imposes on others is defined as its ***Competitive Strength Index (CSI)***, and the summation of competitive pressure that an industrial sector receives from others is defined as the ***Competitive Weakness Index (CWI)***.

Judged from the perspective of complex networks, *CSI* and *CWI* are the out-strength S^{OUT} and in-strength S^{IN} of nodes respectively in the GIRCN model, to be calculated as follows:

$$CSI(i) = S^{OUT}(i) = \sum\nolimits_{j=1}^{N} w_{ij}^P \tag{8.8}$$

$$CWI(i) = S^{IN}(i) = \sum\nolimits_{j=1}^{N} w_{ji}^P \tag{8.9}$$

The strength conveys not only the degree of the node but also the weights of its connecting edges, proving itself to be the local information integrator on the network. *CSI* and *CWI* cover both the scale and intensity of competition, and we hence use them to show the competitive status of industrial sectors on the GVC in the view of econophysics through evaluation of the strengths among the downstream industrial sectors in their competition for the limited supply of intermediates from the upstream industrial sectors. Then, we can find more information about the competitive status from the distribution and correlation of *CSI* and *CWI*.

The distribution of *CSI* for all sectors in GIRCN-Eora26-2015 is shown in Fig. 8.8a, b. It is heavy-tailed and follows the significant levy-stable distribution on double logarithmic axes [9], i.e., the number of nodes with overwhelming *CSI* is relatively small. This phenomenon means industrial sectors' competitive strengths vary tremendously.

In Fig. 8.8c, the distribution of *CWI* is totally different from that of *CSI*, and we find no obvious evidence (Pearson correlation coefficient is only −0.392) to confirm they are linearly dependent in Fig. 8.8d. Back to Eq. (8.7), we can see w_{ij}^{P} is proportional to the quantity demanded by sector i. In other words, the more intermediate goods sector i requires from the mutual providers of sectors i and j, the bigger *CSI* sector i will have. Similarly, the more intermediate goods the sector j requires from the mutual providers of sectors i and j, the bigger *CWI* sector i will have. Therefore, a given sector's *CSI* is not necessarily correlated with its *CWI* but up to the consumption of both sides.

In sum, few industrial sectors with huge intermediate goods consumption earn themselves big *CSI*, and many industrial sectors with tiny intermediate goods consumption contribute little to the others' *CWI*.

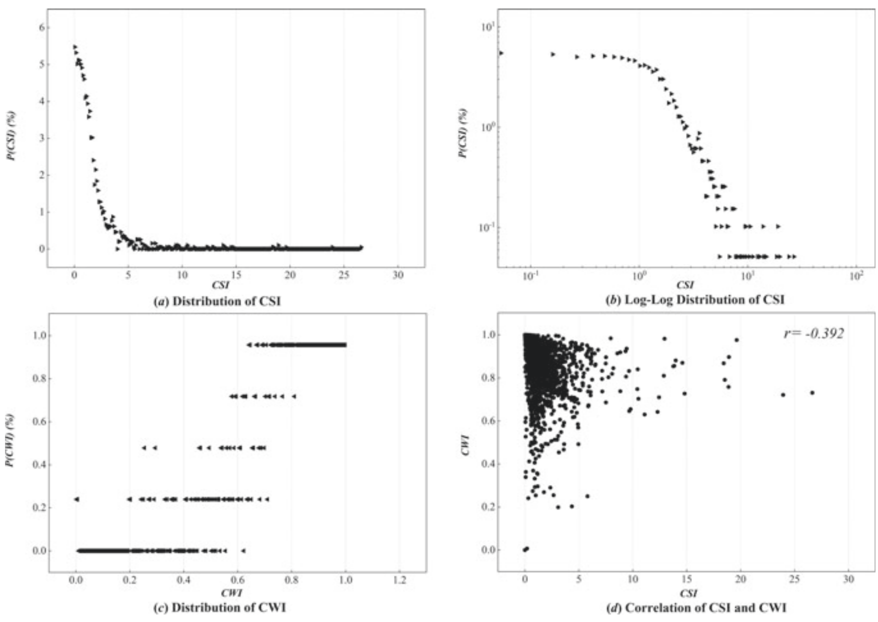


Fig. 8.8 Distribution and correlation of CSI and CWI in GIRCN-Eora26-2015

8.4.2 Country-Level Indices

On the basis of *CSI* and *CWI*, notions of ***National Competitive Strength Index (NCSI) and National Competitive Weakness Index (NCWI)*** are here introduced:

$$NCSI(u) = \sum\nolimits_{i \in \tau(u)} CSI(i) \tag{8.10}$$

$$NCWI(u) = \sum\nolimits_{i \in \tau(u)} CWI(i) \tag{8.11}$$

where $NCSI(u)$ and $NCWI(u)$ are used to measure the competitive strength and weakness of country u.

Eora26 provides ICIO data of 24 years from 1990 to 2015. In these GIRCN models, we calculate *NCSI* and *NCWI* of each country, and top 10 of the leading countries in the world GDP in 2015 are shown in Figs. 8.9 and 8.10.

In Fig. 8.9, China's competitive strengths experienced a sustained rise since 1990 and Japan seemed to continue to be affected by the "***Plaza Accord***" in recent decades, while the others remained stable. On the other side, in Fig. 8.10, almost all the major economies' competitive weaknesses surpassed China except Brazil and Germany. According to our explanation on *CSI* and *CWI*, *NCSI* and *NCWI* reflect the country-level competitive status as the sectoral-level combination, so they may be somehow related to certain international trade.

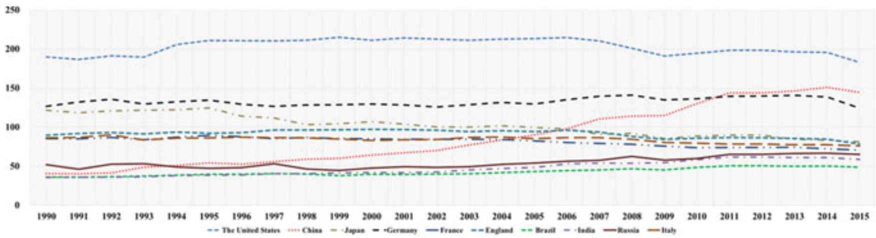


Fig. 8.9 Trend of major economies' NCSIs in GIRCN-Eora26 models

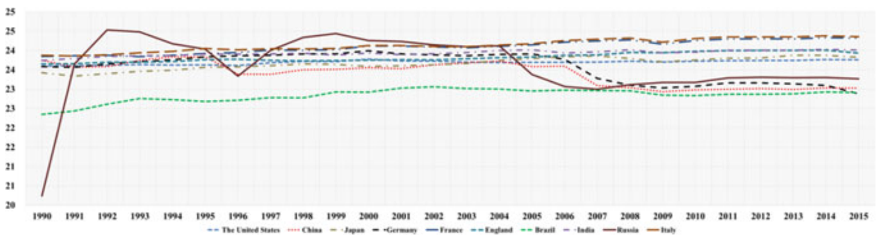


Fig. 8.10 Trend of major economies' NCWIs in GIRCN-Eora26 models

8.4.3 Correlation with GDP

In this section, we discuss the relations between *NCSI* and GDP of country—how network-based measurements affect the macroeconomic performance. Due to the lack of adequate data of countries including British Virgin Islands, North Korea, French Polynesia, Netherlands Antilles, New Caledonia, Somalia, South Sudan, Taiwan, and Former USSR, these countries are deleted in the following modeling process. The GDP data of the rest of 180 countries are regarded as the dependent variable and their *NCSI* as independent variables. The distribution of GDP of the 180 countries is shown in Table 8.1. Obviously, the majority have relatively low GDP, which totals less than 50 billion and accounts for only 67%.

Next, the relations between the *NCSI* and GDP are studied. First, a mixture regression model is built, with results shown in Table 8.2.

By contrast, three sorts of estimators are used here as shown in Table 8.3, since a Hausman test shows that the fixed effects estimator is better than the random effects estimator.

Overall, there is a significant positive correlation between *NCSI* and GDP: the larger *NCSI* in GIVCN model is, the higher the corresponding country's GDP goes. However, R^2 (within) in the results is relatively low, which means the trend of certain countries' *NCSI* and GDP is of relatively lower significance, though there exists a negative correlation in some cases, as shown in Table 8.4. We believe this phenomenon is due to the irrational industrial structure of economies, especially small countries, including Aruba, Bahamas, Barbados, Bermuda, Bolivia, Lesotho, Liberia, Liechtenstein, Maldives, Sierra Leone, Tajikistan, and Togo. Some of them may gain relatively higher competitiveness on the GVC through a minority of industrial sectors, but the pattern of imbalanced development will undermine their economic performance in the end.

Table 8.4 shows that countries can be divided into 3 classes based on the correlations between GDP and *NCSI*, namely countries with strong positive correlation, with

Table 8.1 Distribution of average GDP from 1990 to 2015 (Billion, Current US$)

GDP range	0–10	10–50	50–100	100–300	300–
Number of Countries	74	45	13	25	23
Ratio (%)	41	25	7.2	13.9	12.8

Table 8.2 Results of mixture regression model

Variables	Coeff.	Std. Err	t	P	0.95 Confidence interval
NCSI	44.095	0.380	115.890	0.000	[43.350, 44.841]
Intercept term	−817.751	12.270	−66.650	0.000	[−841.805, −793.696]
R^2 (adjusted)	0.742		**Root MSE**	510.14	

Table 8.3 Three different estimators from OLS, fixed effect model and random effect model

Model	REG	FE	RE
NCSI	44.095***	51.084***	47.607***
Std. Err	(0.380)	(1.444)	(1.040)
Intercept term	−817.751***	−987.244***	−902.923***
Std. Err	(12.270)	(35.432)	(40.240)
R^2 (overall)	0.742	0.742	0.742
R^2 (within)	-	0.218	0.218
R^2 (between)	-	0.828	0.828

Notes $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 8.4 Regression results for individual countries (Partly)

Countries	Constant	NCSI	R^2	Countries	Constant	NCSI	R^2
TZA	171.6	−7.568	0.951	SEN	29.99	−1.045	0.009
SVK	−360.8	25.92	0.946	HUN	188.7	−5.507	0.008
IND	−2217	65.78	0.942	ARG	471.4	−5.428	0.007
BRA	−5098	147.2	0.915	BEN	12.47	−0.417	0.007
CHN	−4104	85.63	0.905	AFG	41.05	−1.678	0.006
KOR	−3782	100.3	0.901	COG	−5.188	0.613	0.006
RUS	−4126	92.29	0.901	MAC	45.87	−1.649	0.005
AZE	−201.2	11.61	0.873	TUN	1.753	1.546	0.004
ZMB	−196.3	10.46	0.860	MNG	12.52	−0.496	0.003
MLT	39.19	−3.355	0.850	MCO	0.555	0.122	0.002
CUB	514.4	−22.67	0.847	BIH	12.97	−0.204	0.001
BFA	39.86	−2.077	0.837	BRN	2.71	0.314	0.001
AUS	−6616	140.2	0.834	LUX	18.43	1.509	0.001
SDN	16.01	2.332	0.832	BMU	3.374	0.013	0.000
TJK	39.22	−2.104	0.829	GRC	190.2	0.304	0.000

Notes The top 15 with the descending order of R^2 are listed in the left part of Table 8.4, and the bottom 15 in the right part

strong negative correlation and with weak correlation. Countries with a strong positive *NCSI*-GDP correlation, such as India, Slovakia, China, Russia, Korea, Brazil, Azerbaijan, Zambia, Australia, and South Sudan, are supposed to be the beneficiaries of economic globalization, which means global competition bring them more market opportunities than status deprivation. On the contrary, countries with strong negative correlations, such as Tanzania, Cuba, Malta, Burkina Faso, and Tajikistan, didn't benefit from global competition due to various inferiorities. Weak correlation indicates there is no obvious relation between an economy's *NCSI* and GDP, so we are not sure how globalization influences these economies' status and performance on the GVC. These countries (for instance, the United States) are facing hard

Table 8.5 Fitting results in different periods

Fitting range	1990–1997	1998–2006	2007–2015
NCSI	29.207***	40.480***	59.486***
Std. Err	(0.358)	(0.503)	(0.726)
Cons	−551.849***	−775.896***	−1064.194***
Std. Err	(11.353)	(16.294)	(23.740)
R^2 (adjusted)	0.822	0.801	0.807

Notes *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

trade-offs: globalization or anti-globalization. Given the limitation of this section, we will further discuss this phenomenon in our future works by analyzing the relations between *CSI* and value-added on the level of industrial sector.

Furthermore, whether the correlation results vary significantly in different periods is examined. As for comparable mixture regression, 26 years are divided into 3-time intervals, namely 1990–1997, 1998–2006 and 2007–2015, and the fitting results are shown in Table 8.5.

All the coefficients are significant at 0.001 confidence level, and the models exhibit a good fit with large R^2 (0.822, 0.801 and 0.807). More importantly, the *NCSI*'s influence on GDP is growing over time. In other words, national economic strength reflected by *NCSI* is increasing up to its status on the GVC, and the global economic integration has greatly changed both the internal and external industrial structure of each country, and in turn the world economic situation. In sum, we believe that *NCSI* can predict the macroeconomic trends via econometric approaches.

8.5 Empirical Analysis: Competitive Strength of TPP-Related Nations

TPP, as a trade agreement between Australia, Brunei, Canada, Chile, Japan, Malaysia, Mexico, New Zealand, Peru, Singapore, the United States, and Vietnam, contains measures to lower both non-tariff and tariff trade barriers and establish an ***Investor-State Dispute Settlement (ISDS)*** mechanism. It can be treated as a multilateral trading system in brief. Some think tanks believe that the final agreement would, if ratified, lead to net positive economic outcomes for all signatories. In fact, many have argued that the trade deal would have served a geopolitical purpose, namely, to reduce the signatories' dependence on trade with China and bring the signatories closer to the United States. Although currently it cannot be ratified due to the United States' withdrawal from the agreement in January 2017, the other 11 TPP countries are willing to revive the deal without the United States' participation, with the possibility of China joining in as a leading role someday.

Current trade agreements between participating countries, such as ***NAFTA***, ***ASEAN Free Trade Agreement (AFTA)***, ***China-ASEAN Free Trade Agreement (CAFTA)***, ***Japan-ASEAN Comprehensive Economic Partnership Agreement (JACEPA)***, ***ASEAN-Australia-New Zealand Free Trade Agreement (AANZFTA)***, ***Trans-Pacific Strategic Economic Partnership Agreement (TPSEPA)***, greatly complicate the development of the TPP. The trade relations among all the participants are shown in Table 8.6.

8.5.1 Time-Series Analysis on TPP-Relat Ed Nations

Eora26 has provided necessary ICIO data covering 26 years. Statistics on *NCSI* of each TPP-related country are examined in GIRCN-Eora26 models, thus developing a time-sequential trend as shown in Fig. 8.11.

According to the trends in Fig. 8.11, four firm conclusions can be reached as follow:

(1) *NCSIs* of China and Singapore in the global economic system are continuously rising, embodying strong competitive power and tremendous potential.
(2) *NCSI* of the United States is consistently higher than those of other countries. With rising after descending, it experienced a turning point in 2009 marked probably by the subprime mortgage crisis, which incurred a tsunami to the rest of the world. Other NAFTA countries with intense trade relations with the United States, such as Canada and Mexico, also went through a similar situation.
(3) Only *NCSI* of Japan has undergone continuous declination since 1995, due to Japan's economic crisis and consequent high-level trade deficit during that period. Even today, this country still has not emerged from recession, and its competitiveness on the GVC is still diminishing. For similar reasons, Viet Nam's currency inflation led to its brutal markets and worse macroeconomic performance.
(4) As for those relatively smaller economies, such as Brunei, Chile, Malaysia, New Zealand, and Peru, their *NCSIs* remain steady in recent years.

In sum, *NCSI* is proven feasible in measuring competitive strength on the level of the nation from the perspective of econophysics, which differs from the frameworks of both macroeconomics ad microeconomics.

8.5.2 Simulation on International Trade Policy

As mentioned above, Japan and other members of TPP agreed to pursue their trade deal without the United States due to the Trump administration's "America First" policy. Thus, we assume that 11 TPP countries are supposed to come to an agreement

Table 8.6 FTAs among TPP-related nations

Economic entity	Country	ASEAN				Northeast Asia		Oceania		North America			South America	
		BRN	MYS	SGP	VNM	CHN	JPN	AUS	NZL	USA	CAN	MEX	CHL	PER
ASEAN	BRN	AFTA					●							
	MYS						●	●	●				●	
	SGP					●	●	●	●	●				●
	VNM						●						●	
Northeast Asia	CHN			●				●	●				●	●
	JPN	●	●	●	●			●				●	●	●
Oceania	AUS		●	●		●	●		●	●			●	
	NZL		●	●		●		●						
North America	USA			●				●		NAFTA			●	●
	CAN												●	●
	MEX						●						●	●
South America	CHL		●		●	●	●	●		●	●	●		●
	PER			●		●	●			●	●	●	●	

Data source FTAs/RTAs database of World Trade Organization (WTO) and Asian Development Bank (ADB)
Notes Brunei, Malaysia, Singapore, and Viet Nam belong to the ASEAN, and Canada, Mexico, and the United States the NAFTA. Therefore, Gray zone stands for the regional FTAs implemented, and ● for the bilateral FTAs implemented

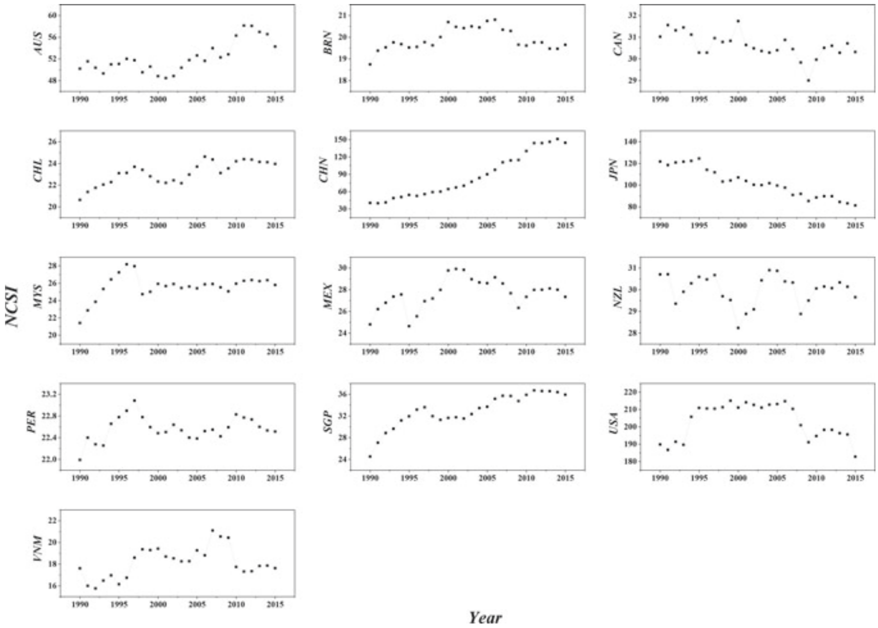


Fig. 8.11 Trends of TPP-related nations' NCSIs in GIRCN-Eora26 models

on a new TPP sooner or later, and then we shall consider more circumstances. In this section, four kinds of circumstances are simulated according to whether the United States or China will join the TPP when other relevant countries certainly come to an agreement and analyzed the possible happenings to the participants' national competitive strength. These scenarios are named P11, P12-1, P12-2, and P13 as shown in Table 8.7.

Table 8.7 Four kinds of circumstance in simulation analysis

Country	Action	China	
		Join	Not join
The United States	Not Quit	There will be an increase in the trade between China and its non-FTA countries, the United States and non-NAFTA, ASEAN and the others. (P13)	There will be an increase in the trade between the United States and non-NAFTA except China, ASEAN and the others except China. (P12-1)
	Quit	There will be an increase in the trade between China and its non-FTA countries except the United States, ASEAN and the others except the United States. (P12-2)	There will be an increase in the trade between ASEAN and the others except the United States and China. (P11)

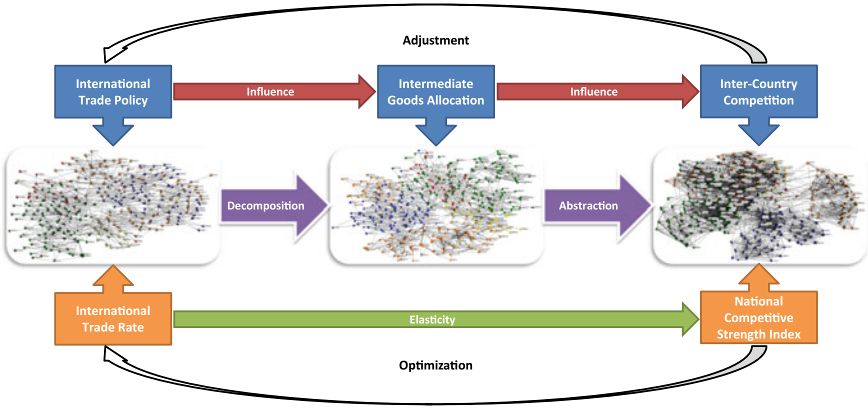


Fig. 8.12 Framework of simulation

An important assumption is made here for these simulations: the emerging FTAs within TPP-related nations will simultaneously promote inter-country imports and exports thanks to zero tariffs, free flow of personnel and capital, etc. Adjustments are thus made to the gross value of nations' export to the other in both directions, i.e., increasing from 100% of the basis to 200%. In addition, for every 10% of the fluctuation in GIVCN-Eora26-2015, calculations on *NCSIs* of all the countries in GRICN-Eora26-2015 are to be made, so as to monitor the tendency of the TPP-related nations under each scenario.

Simulation designed in this chapter is inspired by the elasticity notion in microeconomics (see Fig. 8.12). As we can see, the linear relation between inter-country competition (*NCSI*) and international trade policy (International Trade Rate) has so long been complex non-linear relation. The slope of the simulation result curve in the figure represents the elasticity of industrial competitive ability to changes in trade volume. The following research will focus on detailed international trade policies (for instance, on the level of specific industrial sectors, or, by varying international trade rate) for better serving the relevant policy formulation.

(1) **Scenario P11: Neither the United States nor China is in**

After seven years of negotiation, the TPP was widely expected to become the world's third-biggest regional trade agreement after NAFTA and the EU agreement. But for now, without the United States' engagement in this regional trade deal, in which way shall the Pacific economic agreement develop? Some think that the 11 remaining signatories will continue negotiating the agreement without the United States. If this happened, a new bilateral FTAs pattern would emerge, with new trade flows among nations.

As seen in the simulation on relevant countries in GIRCN-Eora26-2015 (see Fig. 8.13), neither the United States nor China could benefit from scenario P11, while Canada is the biggest winner, followed by Australia, Japan, and Mexico at the same level. The absence of TPP is not a mortal blow to China,

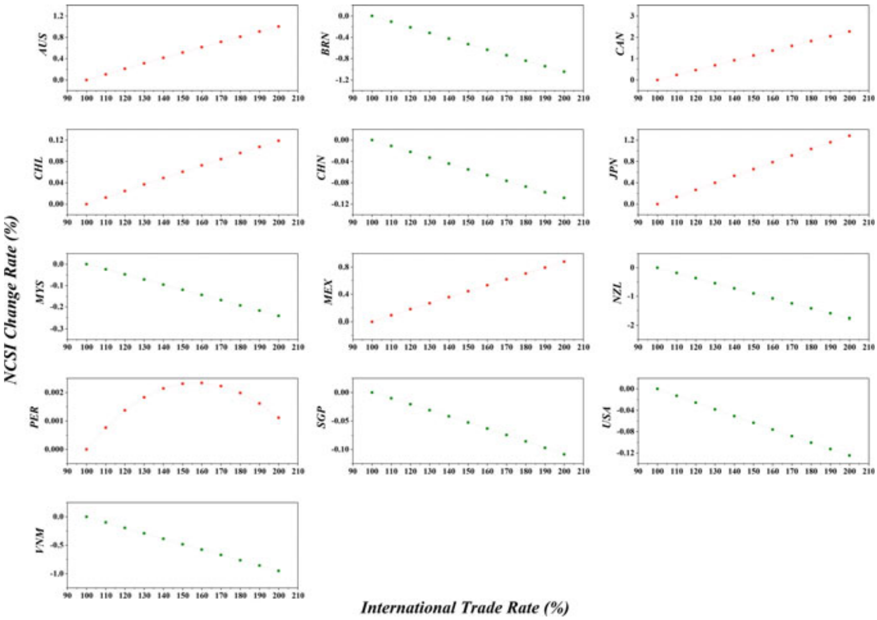


Fig. 8.13 Influence on TPP-related nations' NCSIs under scenario P11

for its FTAs network serves as the hub and spoke to the damage. But the limited impacts will indeed harm relevant trade in goods, for China's major trading partners are mostly developed countries. China will be incurred around an extra 5% of customs tariff for its commodity exports to developed countries like the United States and Japan, even if it has no access to TPP. The academic circle has already agreed on this limited negative impact with quantitative analysis. A typical example is the calculation result, based on the CGE model, of a − 0.14% influence on China's GDP in case it is not admitted to TPP. This is very close to the level of the simulation result that 11 TPP-related nations double their international trade.

Nevertheless, it is more likely that neither the United States nor China will take the lead and Asia–Pacific economic integration will take a back seat for some years.

(2) **Scenario P12-1: The United States is in but China not**

TPP used to be a trade pact dominated by the United States who seeks to be the dominant power in writing rules for global trade and investment in this century. The domination in the Asia–Pacific economic sphere and greater involvement in the Asia–Pacific economic integration are also in their blueprint. The partnership, through setting high standards on comprehensive market access and rules of origin, will significantly reduce trade barriers among TPP member states, and facilitate the United States' trade and investment in the Asia–Pacific region. TPP might help to push the frontiers of liberalization, but people still believe the well-functional TPP should include China. However, is that likely to happen?

The answer is negative, according to both the simulation results in Fig. 8.14 and the mainstream views of economists. Regarding the existing FTAs among the United States, Australia, Canada, Chile, Mexico, Peru, and Singapore, the TPP agreement may extend market openings and improve the rules. However, negative impacts may also appear in some countries, such as Peru and Singapore. Those countries excluded by FTA, such as Brunei, Japan, Malaysia, New Zealand, and Vietnam, have a huge combined GDP, and Malaysia and Vietnam are even likely to be significant markets in the future. So it is not strange the United States would enhance the competitiveness on the GVC under scenario P12-1, as well as most of its FTA-related trade partners (not good choice for them actually) and Japan. However, this scenario also goes against the interests of China.

(3) **Scenario P12-2: China is in but the United States not**

There are two kinds of voices on TPP in the post-Obama era: one is that the full-fledged agreement on TPP is scarcely possible without the United States, and another is that there is potential for China to join the TPP. As the world's second-largest economy, China's absence from TPP will bring no benefit to economic integration. And even worse, it could provoke China into playing the regionalism game, such as re-energizing the RCEP with ASEAN and other economies. Imagine if China were to retaliate by negotiating an FTA that would

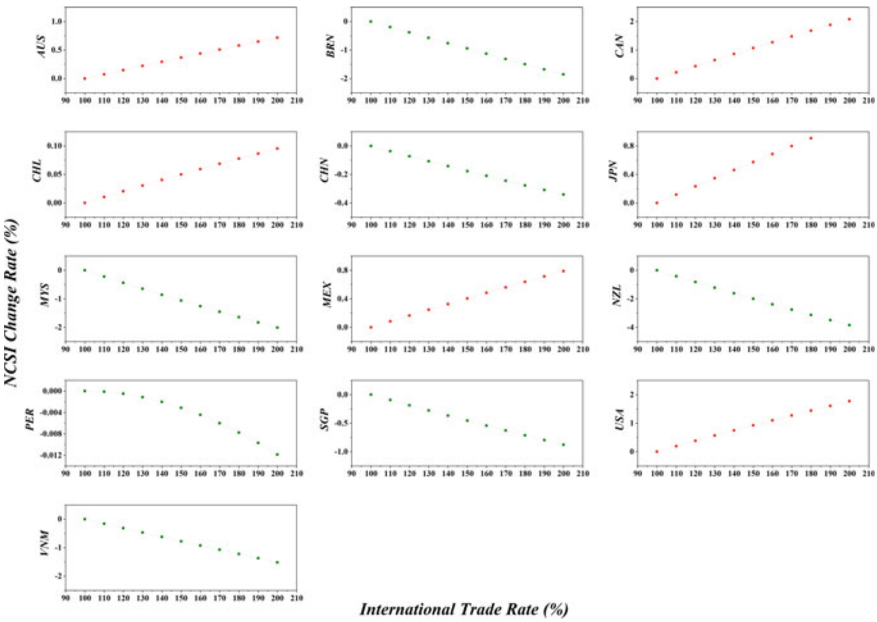


Fig. 8.14 Influence on TPP-related nations' NCSIs under scenario P12-1

exclude the United States. Down this path lies the fragmentation and folly of the inter-war years. If China might replace the United States as the TPP anchor, what will then happen to the relatively competitive advantages of TPP-related nations?

China will benefit from, yet the United States (as well as Japan) will suffer from scenario P12-2 (see Fig. 8.15). The United States' withdrawal from TPP has created an economic and security vacuum, so China will naturally seize the opportunity to step in and assert its own agenda. However, even though Scenario P12-2 would not happen, China is poised to intensify negotiations for the RCEP, a China-led alternative that includes 16 countries (seven of which are TPP negotiating parties). Although the RCEP is under negotiation, it is doomed to focus on cutting tariffs on trade in goods. As a non-party, the United States will be denied the benefit of these tariff cuts. Moreover, the RCEP may green-light emerging forms of protectionism in areas including, but not limited to, digital trade, cybersecurity, state-owned enterprises, competition law, i.e., all of which would have been tackled by TPP. If so, this would set a bad precedent that handicaps the United States' companies and workers competing globally and erodes the United States' economic competitiveness and long-run growth.

(4) **Scenario P13: Both the United States and China are in**

According to Peterson Institute calculations, the old version TPP plus China would increase 4.7% of China's national income over a decade, 1.6% of the United States', and even 4.4% of Japan's. In other words, a TPP plus China will

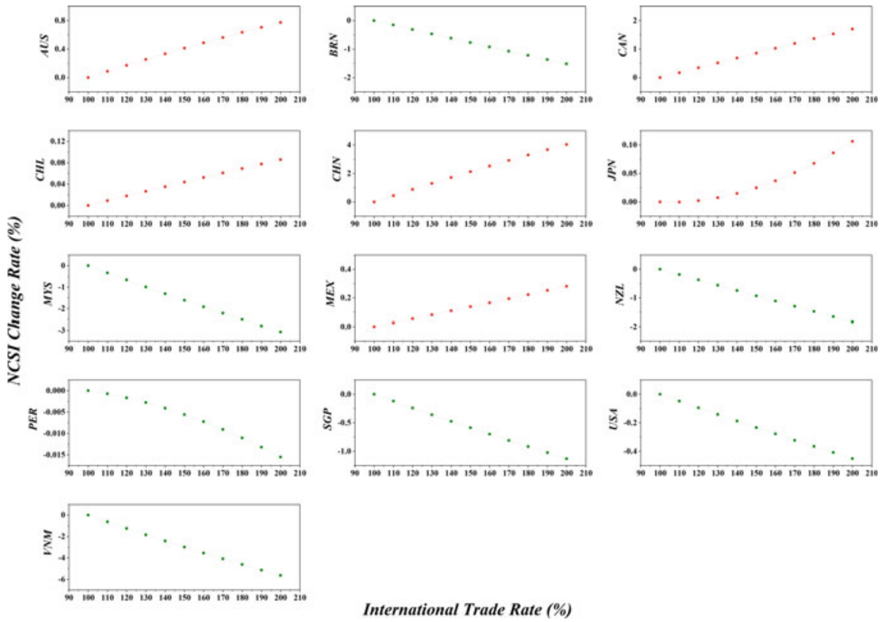


Fig. 8.15 Influence on TPP-related nations' NCSIs under scenario P12-2

bring China on a path to deeper Asian integration and serve both the United States' foreign policy and economic interests [10]. If China and the United States agreed in about TPP, it will probably lead to a win–win result for both at least.

As assumed above, TPP including both the United States and China is optimal for all parties according to simulation results under scenario P13 (see Fig. 8.16), i.e., the TPP aiming at more than just strengthening the United States' competitive strength while blocking China. By formulating various trading policies and regulations, the United States strove to reinforce its advantages and not strike and destroy China's economy. At that time, the United States' employment downturn was a significant signal of being affected by the weakening of the global economy. Only through Sino-US cooperation can a win–win situation be reached, and even a long-term Sino-US free trade area cannot be graded as impossible. In addition, Japan certainly does not want this to occur but a TPP without China.

Under such circumstances, there are four feasible strategies for China. Firstly, China could promote the development of regional and bilateral FTA negotiations, just like RCEP and China-Japan-South Korea FTA. Secondly, China could think about how to negotiate a Sino-US bilateral FTA in the post-pandemic ear. The Sino-US ***Bilateral Investment Treaty (BIT)***, if reached, can be a good basis for a future bilateral FTA. Thirdly, when the time to seek to join the CPTPP is ripe (on September 16th, 2021, China formally applied to join

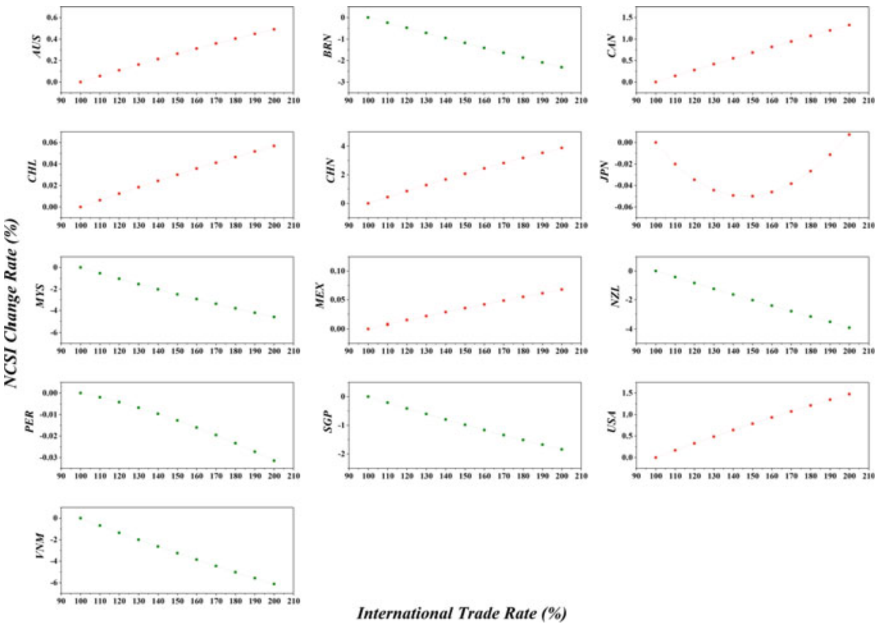


Fig. 8.16 Influence on TPP-related nations' NCSIs under scenario P13

the CPTPP), China should negotiate entrance as soon as possible and promote contents beyond the TPP that are key to its interests (such as antidumping). Fourthly, China should deepen domestic economic reform to offset the adverse influence from abroad.

8.6 Summary

How to reproduce the topological structure of the global economic system from the perspective of system science and excavate its operation law has been a major problem that puzzles the academia for a long time. With the research framework based on econophysics, we analyze the IO relation of intermediates among TPP-related nations in 1990–2015 with ICIO data from Eora26 and extract the competitive relations among them via RAP approaches. Contributions of this chapter are as follows:

(1) **Establish the GIRCN model to embody the competitive relations among industrial sectors.** In consideration of the scarcity of industrial resources, we use bipartite graphs to distinguish the roles of industrial sectors on the GVC as upstream and downstream ones. Then, we extract the competitive relations hidden in the IO/ICIO table via RAP approach, transforming the GIVCNBG model into the GIRCN model. Although the number of nodes doubled in the former, the nature of economic relations reflected by network architecture is the same with the GIVCN model. The latter depicts competitions among countries and their industrial sectors.

(2) **Propose network-based measurement tools to reveal the competition status on the sectoral level and the national level.** After getting the competitive relations among industrial sectors, the summation of the competitive pressure that one imposes on others is defined as the *CSI*, and the summation of competitive pressure that one receives from others is defined as the *CWI*, which are the out-strength S^{OUT} and in-strength S^{IN} of nodes respectively in the GIRCN model. As well, *NCSI* and *NCWI* standing for the country-level competitiveness can be further calculated. Of course, we pay more attention on the economies' competitive strength measured by *NCSI* in the empirical analysis.

(3) **Simulate competitive strengths of TPP-related nations.** The idea of simulation is inspired by the elasticity notion in microeconomics, and we can observe the linear relation between inter-country competition and international trade policy, which has so long been a complex non-linear relation. We do believe that more and more countries are supposed to reach an agreement on the future CPTPP sooner or later, and then we may take more circumstances into consideration.

In this chapter, four kinds of circumstances are simulated according to whether the United States or China will join the TPP when other relevant countries certainly come to an agreement, so as to figure out what will happen to the participants' national competitive advantage via simulation analysis. An important assumption is made here for these simulations as that: the emerging FTAs within the TPP-related countries will simultaneously promote inter-country imports and exports because of zero tariffs, free flow of personnel and capital, etc.

As results, a TPP without both the United States and China will undermine the two countries' competitiveness, and if it arrived at an agreement led by the United States, this situation will truly weaken China's impacts on the GVC and vice versa. Anyway, A TPP that involves China in the path to deeper Asian integration, would serve both foreign policies and real economic interests of the United States.

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Chapter 9
Quantify the Collaborative Opportunity and Threat of Economies

9.1 Introduction

At present, China has entered the "***New Normal***" development stage of the economy, and BRI is being implemented in depth. In September 2016, General Secretary Jinping Xi pointed out in the keynote speech at the opening ceremony of the B20 Summit (a major support group for the G20 from industrial and commercial circles): "China's development benefits from the international community and is willing to provide more public goods to the international community. China has proposed the 'One Belt and One Road Initiative', which aims to share China's development opportunities and achieve common prosperity with countries along the routes." China is actively promoting the economic development of BRI-related nations, supporting and driving domestic superior and surplus production capacity to countries/regions that have fewer comparative advantages. Finally, to construct a fair and reasonable international order, China will offer both value ideas and institutional design ideas that reflect Chinese wisdom and China's plans.

Rapidly promoting China's position and competitiveness on the GVC and shaping new comparative advantages in the context of BRI is either the important guarantee for the continuous and in-depth development of ***Global Cooperation on Production Capacity*** strategy or the realistic requirement for China's industrial restructuring and factor allocation optimization at this stage. BRI aims to build an open, inclusive and balanced regional economic cooperation architecture for the twenty-first century, strengthen the weak points of globalization, and transform the partial globalization to an inclusive one. Under this context, it is the urgent need to rationally distribute international productivities to enhance the competitive advantages of both China and BRI-related nations. Therefore, how to realize the positive interaction between China's industrial structure and foreign trade upgrade in the process of international economic integration and BRI, and how to fully utilize the institutional dividend brought by such cooperative strategy to build a new regional trade system, will definitely be the key research direction at the nationally strategic level for a long period of time in the future.

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Based on a mature industrial system, the high-cost performance of equipment capacity, and mighty construction abilities, enhancement on the international capacity cooperation with nations along the route, are feasible ways for China to achieve mutual benefits and the win–win goal. Nevertheless, the paradox is that the international public opinion has many doubts and even dissatisfaction with China's BRI, which they think is a Chinese version of the Marshall Plan. In recent years, some countries have implemented a series of measures to weaken China's role and status on the GVC. This approach is equivalent to treating international trade as a zero-sum game, thus failing to achieve a win–win goal. Of course, under the perspective of systems science, it is impractical and will inevitably lead to negative impacts flowing along the GVC and ultimately leading to a decline in the global competitiveness of the industrial sectors within many countries. Accordingly, our econophysics framework will be adopted to simulate the international trade process under different policy backgrounds and development scenarios. We hope the network-based measurements proposed in this chapter can be used as the evaluation criteria to deeply understand the policymaking of international trade and its long-term consequences.

9.2 Methodology

Through reverse thinking, RAP approach can also embody certain status within each pair of object nodes. If the participants compete for limited resources and thus form the inter-node competitive relations, do the objects that play the role of brokers work together to optimize the allocation of resources? With this question, we try to analyze the complete subgraph of the participant, which is described in Fig. 9.1

In Fig. 9.1, the basic settings of the bipartite graph are the same as in Sect. 8.2. The edges in green coming from the projection of two black edges constitute the Complete Participant Subgraph.

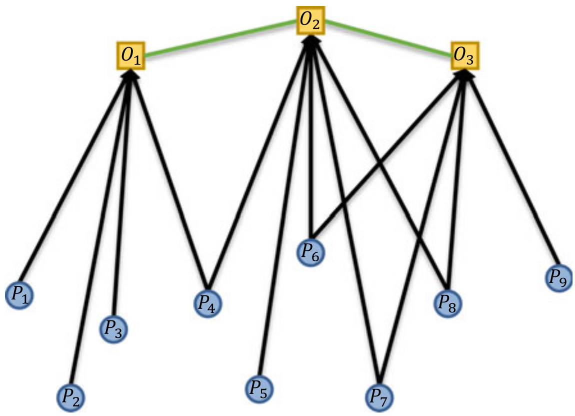


Fig. 9.1 A two-mode network and its projection onto objects

Let $f : O \cup P \rightarrow \mathbb{R}_+$ be a function such that $f(O_h) = 1$ for all h in $\{1, 2, \ldots, m\}$, which means the initial demand of each object is the same. Firstly, we assume that the $O \rightarrow P$ primary distribution of initial demands is equal, as shown in Fig. 9.2.

The required resource on the j-th node in P is:

$$f\left(P_j\right) = \sum_{h=1}^{m} \frac{a_{jh} f(O_h)}{K(O_h)} \tag{9.1}$$

where, $K(O_h)$ is the degree of O_h, $\left\{a_{jh}\right\}$ is a $n \times m$ matrix (equivalent to $\{a_{ik}\}$ in Sect. 8.2.2.

$$a_{jh} = \begin{cases} 1 \; P_j O_h \in E \\ 0 \; otherwise \end{cases} \tag{9.2}$$

With all the demand signals converging to set O, the required resources of objects are shown in Fig. 9.3. Note that, the assumption of equal distribution still holds for the secondary distribution.

The satisfied demand of node O_h is:

$$f'(O_h) = \sum_{j=1}^{n} \frac{a_{jh} f\left(P_j\right)}{K\left(P_j\right)} = \sum_{j=1}^{n} \frac{a_{jh}}{K\left(P_j\right)} \sum_{k=1}^{m} \frac{a_{jk} f(O_k)}{K(O_k)} \tag{9.3}$$

Obviously, the satisfied demand of objects is not consistent with their initial one, i.e., $f'(O_h) \neq f(O_k)$, which means their status is different in the complete participant subgraph. This difference cannot be reflected just via the co-occurrence projection. Thus, the hidden collaborative relations among them can be expressed by:

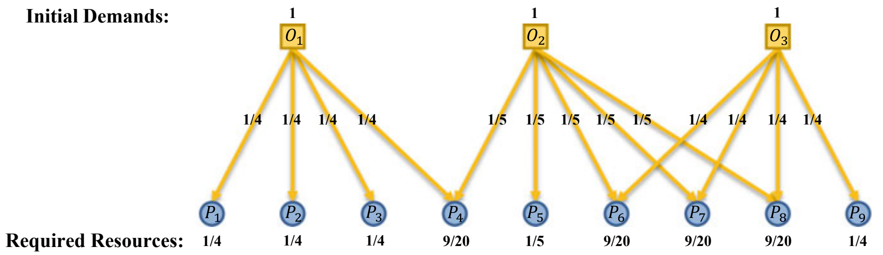


Fig. 9.2 Primary distribution: Initial demands from objects are equally sent to participants. *Notes* for simplicity, we assume all objects here own an equal size of demand, i.e., $f(O_h) = 1$. As we can see, O_1 connects to $P_1, P_2, P_3,$ and P_4, so $K(O_1) = 4, a_{11} = 1, a_{21} = 1, a_{31} = 1,$ and $a_{41} = 1$. Within them, only P_4 is additionally connected to O_2, so $a_{42} = 1$ while $K(O_2) = 5$. Thus, $f(P_1) = \frac{1}{4}, f(P_2) = \frac{1}{4}, f(P_3) = \frac{1}{4},$ and $f(P_4) = \frac{1}{4} + \frac{1}{5} = \frac{9}{20}$

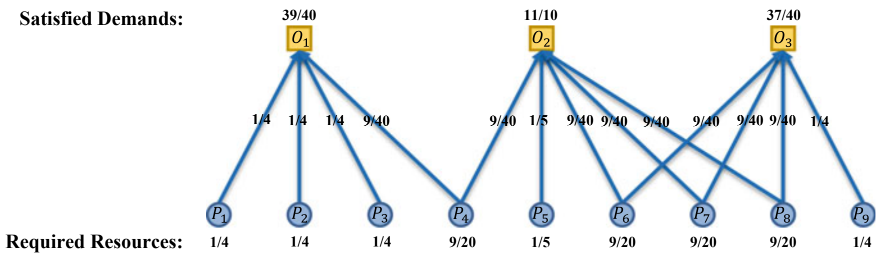


Fig. 9.3 Secondary distribution: Required resources from participants are equally allocated to objects. *Notes* When a participant equally allocates its required resource to relevant objects, the secondary distribution depends on the number of relevant objects. Thus, the new amount of object's satisfied demand is equal to the sum of required resources back from all its participants, e.g., $f'(O_1) = \frac{f(P_1)}{K(O_1)} + \frac{f(P_2)}{K(O_2)} + \frac{f(P_3)}{K(O_3)} + \frac{f(P_4)}{K(O_4)} = \frac{1}{4} + \frac{1}{4} + \frac{1}{4} + \frac{9}{20} \times \frac{1}{2} = \frac{39}{40}$

$$f'(O_h) = \sum_{k=1}^{m} w_{hk}^{O} f(O_k) \tag{9.4}$$

where, w_{hk}^{O} is the relation strength produced in the two resources demand states between O_h and O_k, and describes the advantage of O_h in cooperating with O_k to allocate resources of their common participants.

The w_{hk}^{O} in Eq. 9.4 could be written as:

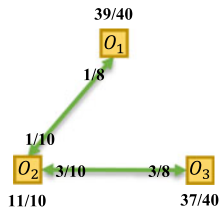
$$w_{hk}^{O} = \frac{1}{K(O_k)} \sum_{j=1}^{n} \frac{a_{jh}a_{jk}}{K\left(P_j\right)} \tag{9.5}$$

Finally, we get the matrix $W^O = \left\{w_{hk}^{O}\right\}_{m\times m}$ as the weight set of complete participant subgraph through RAP approach, as shown in Fig. 9.4.

$$\begin{bmatrix} f'(O_1) \\ f'(O_2) \\ f'(O_3) \end{bmatrix} = \begin{bmatrix} w_{11}^{O} & w_{12}^{O} & w_{13}^{O} \\ w_{21}^{O} & w_{22}^{O} & w_{23}^{O} \\ w_{31}^{O} & w_{32}^{O} & w_{33}^{O} \end{bmatrix} \begin{bmatrix} f(O_1) \\ f(O_2) \\ f(O_3) \end{bmatrix}$$

$$= \begin{bmatrix} 7/8 & 1/10 & 0 \\ 1/8 & 3/5 & 3/8 \\ 0 & 3/10 & 5/8 \end{bmatrix} \begin{bmatrix} f(O_1) \\ f(O_2) \\ f(O_3) \end{bmatrix}$$

(*a*) Matrix-Form Linear Relation



(*b*) Complete Participant Subgraph

Fig. 9.4 Collaborative relations reflected by complete participant subgraph. *Notes* In Fig. 9.4a, the matrix W^O represents the linear relation between each object's satisfied demand and initial demand, whose different values reflect their different status in the resource allocation process. Therefore, the weighted and directed graph in Fig. 9.4b embodies the unsymmetrically and unequally collaborative relations among three objects, while the values on the diagonal of matrix W^O are useless

Furthermore, in the weighted two-modes network, Eq. (9.5) is expanded to another form by replacing the adjacency matrix $A = \{a_{jh}\}$ with weight set $W = \{w_{jh}\}$:

$$w_{hk}^{O} = \frac{1}{S(O_k)} \sum_{k=1}^{n} \frac{w_{jh} w_{jk}}{S(P_j)} \tag{9.6}$$

where $S(O_k)$ is the weight of object node O_k, $S(O_k) = \sum_{j=1}^{n} w_{jk}$; $S(P_j)$ is the weight of participant node P_j, $S(P_j) = \sum_{h=1}^{m} w_{jh}$; w_{jh} and w_{jk} are the weights on edges connecting O_h and O_k with P_j, respectively.

9.3 Modeling

9.3.1 Database Selection

As we all know, BRI is a hotly-debated topic in the field of the global economy, as well as GVC, which is a global development strategy proposed by Chinese government involving infrastructure construction and investments in 152 countries and international organizations in Asia, Europe, Africa, the Middle East, and the Americas. "Belt" refers to the overland routes for road and rail transportation, called "the Silk Road Economic Belt"; "Road" refers to the sea routes or the 21st Century Maritime Silk Road. From the Chinese government's international viewpoints on politics and economy, BRI is supposed to the developing blueprint that meets the demands of relevant countries and delivers mutual benefits. However, some observers see it as a push for Chinese dominance in global affairs with a China-centered trading network, and even consider BRI as a potential threat to countries involved [1].

At the end of 2021, there are 141 countries that have signed cooperation agreements with China on Belt and Road Initiative—we call them BRI-related nations. Among ICIO databases, Eora26 has the widest coverage of countries, including 129 BRI-related nations, and we hence use it to conduct an empirical analysis of capacity cooperation between them. In the analytical process, we further focus on Asian, European, and African nations respectively, which are listed in Tables 9.1, 9.2 and 9.3.

With the proposal and promotion of BRI, China is playing a leading role in the RVC networks constituted of Asian, European, and African nations. Accordingly, the global cooperation with China on production capacity will impact the economic development of BRI-related nations. Therefore, it is necessary to comparatively and empirically analyze how their status will change on the GVC and what kinds of influence the BRI will bring to them.

Before doing this, we need to extract three sub-networks out of the GVICN-Eora26 model, i.e., GIVCN-Eora26-AS, GIVCN-Eora26-EU, and GIVCN-Eora26-AF, reflecting the ICIO relations between China and other economies respectively.

Table 9.1 36 BRI-related Asian Nations in Eora26

Abbr	Country	Abbr	Country
AFG	Afghanistan	MNG	Mongolia
ARM	Armenia	MMR	Myanmar
AZE	Azerbaijan	NPL	Nepal
BHR	Bahrain	OMN	Oman
BGD	Bangladesh	PAK	Pakistan
BRN	Brunei	PHL	Philippines
KHM	Cambodia	QAT	Qatar
GEO	Georgia	KOR	South Korea
IDN	Indonesia	SAU	Saudi Arabia
IRN	Iran	SGP	Singapore
IRQ	Iraq	LKA	Sri Lanka
KAZ	Kazakhstan	TJK	Tajikistan
KWT	Kuwait	THA	Thailand
KGZ	Kyrgyzstan	TUR	Turkey
LAO	Laos	ARE	UAE
LBN	Lebanon	UZB	Uzbekistan
MYS	Malaysia	VNM	Viet Nam
MDV	Maldives	YEM	Yemen

Table 9.2 27 BRI-related European Nations in Eora26

Abbr	Country	Abbr	Country
ALB	Albania	LUX	Luxembourg
AUT	Austria	MLT	Malta
BLR	Belarus	MNE	Montenegro
BIH	Bosnia and Herzegovina	POL	Poland
BGR	Bulgaria	PRT	Portugal
HRV	Croatia	MDA	Moldova
CYP	Cyprus	ROU	Romania
CZE	Czech Republic	RUS	Russia
EST	Estonia	SRB	Serbia
GRC	Greece	SVK	Slovakia
HUN	Hungary	SVN	Slovenia
ITA	Italy	MKD	TFYR Macedonia
LVA	Latvia	UKR	Ukraine
LTU	Lithuania		

Table 9.3 44 BRI-related African Nations in Eora26

Abbr	Country	Abbr	Country
DZA	Algeria	MDG	Madagascar
AGO	Angola	MLI	Mali
BEN	Benin	MRT	Mauritania
BWA	Botswana	MAR	Morocco
BDI	Burundi	MOZ	Mozambique
CMR	Cameroon	NAM	Namibia
CPV	Cape Verde	NER	Niger
TCD	Chad	NGA	Nigeria
COG	Congo	RWA	Rwanda
CIV	Cote dIvoire	SEN	Senegal
COD	DR Congo	SYC	Seychelles
DJI	Djibouti	SLE	Sierra Leone
EGY	Egypt	SOM	Somalia
ETH	Ethiopia	ZAF	South Africa
GAB	Gabon	SDS	South Sudan
GMB	Gambia	SUD	Sudan
GHA	Ghana	TGO	Togo
GIN	Guinea	TUN	Tunisia
KEN	Kenya	UGA	Uganda
LSO	Lesotho	TZA	Tanzania
LBR	Liberia	ZMB	Zambia
LBY	Libya	ZWE	Zimbabwe

Their brief topological structures in six different periods are as shown in Figs. 9.5, 9.6 and 9.7.

9.3.2 GPCCN Model

To reproduce the collaborative relations between industrial sectors on the GVC, we design a generation algorithm based on RAP approach:

$$w_{ij}^{O} = \begin{cases} \frac{1}{\vec{w}_j} \sum_{k=1}^{N} \frac{w_{ik} w_{jk}}{\overleftarrow{w}_k} & , i \neq j \\ 0 & , i = j \end{cases} \tag{9.7}$$

where, $w_{ik}(w_{jk})$ is the i-th (j-th) row and k-th column element of the adjacency matrix of GIVCN model, representing the upstream sector i (j) and downstream sector k

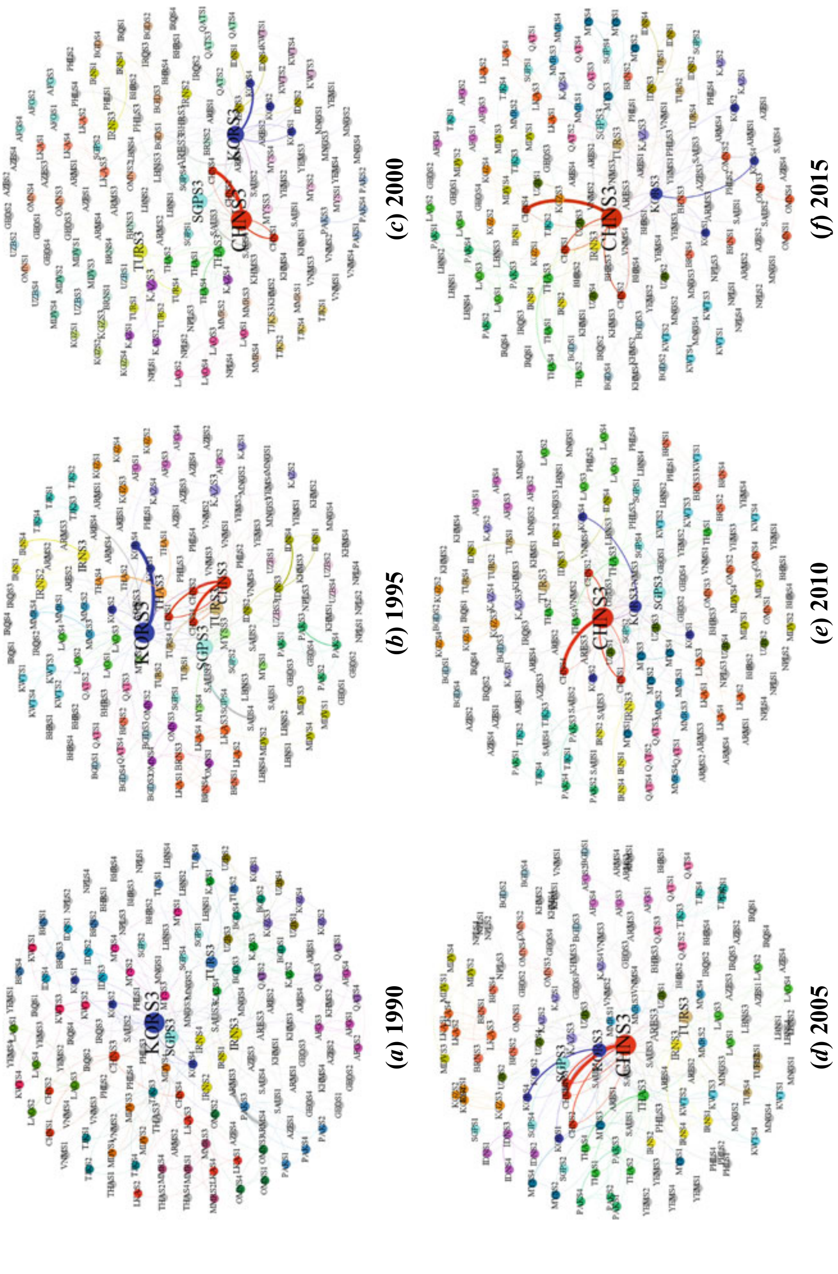


Fig. 9.5 GIVCN-Eora26-AS models

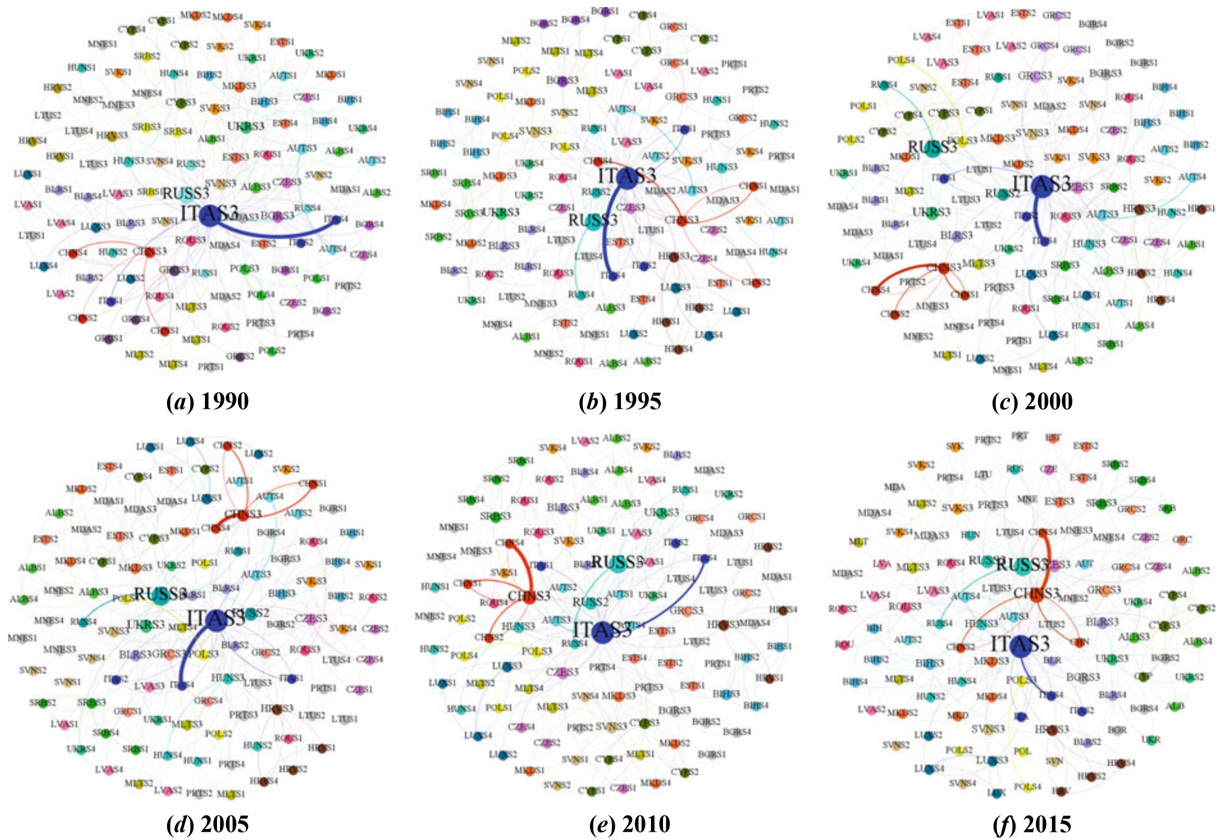


Fig. 9.6 GIVCN-Eora26-EU models

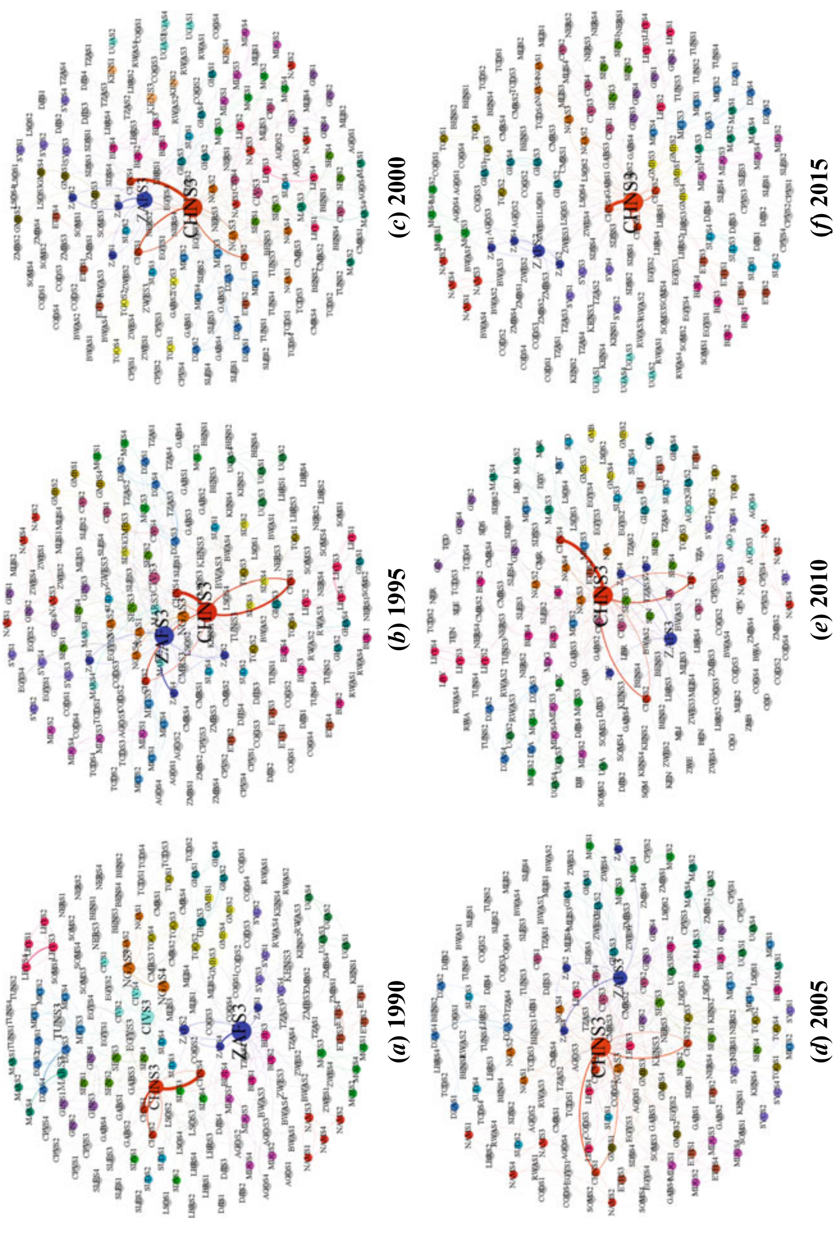


Fig. 9.7 GIVCN-Eora26-AF models

respectively; $\underset{k}{\overleftarrow{w}}$ is the gross inputs of downstream sector k, and it is numerically equal to the in-degree strength of node k in GIVCN model, say $\underset{k}{\overleftarrow{w}} = S^{IN}(k) = \sum_{i=1}^{N} w_{ik}$; $\vec{w}_j$ is the gross outputs of upstream sector j, i.e., $\vec{w}_j = S^{OUT}(j) = \sum_{k=1}^{N} w_{jk}$; w_{ij}^{O} measures the ***Collaborative Attraction*** from the sector i to j; upstream sectors i and j are connected by an edge denoted by e_{ij}^{O} in the complete participant subgraph.

Finally, the edge set $E^O = \left\{e_{ij}^{O}\right\}$ and weight set $W^O = \left\{w_{ij}^{O}\right\}$ reflect all the collaborative relations among sectors in the global production system. We name the graph $G = \left(V, E^O, W^O\right)$ as the ***Global Production Capacity Collaboration Network (GPCCN).*** Accordingly, we separate three types of GPCCN-BRI models from the whole network, which are GPCCN-Eora26-AS, GPCCN-Eora26-EU, and GPCCN-Eora26-AF.

9.4 Measurement

9.4.1 Sector-Level Indices

In the previous chapter, when we discuss the inter-industry competitive relations in the GIRCN model, the sum of competitive pressure imposed on other sectors (out-strength) is used to measure the competitive strength (CSI), and the sum of competitive pressure obtained from other sectors (in-strength) is used to measure the competitive weakness (CWI). As a continuation of this idea, when discussing the cooperation relations in the GPCCN model, we define the sum of the collaborative attraction obtained from other sectors (out-strength) as one sector's ***Collaborative Opportunity Index (COI)***, i.e., the greater the COI, the stronger the collaborative relations between this sector and the others. Also, the sum of the collaborative attraction is exerted to other sectors (in-strength) is defined as one sector's ***Collaborative Threat Index (CTI).*** Once the collaboration degree declines, and the uncertainty of industrial development will go up, because a greater CTI indicates that the sector needs to rely on many collaborative relations to maintain its function and status on the GVC. Their statistical formula is as follows:

$$COI(i) = S^{OUT}(i) = \sum_{j=1}^{N} w_{ji}^{O} \tag{9.8}$$

$$CTI(i) = S^{IN}(i) = \sum_{j=1}^{N} w_{ij}^{O} \tag{9.9}$$

As the counterparts of CSI and CWI, we are interested in the distribution and correlation of COI and CTI. As shown in Fig. 9.8, the heavy-tailed distribution of COI

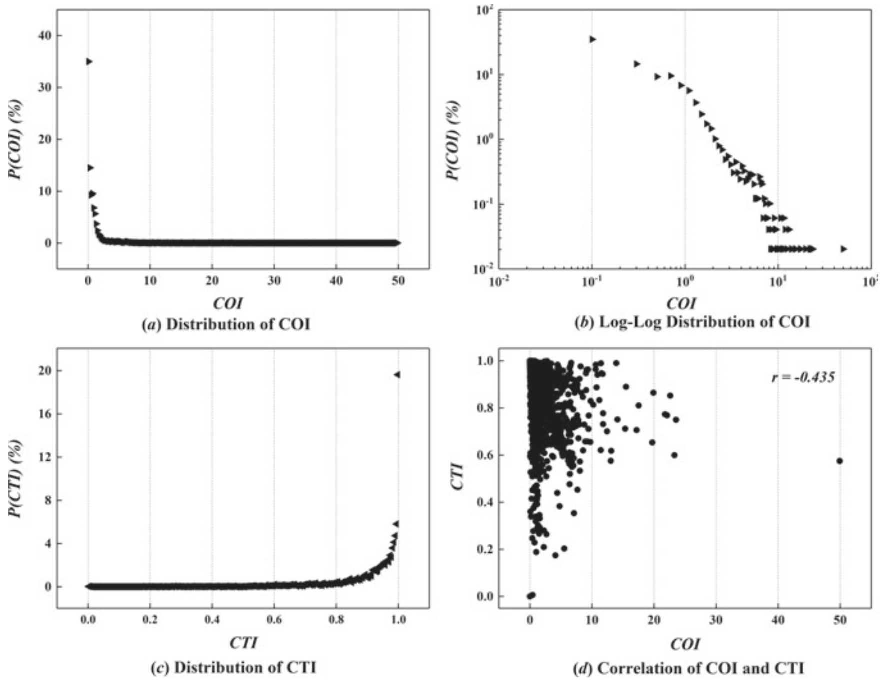


Fig. 9.8 Distribution and correlation of COI and CTI in GPCCN-Eora26-2015

for all sectors in GPCCN-Eora26-2015 also follows the levy-stable distribution, but that of *CTI* is mainly concentrated in a narrow numerical range. The heterogeneity of *COI* and the homogeneity of *CTI* together result in that there is no strong correlation between them (Pearson correlation coefficient is only −0.435).

In our opinion, the collaborative opportunities brought by globally economic integration to various countries are very different, while the threats of collaboration are almost the same. The fundamental reason is that today's advanced information technology and convenient supply chains have greatly reduced the difficulty for the industrial sector to find partners. However, which economies can seize the opportunities in the global market depends on their function and position on the GVC. We can find the answer from the Part II and Part III.

9.4.2 Country-Level Indices

On the basis of COI and CTI, notions of ***National Collaborative Opportunity Index (NCOI)*** and ***National Collaborative Threat Index (NCTI)*** are here introduced:

$$NCOI(u) = \sum_{i \in \tau(u)} COI(i) \tag{9.10}$$

$$NCTI(u) = \sum_{i \in \tau(u)} CTI(i) \tag{9.11}$$

where $NCOI(u)$ and $NCTI(u)$ are used to measure the collaborative opportunity and threat of country u.

Since the difference in collaborative threats is not obvious, we focus on the changes in the *NCOIs* of BRI-related nations. Tables 9.4, 9.5 and 9.6 list six countries with the highest *NCOI* in three sub-networks from 1990 to 2015. Obviously, China's *NCOI* rankings in the three sub-networks are constantly rising, which shows that the prospects for its cooperation with countries in multiple RVCs are as good as possible.

9.4.3 Correlation Analysis Between Competitive Strengths and Collaborative Opportunities

By observing the relation of *NCSI* and *NCOI* in different years, we find that there is a very significant positive correlation between them, as is shown in Fig. 9.9. In our opinion, the latter is the leading index of the former.

As is well known, vertical specialization and international trade are the foundation and embodiment of global economic integration. In most cases, one country/nation's economic development is based on making full use of its own and the others' resource endowments, so reaching a consensus is more important than creating a conflict of interest. The world of the twenty-first century has long since gotten rid of the colonial and semi-colonial development model. Each nation uses its comparative advantages to engage in economic and political games on the world stage. Therefore, we believe that the reason why countries/nations' competitive strengths and collaborative opportunities are closely related is mainly because they first establish a connection with the world through cooperation, and then consolidate their industrial function and status on the GVC through competition.

9.5 Empirical Analysis: Collaborative Opportunity of BRI-Related Nations

Three sets of scenario simulations have been designed to observe the effects on national collaborative opportunities of both China and main BRI-related nations under international trade fluctuation in GIVCN and GPCCN models. If the new trade policy was signed or the original trade one was withdrawn between two countries,

Table 9.4 Top 5 BRI-related Asian Nations' *NCOIs* in GPCCN-Eora26-AS models

Rank	1990		1995		2000		2005		2010		2015	
	Country	NCOI	Country	NCOI	Country	NCOI	Country	NCOI	Country	NCOI	Country	NCOI
1	KOR	37.992	KOR	42.409	CHN	49.699	CHN	58.448	CHN	74.766	CHN	77.275
2	THA	33.407	CHN	40.414	KOR	41.204	KOR	41.015	KOR	38.313	KOR	37.601
3	UZB	30.817	THA	38.097	THA	36.087	THA	37.827	THA	34.572	THA	34.614
4	CHN	30.440	IDN	31.849	IDN	29.806	IRN	31.301	IRN	31.483	IRN	31.685
5	IRN	28.771	SGP	30.356	IRN	29.651	SGP	30.130	SGP	29.588	SGP	28.839
6	IDN	28.642	IRN	29.870	SAU	29.614	SAU	28.181	IDN	28.238	IDN	27.845

Table 9.5 Top 5 BRI-related European Nations' *NCOIs* in GPCCN-Eora26 models

Rank	1990		1995		2000		2005		2010		2015	
	Country	NCOI	Country	NCOI	Country	NCOI	Country	NCOI	Country	NCOI	Country	NCOI
1	ITA	60.996	ITA	67.608	ITA	68.827	ITA	65.879	ITA	63.145	ITA	60.212
2	RUS	54.947	RUS	53.430	RUS	62.334	RUS	56.649	RUS	59.270	RUS	59.401
3	SRB	30.137	AUT	29.366	CHN	31.486	CHN	33.962	CHN	43.633	CHN	44.524
4	UKR	28.860	SRB	29.084	GRC	29.172	POL	28.177	SRB	33.570	SRB	37.034
5	AUT	26.898	CHN	28.763	AUT	28.746	AUT	27.745	POL	28.585	POL	28.103
6	GRC	24.992	GRC	27.841	POL	28.508	GRC	27.639	AUT	26.809	AUT	26.274

Table 9.6 Top 5 BRI-related African Nations' *NCOIs* in GPCCN-Eora26 models

Rank	1990		1995		2000		2005		2010		2015	
	Country	NCOI	Country	NCOI	Country	NCOI	Country	NCOI	Country	NCOI	Country	NCOI
1	ZAF	48.196	ZAF	59.683	ZAF	60.514	ZAF	59.005	CHN	70.547	CHN	72.044
2	LSO	39.341	CHN	40.776	CHN	46.740	CHN	56.222	ZAF	52.555	ZAF	50.861
3	CHN	33.572	KEN	27.445	KEN	29.039	KEN	27.919	AGO	25.332	AGO	25.585
4	CIV	28.893	NGA	26.717	NGA	26.535	DZA	25.889	KEN	25.289	KEN	25.577
5	MAR	26.592	LSO	26.425	DZA	26.354	AGO	25.860	DZA	24.708	DZA	24.523
6	KEN	25.619	DZA	25.788	CIV	25.528	SEN	25.529	EGY	24.047	MAR	24.292

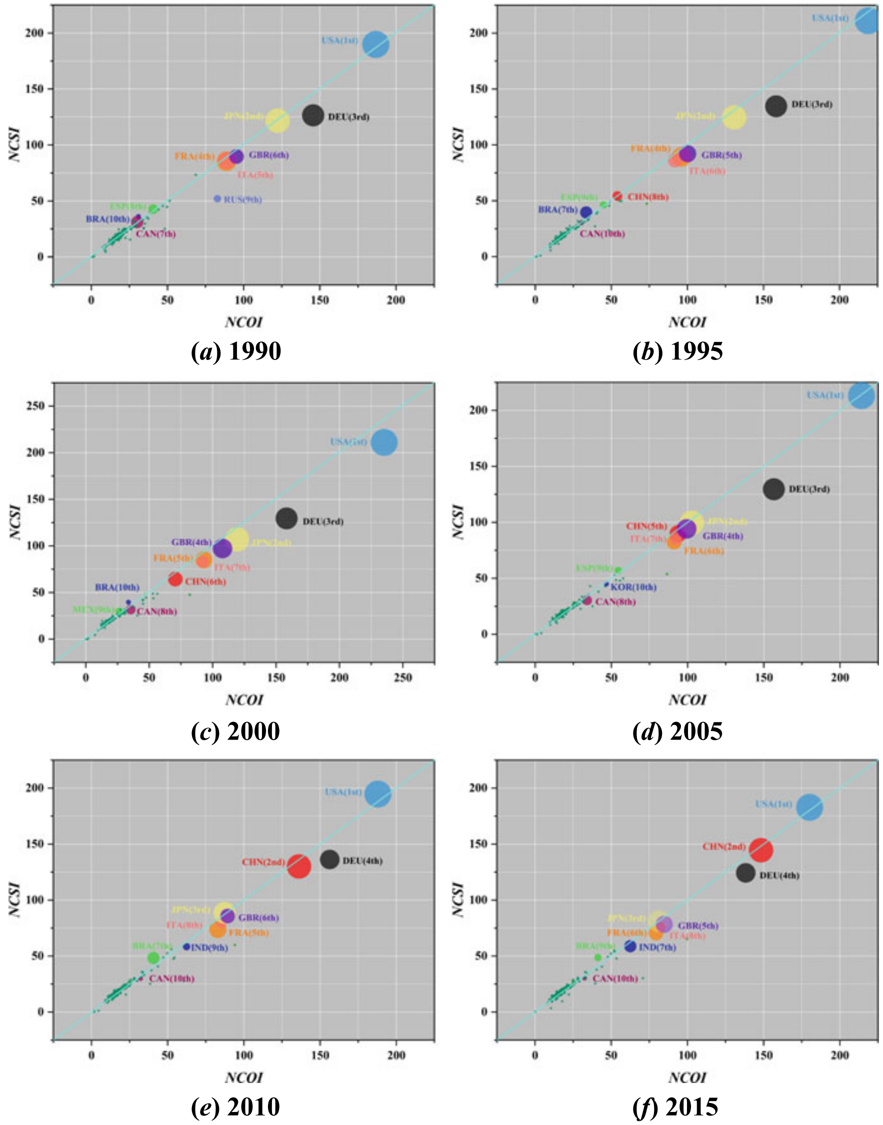


Fig. 9.9 Correlation of NCSI and NCOI in GPCCN-Eora26 Models. *Notes* We use different colors to distinguish the top 10 nations in GDP in each year. In addition, the size of each point is proportional to the GDP of corresponding nation

there will be three possibilities for the volume of import and export trade between them as tariffs may change [2]:

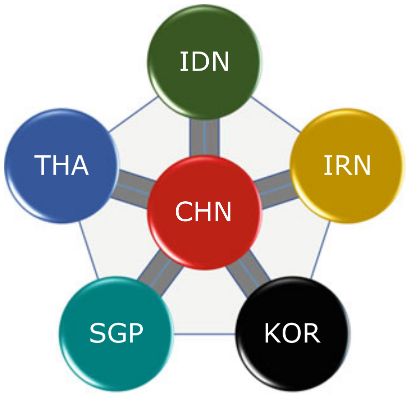
Scenario I: X increases or decreases its export to Y while its counterpart remains stable.
Scenario II: Y increases or decreases its export to X while its counterpart remains stable.
Scenario III: Both parties increase or decrease its export to the counterpart simultaneously (there is no need to distinguish X and Y under this scenario).

Considering that the meaning of BRI is to promote interconnection and trade prosperity for all interested parties, we choose the Scenario III as the only possibility. Then, simulations are carried out by increasing the volume of bilateral trade between two given nations from 0% (disruption of both import and export trades) of the initial value to 100% (gross value of trade in the ICIO table), and further up to 200% (both import and export trades doubled) in the specific GIVCN-BRI model, with every 10% as intervals. In the meanwhile, calculations on their *NCOIs* will be repeated in the corresponding GPCCN-BRI model, and simulation curves are acquired in this way for both parties of X and Y.

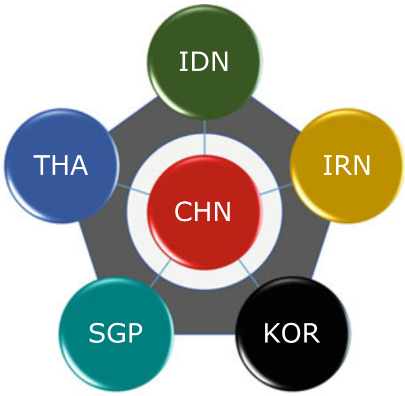
Despite trade volumes, we also need to consider the possible trade agreements, which have a more significant influence on the international trade itself. We set three kinds of cases to observe how the collaborative status of China and BRI-related nations will change as shown in Fig. 9.10.

Case A: China strengthens its trade collaboration with the others respectively—As in the initial stage of BRI, China needs to establish mutually beneficial and collaborative relations with one country after another, in order to promote its transfer of excess production capacity.
Case B: Other nations bypass China to form an economic community—This is an undesirable situation for China since its economic development driven by foreign trade will be hindered, just like the TPP initiated by the United States
Case C: All the nations strengthen the trade collaboration in between under an unified trade agreement—The newly formed RCV will be more benefit to some nations than in other cases.

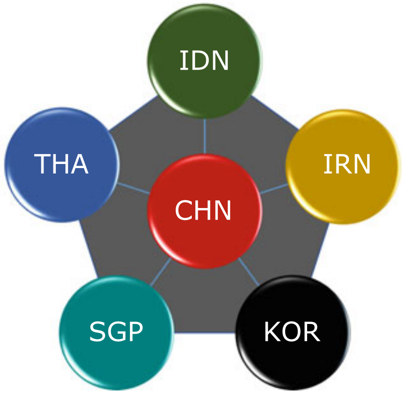
Based on these cases under Scenario III, this section lists the *NCOI* trends of the major economies (China and the top five countries in *NCOI*) in the GPCCN-BRI-2015 models with China as the core. As shown in Figs. 9.11, 9.12, 9.13, 9.14, 9.15, 9.16, 9.17, 9.18 and 9.19, the slope of the simulation result curve represents the elasticity of industrial collaborative ability to changes in trade volume. We try to find a better solution for both China and BRI-related nations in consideration of a win–win outcome.



(*a*) Based on Pairs of China and Asian BRI-Related Nations



(*b*) Based on the Group of Asian BRI-Related Nations without China



(*c*) Based on the Group of Asian BRI-Related Nations with China

Fig. 9.10 Three Cases of Realization of Collaboration at the Scale of RVC. *Notes* We take China and five main BRI-related nations in Asia as example, and the basic settings are the same as those in the European group and African group

9.5.1 Simulation on Asian Nations

According to the simulation results in Figs. 9.11, 9.12 and 9.13, we find that: (1) In Case A, China's *NCOI* sharply increases as the volume of international trade goes up, while other countries decrease to varying degrees; (2) In Case B, *NCOIs* of China, Iran (slightly), and Singapore decrease, while Indonesia (sharply), South Korea (sharply), and Thailand (slightly after the trade rate is positive) increase; (3)

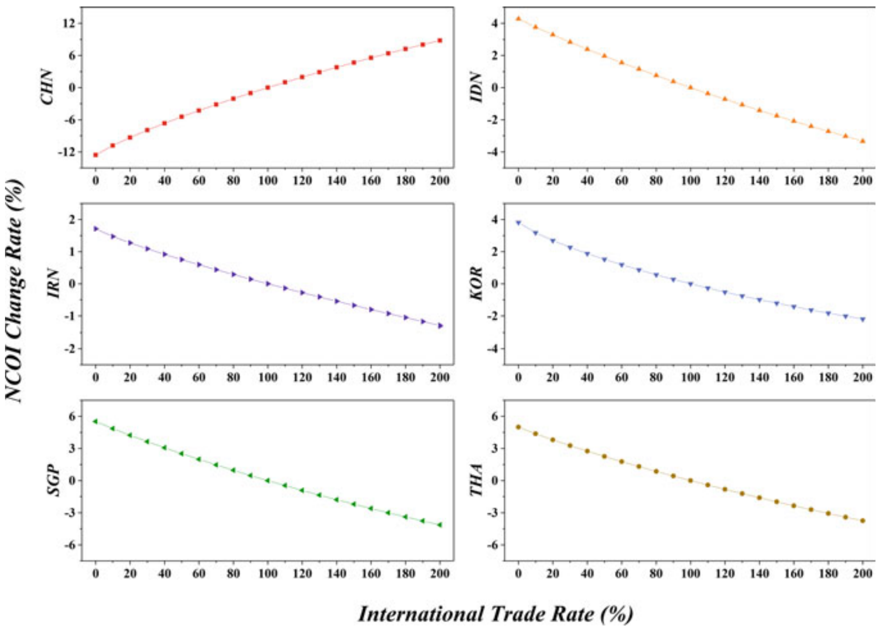


Fig. 9.11 Influence on China and Main Asian Nations in case A

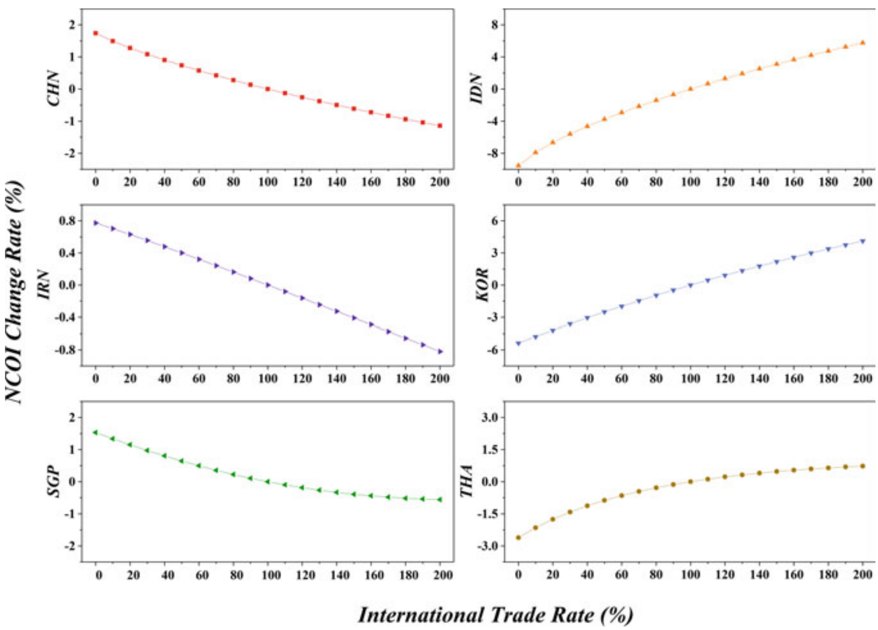


Fig. 9.12 Influence on China and Main Asian Nations in case B

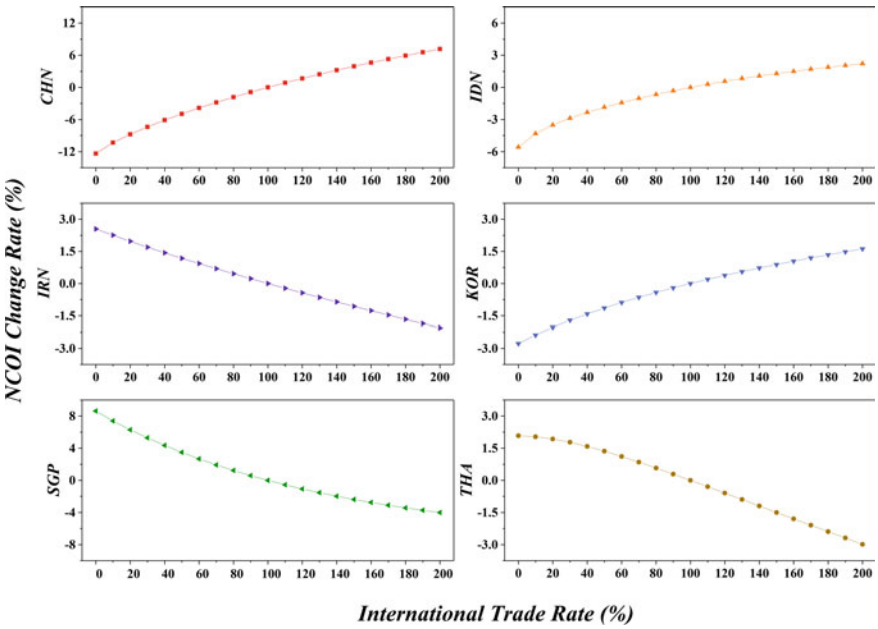


Fig. 9.13 Influence on China and Main Asian Nations in case C

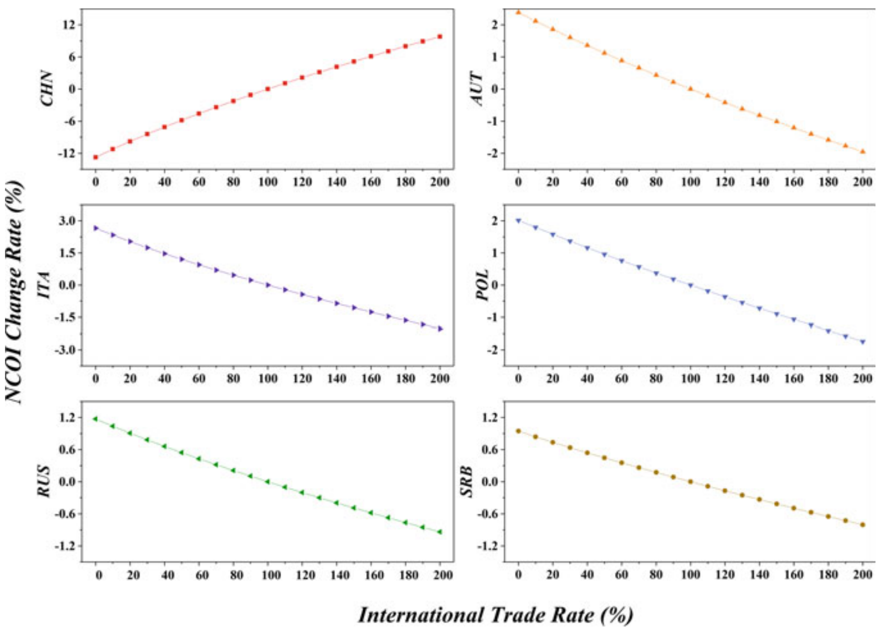


Fig. 9.14 Influence on China and Main European Nations in case A

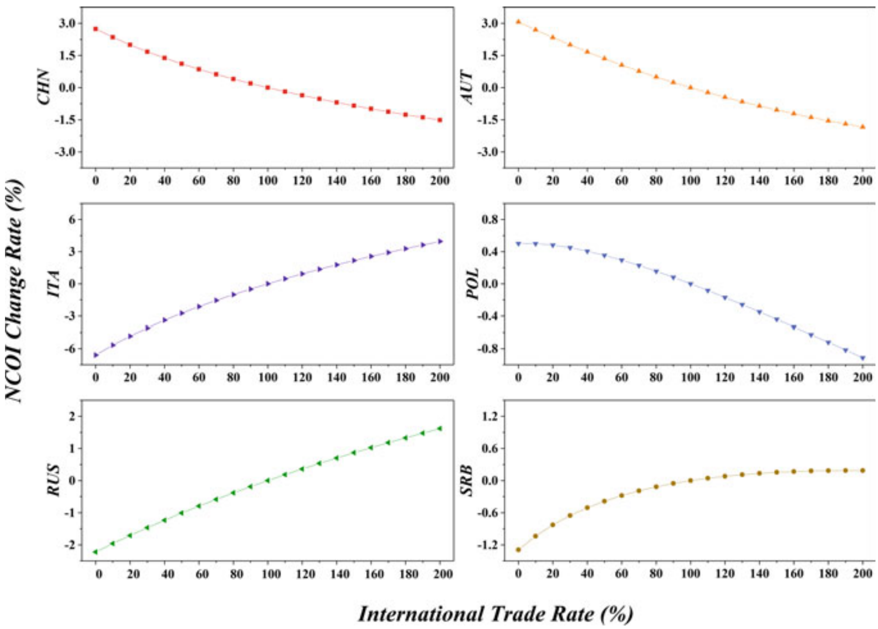


Fig. 9.15 Influence on China and Main European Nations in case B

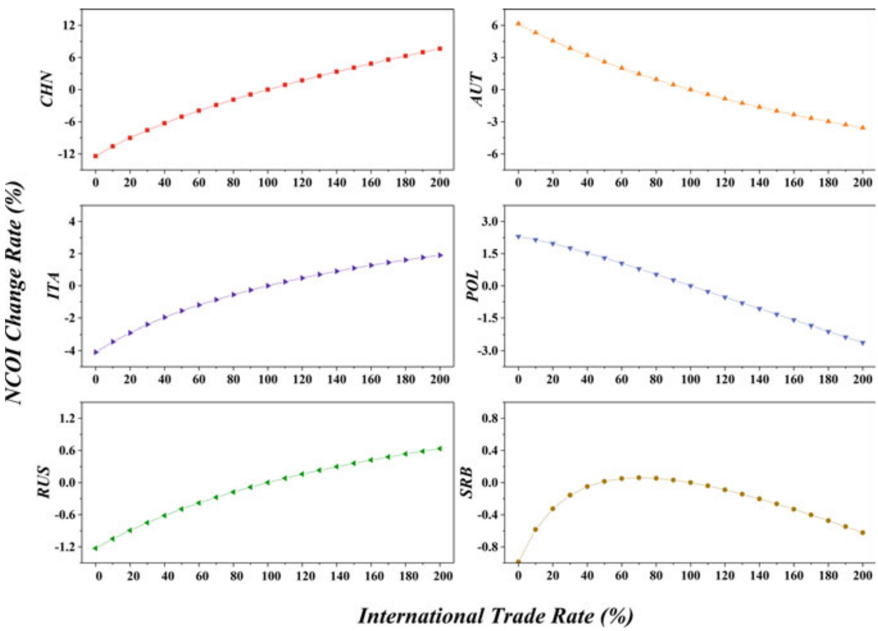


Fig. 9.16 Influence on China and Main European Nations in case C

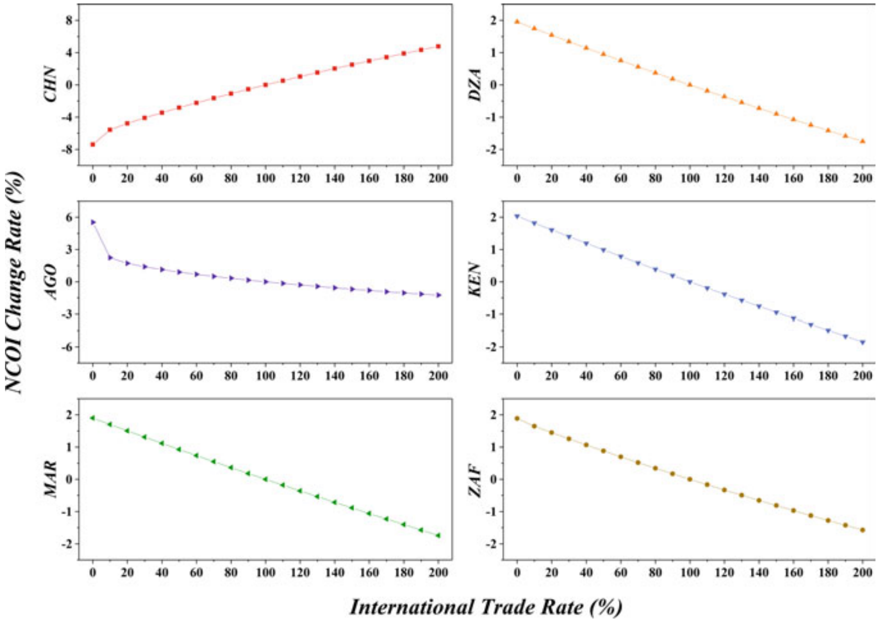


Fig. 9.17 Influence on China and Main African Nations in case A

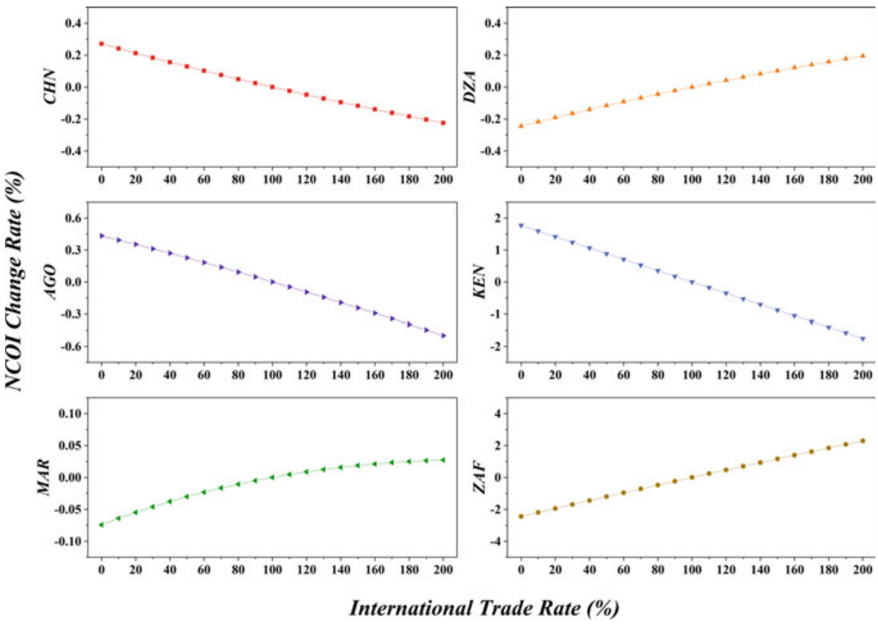


Fig. 9.18 Influence on China and Main African Nations in case B

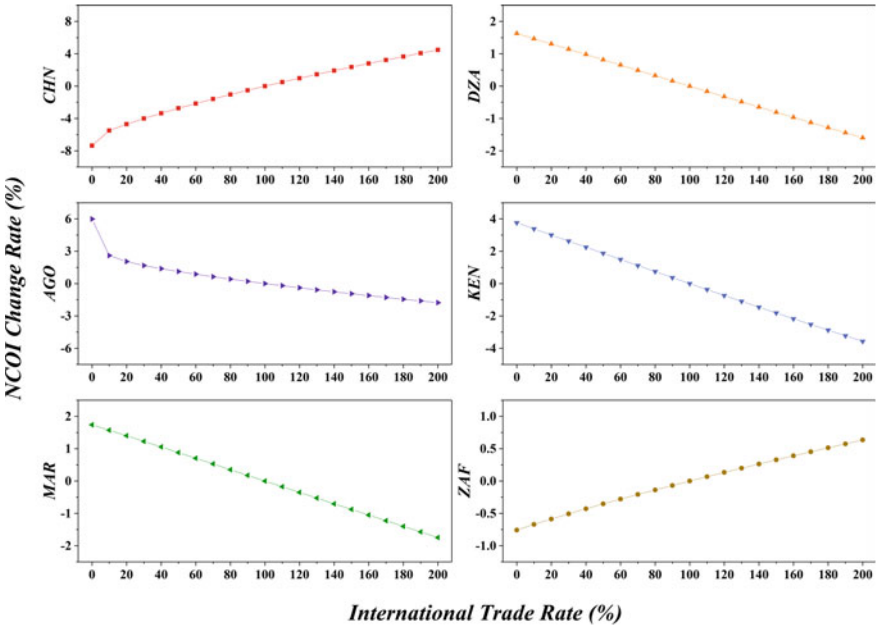


Fig. 9.19 Influence on China and Main African Nations in case C

In Case C, *NCOIs* of China (sharply), Indonesia (sharply), and South Korea increase, while Iran, Singapore (sharply), and Thailand decrease.

Next, we will specifically analyze the production capacity cooperation potential between China and major Asian countries.

(1) Indonesia

Though hit by the financial crisis in 2008, Indonesia's economy managed to maintain a relatively fast growth rate, being the largest and fastest growing in Southeast Asia. Yet in recent years, its economic growth has slowed due to the shrunk volume of imports and exports significantly affected by global demand and prices. As a large agricultural country, Indonesia is the third largest producer of rice and the second largest producer and exporter of palm oil in the world. In the industrial sector, it is dominated by mining, oil and gas, textile, and light industry. China and Indonesia are highly complementary in various fields of industrialization and enjoy a wide scope for cooperation. Not only Indonesia has a strong willingness to cooperate with China in production capacity, but Chinese companies are also quite attracted to the potential market and fastest growing economy in the Southeast region. Chinese investment in Indonesia has mainly taken advantage of its infrastructure needs and labor force, focusing on infrastructure construction, energy development, palm oil plantation industry and labor-intensive manufacturing industries such as textiles and cell phone assembly.

(2) Iran

As one of the major economies in Asia, Iran's economic strength is second only to Saudi Arabia in the Middle East area, and its total population second only to Egypt, making it a pivotal regional power. The industrial structure of Iran is relatively simple, with the oil industry dominating the national economy. However, suffering from the long-lasting economic sanctions from Europe and the United States, its crude oil exports have been greatly restricted. The Iranian government has been increasing trade with other countries in recent years to revive the export trade volume, so as to free its economy from dependence on oil exports by increasing the income from non-oil products. China has been Iran's top trading partner for eleven consecutive years, and there is great room for economic cooperation between the two countries. In the energy sector, with its abundant oil and gas reserves, Iran has prioritized the attraction of foreign investment and technology in the oil and gas sector, and meanwhile China boasts advanced technology and rich experience in energy exploration, exploitation and equipment export. In the field of infrastructure construction, the current focus of economic and trade cooperation between China and Iran is closely on interconnection and international production capacity cooperation, carrying out the construction of infrastructure, steel, electricity, railroads and other projects. In the field of trade, Iran has been able to play the role of a trade hub in Eurasia thanks to its advantages as a transportation hub and a major re-exporting country, and the established free trade zones and special economic zones in Iran have provided convenient conditions and platforms for Chinese enterprises to make direct investment. In the manufacturing sector, China is promoting the participation of China-invested enterprises with world-leading technologies in the construction of Iran's high-tech industries, such as high-speed rail, satellite, communications and nuclear power, to meet the huge demand for manufacturing products in Iran's domestic market. Overall, the economies of China and Iran are highly complementary. As the BRI progresses, cooperation between the two countries in energy, infrastructure, transportation, communications, machinery manufacturing and agriculture will be further deepened.

(3) South Korea

South Korea witnessed an economy boom since the 1970s, and then was hit by the Asian financial crisis in 1997, dragging its economy into a stage of medium-rate growth. Due to the limited natural resources, its industrial structure is dominated by manufacturing and services industries. Its manufacturing industry is mainly technology- and knowledge-intensive, and has strong international competitiveness in shipbuilding, automobiles, electronics, and steel, yet the industrial materials of which are all dependent on imports. With China being Korea's top trading partner, the two countries enjoy broad prospects for cooperation in the manufacturing sector. As China's industrial structure gradually upgrades, China and Korea are mainly trading on high value-added electromechanical products, and the trading structures of the two countries are highly similar. The establishment of China-South Korea FTA will further deepen the trade and investment between the two countries, form strong synergy in manufacturing industries, and become a new growth engine for the multilateral cooperation in the Asian region, regional trade markets and regional industrial development. China and South Korea can cooperate more extensively in the future in emerging industries such as the Internet, and also in energy development, finance, and power grid construction in the Asian region.

(4) **Singapore**

With its well-developed services sector, Singapore has a and is the fourth largest international financial center and the third largest foreign exchange trading center in the world. The three sectors account for less than 1%, 30% and 70% of GDP respectively. Singapore's unique geographical location has contributed to its status as a world powerhouse in the marine industry; high-quality logistics infrastructure wins it a reputation for reliability and speed of delivery; world-class port and airfreight facilities, excellent warehousing and delivery channels, and unparalleled regional and global connectivity gain it a firm foothold in global sourcing and integrated manufacturing. In terms of existing Sino-Singaporean economic and trade cooperation, Chinese investment in Singapore has seen a surge in recent years, mainly in contract labor, transportation, construction, energy and other areas. Combined with Singapore's economic situation and the fruits of Sino-Singaporean economic and trade exchanges, Singapore has a limited role in absorbing and converting China's excess capacity in industries owing to its high stage of industrialization and services-dominted industrial structure. However, the two countries have potentials for cooperation in capital-intensive manufacturing and services industries. Chinese enterprises can invest in high-end enterprises in Singapore's manufacturing industry chain to learn from its advanced management experience and technology; also, they can take advantage of Singapore's convenient transportation conditions and its status as an international financial center to develop trade and financial services, etc.

(5) **Thailand**

Located in the center of Southeast Asia, Thailand stands at the natural intersection of the ASEAN market, and will become a booster rocket for the 21st Century Maritime Silk Road thanks to its relatively sound infrastructure. Thailand's economy is highly export-dependent, with exports accounting for about 2/3 of its GDP. Agriculture is the country's traditional economic sector, with agricultural products being one of the main sources of foreign exchange earnings. Thailand is the only net exporter of food in Asia, living up to its reputation as the "breadbasket of Southeast Asia". Among its top 10 export commodities, six are agricultural products, accounting for about 40% of the total export value. According to Chinese customs statistics, the total bilateral trade volume between China and Thailand accounts for 1/6 of the total bilateral trade between China and ten ASEAN countries, making Thailand China's fourth largest trading partner among ASEAN countries. Meanwhile, China is Thailand's largest trading partner, largest source of imports and largest export destination. The trading structure between China and Thailand has been optimized in recent years, depicting a pattern featuring complementary advantages and mutual benefits. Among all the trading products, electrical and mechanical products take the largest share, and the proportion of plastics and their products is also increasing.

9.5.2 Simulation on European Nations

According to the simulation results in Figs. 9.14, 9.15 and 9.16, we find that: (1) In Case A, China's *NCOI* sharply increases as the volume of international trade goes up, while other countries decrease to varying degrees; (2) In Case B, *NCOIs* of China, Austria, and Poland (slightly) decrease, while Italy (sharply), Russia, and Serbia (sharply before the trade rate is positive and then slightly) increase; (3) In Case C, *NCOIs* of China (sharply), Italy, Russia (slightly), and Serbia (before the trade rate 60%) increase, while Austria (sharply), Poland, and Serbia (after the trade rate 60%) decrease.

Next, we will specifically analyze the production capacity cooperation potential between China and major European countries.

(1) **Austria**

Lying at the south end of Central Europe, Austria is an important transportation hub in Europe, with an economy growing faster than the EU average. Austria boasts an ample supply of mineral, forest, and hydraulic resources; in particular, its forest coverage accounts for nearly 50% of its total area. In recent years, as Austria's economy has been developing at a fast pace, machinery industry is its largest industrial sector, its agriculture and tourism industries are well-developed, and services industry occupies an important position. China is Austria's most important trading partner in Asia. China's rising living standards are attracting more and more Austrian companies to make investment, encouraging Sino-Austrian bilateral trade to continuously grow. With the unique advantages in the metal industry, mechanical engineering, food, chemical, automotive, and environmental protection industries, Austria exports high-tech products to China, and thus becomes an important technology importing source for China in the EU. Besides, Austria's position as a hub for China's interconnectivity with the CEE region is also noteworthy. In general, given the highly complementary bilateral trade, the cooperation between Austria and China in the fields of trade, finance, infrastructure construction and culture will unlock significant potential.

(2) **Italy**

Italy is situated on the northern coast of the Mediterranean Sea in southern Europe. It is the second largest manufacturing country in the EU after Germany, and the fourth largest economy in Europe and the eighth largest in the world. Known as the "Kingdom of SMEs", the number Italy's small and medium-sized enterprises accounts for more than 98% of the total number of enterprises. However, in short supply of natural resources, the country's oil and gas production can only meet a small portion of its domestic market demand. In addition, though being highly developed, its economy is facing unbalanced development, with a widening gap between the prosperous northern region and the relatively backward southern region, divided by the capital Rome. Italy was among the first batch of European countries to develop trade relations with China. The two countries signed a communiqué on the establishment of diplomatic relations as early as 1970. After the establishment of the China-Italy comprehensive strategic partnership in 2004, the economic and trade between the two countries has grown rapidly. As of 2018, Italy has become China's fourth largest trading partner, third largest export market and source of imports in the European Union; likewise, China is Italy's top trading partner in Asia. Suffice it to say that the BRI between China and Italy can help bring into play the comparative advantages of both sides. To be specific, Italian companies have comparative advantages in high-end manufacturing and services industries, design, aerospace, biomedicine, etc., but lack capital liquidity, which can be complemented by Chinese companies which are seeking to transform and upgrade their value chains with relatively sufficient funds.

(3) **Poland**

Located in Central Europe and south to Baltic Sea, Poland is the largest and most populous country in Central and Eastern Europe. Poland's unique geographical advantage guarantees its important role in the Belt and Road. China and Poland have planned to use Poland as a hub for new logistics routes to build it a logistics center in Central and Eastern Europe, thereby promoting the inflow and entry of Polish and Chinese products to the European region. As China's BRI and Interconnectivity strategy progresses, a series of China–Europe freight trains by way of Poland have been launched to expand cooperation in trade and investment between the two countries. The economies of China and Poland are highly complementary and have the potential to develop together in the fields of infrastructure and high-tech industries, despite some obstacles such as limited trade volume, insufficient mutual investment, and a small number of large-scale cooperation projects, etc.

(4) **Russia**

Russia, the largest country in the world, straddles the Eurasian continent and includes both the eastern half of Europe and the western part of Asia. Russia's industrial structure is homogeneous and economic structure is overly dependent on energy exports. Its secondary industry is supported by heavy and chemical industries, while agriculture and services are relatively underdeveloped. China and Russia are each other's largest neighbors, and their unique geopolitical advantages facilitate economic and trade cooperation in the border areas of both countries. For a long time, China and Russia have been each other's important trade partners. China has been Russia's largest trading partner for eleven consecutive years, while Russia is the tenth largest trading partner of China. The trading structure of the two countries reflects complementarity. China imports from Russia minerals, wood and wooden products and other less processed primary products, while exporting to Russia electromechanical products, textiles, and raw materials; the various products in which the two countries have significant comparative advantages basically do not overlap.

(5) **Serbia**

Located in Southeastern Europe, Serbia is a landlocked country in the middle of the Balkans that suffered severe damage to its industrial facilities in the 1990s when it was bombed by NATO during the Kosovo War. In the twenty-first century, with the introduction of privatization, Serbia's economy has gradually recovered, but the overall economic level is below the European average. The main economic obstacles are high unemployment rate and large trade deficits. Serbia was the first country in Central and Eastern Europe to establish a strategic partnership with China, and since 2006 China has been Serbia's top trading partner in Asia and the fifth largest trading partner in the world. At present, though developing at a relatively fast pace, its overall economy is still underdeveloped, especially when it comes to the outdated infrastructure. In the future, China and Serbia have great potential for cooperation in infrastructure construction, energy, chemical industry, mineral products, and other fields.

9.5.3 Simulation on African Nations

According to the simulation results in Figs. 9.17, 9.18 and 9.19, we find that: (1) In Case A, China's *NCOI* sharply increases as the volume of international trade goes up, while Algeria, Angola (sharply when the trade rate is very low and then slightly), Kenya, Morocco, and South Africa decrease; (2) In Case B, *NCOIs* of China (slightly), Angola (slightly), and Kenya decrease, while Algeria (slightly), Morocco (slightly), and South Africa increase; (3) In Case C, *NCOIs* of China (sharply) and South Africa (slightly) increase, while Algeria, Angola (sharply when the trade rate is very low and then slightly), Kenya, and Morocco decrease.

Next, we will specifically analyze the production capacity cooperation potential between China and major African countries.

(1) **Algeria**

Located in northwest Africa, Algeria is the largest country in terms of area and the fourth largest economy in Africa. Rich in underground oil and gas resources, Algeria is the second largest gas exporter in the world, with the fifth largest reserves, so the oil and gas industry underpins its economic development. The industrial cooperation between China and Algeria can be mutually beneficial. Firstly, as Algeria's largest source of import, China mainly imports energy and mineral resources such as iron ore and LPG from Algeria, and invests in oil and gas, mining, aerospace, nuclear energy, and other fields. Secondly, the cooperation between China and Algeria in high-tech fields has strongly contributed to the economic growth and industrial development of both countries. Thirdly, China's overseas infrastructure capacity, which is high-level and cost-effective, can help build the infrastructure such as roads, railroads, ports, and airports in Algeria.

(2) **Angola**

Situated in sub-Saharan Africa, Angola is the fourth largest economy and one of the largest capital attracting countries in Africa. It has ample oil, natural gas, and mineral resources, and also a large amount of hydroelectric power, as well as resources of agriculture, forestry and fishery. Its hydropower generation accounts for 3/4 of the country's total power generation. Angola's economy is mainly based on agriculture and minerals, and oil, with oil being the mainstay industry. Although it has taken effective measure to promote economic diversification and reduce dependence of the national economy on the oil industry, the country is still struggling with a low level of economic development and backward infrastructure. China's imports from Angola mainly include crude oil, natural gas and other natural resources, and Angola's imports from China mainly include electromechanical, steel, automobile, and other products. China actively participates in investment in Angola and has obvious competitive advantages in infrastructure construction such as railroads, in addition to many other fields such as oil, construction, power grid and telecommunication. In recent years, the two countries are making great efforts to promote capacity cooperation in areas such as electricity, ports, highways, agriculture, and manufacturing.

(3) **Kenya**

Kenya has the most developed and complete industrial sector in East Africa. Agriculture, services and manufacturing are the three pillars of Kenya's national economy, and the oil, mineral extraction, agriculture, livestock and fisheries, and tourism industries are also developing well. Its natural port Mombasa connects East and Central African countries, with good water transport conditions. Kenya boasts well-operating infrastructure in communication, transportation, resources, and energy, rich natural resources, and huge market potential. However, Kenya's industrial sectors and regions varies greatly in terms of level of development, so it needs to upgrade its industrialization development with reference to the successful stories of other countries. China is Kenya's largest source of imports, and also has a number of maturely developed industries and redundant production capacity. China is now more than ready to make overseas investment and expand exports while sharing its best practices. China and Kenya enjoy high economic coupling—the capital, technology and experience of the former can be fully utilized by the latter. The cooperation between the two countries will undoubtedly bring about mutual benefit and win–win.

(4) **Morocco**

Morocco is a coastal Arabian country in Northwestern Africa and a hub connecting Europe, the Middle East and Africa. Morocco's economy ranks fifth in Africa and third in North Africa. Phosphate exports, tourism, and remittances are the main pillars supporting Morocco's economy. It has a good foundation in agriculture but is not self-sufficient in food. Its rich fishery resources generate the highest production in Africa. But its industry is underdeveloped. The Moroccan government is committed to expanding domestic demand, strengthening infrastructure construction, supporting traditional industries such as textiles and tourism, developing new industries such as information and clean energy, actively attracting foreign investment, and promoting economic growth. As one of the first Arab countries to establish diplomatic relations with China, Morocco's superior geographical location, stable political environment and perfect economic governance system provide conditions for further economic and trade cooperation between China and Morocco, and also serve as a bridge for Chinese enterprises to explore the African and European markets. In recent years, trade and investment between the two sides have continued to thrive, and production capacity cooperation in fisheries, infrastructure, telecommunications, automobiles and other fields has been deepened.

(5) **South Africa**

As the second largest economy in Africa, South Africa is an important member of multilateral organizations such as BRICS, G20 and the United Nations. It maintains close relations with China in international organizations and multilateral mechanisms and is considered as China's important strategic partner. South Africa has abundant natural resources, low labor costs, and relatively complete infrastructure in transportation, electricity and information and communication. Mining and manufacturing are the most important pillar industries in its national economy. The cooperation between China and South Africa in the fields of manufacturing, investment and trade is flourishing and of great significance. First, South Africa's manufacturing development has lagged behind in the past 20 years, and much of the manufacturing industry has been replaced by imports, mainly due to insufficient technology reserves, high factor costs, and insufficient economies of scale. The in-depth cooperation between South Africa and China in the manufacturing sector will enhance its own technological level and international competitiveness. Secondly, South Africa is China's largest trading partner and the most important investment destination in Africa, and China's investment in South Africa has promoted the development of its special economic zones. Thirdly, South Africa is now shifting from a mining and manufacturing-dependent economy to a technology- and services-oriented economy, whose domestic market can be further vitalized through its trade with China.

9.5.4 Results and Discussions

We try to explain the laws and reasons for the variation of collaboration among BRI-related nations from the following three perspectives.

Firstly, China can transfer its excess production capacity to other countries on the RCV through BRI, and then optimize its own industrial structure to move to the middle and high end of multiple IVCs, thereby enhancing its collaborative ability on the GVC, which is reflected by a substantial increase of *NCOI* in Case A and Case B.

Secondly, by strengthening regional cooperation, some nations have made up for the shortcomings of their own industrial structure layout to some extent and enhanced the production transformation capacity within their NVCs. Among them: ***Satisfying Effect*** is observed when the collaborative potential of nations with a single industrial structure is satisfied, which is manifested as a decrease in *NCOI*; ***Incentive Effect*** is observed when the collaborative potential of nations with a diversified industrial structure is further stimulated, which is displayed as a rise in *NCOI*.

Thirdly, under the combined effect of satisfying effect and incentive effect, some nations (e.g., Thailand in Asia, Serbia in Europe, Angola in Africa) have more varying *NCOI* trends under different cooperation strategies—either rise or fall, which requires to be analyzed specifically on the causes at the sectoral level.

Regional collaboration can promote relevant economies to carry out production capacity cooperation, make full use of their comparative advantages to embed in the RVC network, and gradually achieve a rise in the GVC network. From a long-term perspective, the BRI initiated by China will help GVC restructure toward a win–win cooperation. In this chapter, our study provides a reference for how China can better implement the BRI. For example, in its cooperation with Asia, where most countries are rich in oil and gas and mineral resources, but have poor industrial systems, backward development technologies and insufficient development capacity, China can cooperate with them in key areas such as oil and gas and mineral resources via helping them establish sound industrial, transportation and infrastructure systems. In its cooperation with Europe, given the rapid development of the "Construction" sector, China can take advantage of the rapid development cycle of European infrastructure, and use its experiences in rail-road industry to tap in the European rail transportation market. Meanwhile, China should also focus on the cooperation with European HMT sectors. In the cooperation with Africa, China should adhere to the humanitarian spirit, guide African industries to be more scientific and internationalized, and bring into play Africa's comparative advantages in the GVC network.

In the context of drastic changes in the international environment, the traditional countermeasures to the systemic crisis of the national economy have lost efficacy; and the priority is to optimize and upgrade industrial structure. With its complete industrial chain and supply chain and the vast domestic market, China should avoid the "Industrial Hollowing-Out" like Japan, the United States and other countries. From the perspective of economic security, while continuously encourage industrial sectors to "go global", China needs to respond to its dwindled competitiveness in the whole industrial chain and strengthen independent innovation to supplement the shortcomings. Against the backdrop of GVC reconstruction in the post-pandemic era, China shall explore a new development model, use the domestically economic circulation to drive the internationally economic circulation, take the BRI as the focus, and seize new foreign trade opportunities brought by RCEP. By doing so, it will embrace strengthened ties with other countries, and better integration into the GVC with a higher level of openness. This will be a favorable measure to promote global economic integration and counteract reverse globalization.

9.6 Summary

This chapter measures the collaborative relations between industrial sectors and simulates that between countries in consideration of both the actual demand from downstream sectors and the potential industrial-capacity cooperation from upstream ones. We believe this chapter will be helpful to understand the trend of economic globalization and regional economic cooperation. Contributions of this chapter are as follows:

(1) **Establish the GPCCN model to embody the collaborative relations among industrial sectors**. In consideration of the scarcity of productive capacities, we use bipartite graphs to distinguish the roles of industrial sectors on the GVC as upstream and downstream ones. Then, we extract the collaborative relations hidden in the IO/ICIO table via RAP approach, transforming the GIVCNBG model into the GPCCN model. The latter depicts collaborations among countries and their industrial sectors.
(2) **Propose network-based measurement tools to reveal the collaboration status on the sectoral level and the national level**. After getting the collaborative relations among industrial sectors, the summation of the collaborative attraction that one imposes on others is defined as the *COI*, and the summation of collaborative attraction that one receives from others is defined as the *CTI*, which are the out-strengths S^{OUT} and in-strengths S^{IN} of nodes respectively in the GPCCN model. As well, *NCOI* and *NCTI* standing for the country-level cooperation competence can be further calculated. Of course, we pay more attention on the economies' collaborative opportunity measured by *NCOI* in the empirical analysis.
(3) **Simulate collaborative opportunities of BRI-related nations**. GVC is the most sophisticated economic system, whose relatedness, heterogeneity and diversity deserve more attention from the relevant authorities when making international trade policies. Only by studying GVC can China and its trade partners benefit from the BRI. We believe the simulation framework in Part IV possesses considerable reference value and will be a guide for analyzing globalization issues with physical statistics.

In this chapter, we set three kinds of cases to observe how the collaborative status of China and BRI-related nations will change. The premise of global cooperation on production capacity is the complementarity and coupling of the two cooperating countries on the GVC, emphasizing the utilization of their respective advantages in technology, capital, and resources to achieve mutual benefits and win–win situations.

Empirical analysis has shown that China's BRI has indeed brought dividends to nations along the route. Especially for some less developed countries in Asia, Europe, and Africa, continued industrial-capacity cooperation with China in key areas have significantly improved their ability of globally synergic production. This further proves that BRI can provide good development opportunities for relevant countries through complementing advantages, resource sharing, and capacity cooperation, and can help achieve common prosperity.

In the next stage, more detailed analysis on the trade between China and BRI-related nations should be carried out from the perspective of their market sizes and industrial layouts.

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Part V
Evolutionary Mechanism

Chapter 10
Extract the Backbone of Global Value Chain

10.1 Introduction

There is an important premise lying ahead of analyzing the ICIO network, that is, it is too dense to analyze the network properties of GVC or an economic system, which means useful forecasting results with existing methods are under restrictions. Therefore, no matter how we plan to do, the first mission is identifying the key structures of networks, which are defined as the backbone of network, that is, core components extracted from the original network with fewer linkages by making the redundant information invisible.

The growing size and multiscale nature of complex networks are becoming an obstacle to extract relevant information and critical features, bringing about two problems. One is unexpected noise, i.e., a lot of information is weak even misleading or have very little impact on the persistence of network characteristics. For example, removing noisy links can improve the performance of the recommendation systems [1, 2], the network synchronizability will hardly change if redundant links are removed [3]. The other is network simplification, i.e., reducing the number of nodes and links and then downsizing the original network into a backbone with clear visualization and efficient analysis.

The current backbone extraction methods can be classified into three categories: network sampling, coarse graining, and filtering. Firstly, network sampling means obtaining the main network structure through sampling representative nodes or edges, which is extensively overviewed in some articles [4, 5] Secondly, to turn the original network into a smaller skeleton, coarse graining means merging nodes or edges according to certain rules [6] such as the attribute of node or edge [7, 8] and community structure [9]. Thirdly, the filter-based method is the most common and typically defines statistical properties of nodes or edges and then regards them as a criterion to determining whether nodes and links should be retained or not.

There are two filtering perspectives in practice.

An important angle is to preserve the core by removing structures that under a certain characteristic threshold. For nodes, a range of indicators such as degree

L. Xing, *Complex Network-Based Global Value Chain Accounting System*,
https://doi.org/10.1007/978-981-16-9264-2_10

[10–12], local centrality [13] and Leader Rank [14, 15] have been applied to identify influential nodes. Further, backbone network can be obtained by reserving the smallest possible subset of highly influential nodes and their relevant links [16] As for edges, link weights [17–19] and network motifs [20] were used to extract functional backbones while edge betweenness [19, 21, 22] and the shortest path [23, 24] were used to preserve more structural features. For instance, Zhang et al. extracted the skeleton which is the largest connected component of the weight threshold network [17]. Kim et al. identified the spanning tree as communication kernel by maximizing the total edge betweenness centralities [21]. Zhang et al. defined h-backbone method that extract both the high-strength links and network bridges [19].

The other is to retain the components which are statistically significant at the local level. ***Disparity Filter (DF)*** is the most representative method that focus on the local distribution of edge weights, preserving the edges that represent statistically significant deviations with respect to a null model [25]. The improvement of DF comes from different aspects [20, 24, 26–29]. For example, Radicchi et al. proposed a weight-filtering technique based on a global null model, which accounts for the full topology while preserving the heterogeneity of the weight distribution [26]. Foti et al. presented an improvement relying solely on the empirical distribution to judge statistical significance instead of any null model [27]. Bu et al. designed a stricter filter rule and an iterative local search model to avoid outliers and improve efficiency [28]. Zhang et al. and Cao et al. identified which edges for each node should be preserved by evaluating whether their link involvement [17] or motif weights [20] are compatible with the null model respectively.

Despite the above-described efforts, there is no tailored one for the ICIO network which is substantially equivalent to a directed complete multigraph, with the number of edges, including self-loops, is almost equal to the square number of nodes. In this chapter, we develop a mixed strategy reduction algorithm for the ICIO network taking into consideration both pivotal linkage and local information, which can preserve as many crucial edges as possible in such dense, directed, and similarity-weighted network. We also implement the proposed methods and evaluate the performance by comparing with the global threshold and disparity filter methods.

10.2 Formal Problem Setting

While finding an effectual way for weighted network, here come two questions. The first question is that ***the information content of network should be retained as much as possible with the decline of number of edges (Q1)***. In other words, the nature of network pruning has to be a trade-off between the number of retained edges and the gross of retained weights. The second question is that ***only the truly important edges linking nodes are worthy to be retained during downsizing the network (Q2)***. Sometimes, a weighted edge is numerically insignificant but functionally significant, and reckless deletion will result in a useless broken structure.

10.2.1 Global Threshold

In general, the simplest approach to prune a network is to remove all edges with weight below a certain global threshold, based on which we can obtain the ***GIVCN-GT*** ("GT" means setting a certain global threshold) model. In the light of this, an experiment has been designed based on GIVCN-Eora26SC4-2015. First, the edge weight range in the network is divided into 10,000 equal parts, wherein the minimum threshold is one ten-thousandth of the maximum edge weight, which is equal to 9.561E+05, and the second smallest one is 1.912E+06, and so on. Second, each threshold is selected in order from small to large to conduct network pruning, and the number of residual edges is recorded in the new network and the percentage of the residual edge weights for the original network. Finally, a scatter plot is drawn to describe the correspondence between these two indicators, as shown in Fig. 10.1.

In the network extracted at the threshold of 9.561E+05, the number of edges quickly decreases from 571,536 to 2703 and the decline rate reaches 99.527%, while the total edge weight of the network decreases by only 3.338%. Obviously, setting thresholds is acceptable if following the principle of "significantly reducing the number of edges while retaining most of the total edge weight", but it is a theoretically flawed backbone extraction technique. According to Granovetter's "***The Strength of Weak Ties***" [30], a small threshold may lead to the mistaken deletion of some weak, yet important ties. Even though such a scale-effective threshold value exists, the

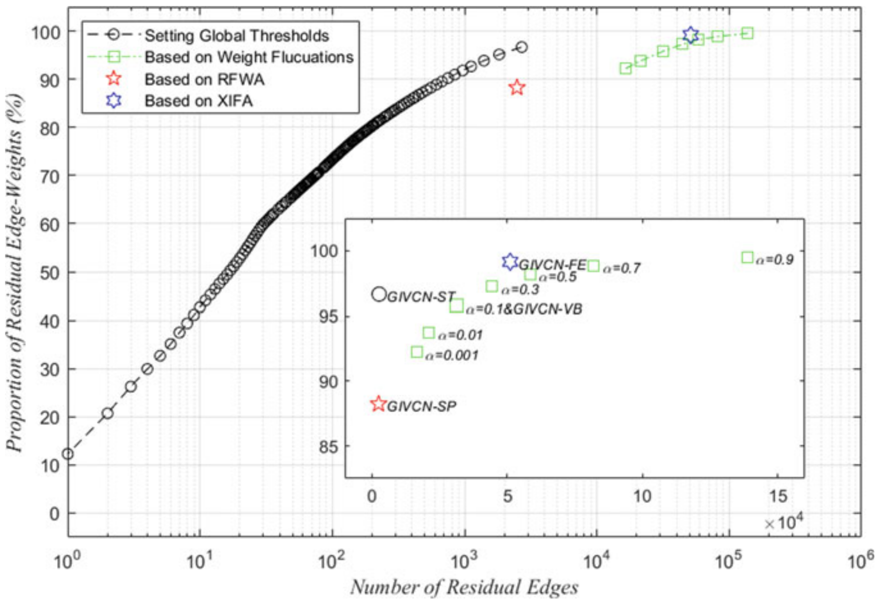


Fig. 10.1 Comparative Results of Network Pruning Algorithms in GIVCN-Eora26SC4-2015. *Notes* The SP, FE, SPFE methods in the following sections are also included in Fig. 10.1 and its inset

Q1 can be solved but not yet the Q2. For investigating the performance of better methods, we establish the GIVCN-GT model by taking the one ten-thousandth of the maximum edge weight as the global threshold.

10.2.2 Disparity Filter

For low-strength nodes, low-weight edges may be significant, even though edges with the same weight may be insignificant for nodes with much higher strength. To address this issue, setting different thresholds for different nodes are necessary [31]. Therefore, we can use the weight fluctuations for each node to identify the edges to be preserved. Vespignani computed the probability $p_{ij=\left(1-w_{ij}/s_i\right)^{k_i-1}}$. that such a value is compatible with the null del: if $p_{ij} < \alpha$, where α is a parameter representing the desired significance level, the edge is preserved, otherwise it is removed [25]. Lower values of α lead to sparser networks, as fewer edges are preserved. Although an edge is connected to two nodes, its direction determines there exists only one value for p_{ij}, that is, based on the out-degree and out-strength of the source node.

As shown in Fig. 10.1, this edge filtering procedure retains more edges than setting global thresholds, and the proportion of residual edge-weights of the former with $\alpha \geq 0.3$ or $\alpha \leq 0.1$ is higher or lower than the latter. For the same reason, we establish the **GIVCN-DF** ("DF" means the disparity filter algorithm proposed by Vespignani) model by pruning the original network using $\alpha = 0.1$, which is superior to the others with smaller or larger α, as well as the GIVCN-GT model, when balancing the edge and weight. So, this method, depended on a null hypothesis that the normalized weight distribution of edges connected to a node follows a uniform distribution, tends to consider the weights whose ranges are of different orders of magnitude, which has in turn led to it only applied to very heterogeneous weighted networks. Moreover, the GIVCN-DF model has nothing to do with getting around the Q2, because all the factors it concerns are just local information rather than network topology, especially when an adjacent link weight is not significant but plays a pivotal role in information transfer between communities.

10.3 Proposed Algorithms

Both the structural and functional information of network are important, and many scholars hence paid attention to find a better way to retain them while having to do the job of network pruning. Thinking in the same way, we also try to determine the core structure of complex network systems, especially the similarity-weight network, in two different directions. In this section, searching paths and filtering edges methods are chosen to achieve those two purposes, respectively.

10.3.1 Searching Paths

By comparison of the numerical matrix of *SRPL* and edge weight, we notice that some elements in the same place of them are identical. That is to say, a part of *SRPLs* between any two sectors (could be the same one) is directly equal to their IO values. This phenomenon means there exists both the strongest and the most immediate industrial relevance in the IO network. Thus, these same elements could be extracted to form a new matrix, and the equations are:

$$\tilde{\mathrm{w}}_{ij} = \begin{cases} w_{ij}\ ,\ w_{ij} = SRPL_{ij}^{(N)} \\ 0\ \ ,\quad otherwise \end{cases} \tag{10.1}$$

Taking $\tilde{W} = \{\tilde{w}_{ij}\}$ as an adjacency matrix, we establish the **GIVCN-SP ("SP" means searching paths)** model to abstract the optimized value chains within the scope of the global production system, which could be called the "Backbone of GVC". Notice that, a given node's self-loop may disappear in this newly refined network, which depends on whether its inner-node *RPL* is a *SRPL* or not.

In GIVCN-SP-Eora26SC4-2015, the proportion of residual edge weights is 88.242% while the number of residual edges is 2,703 which is much higher than the latter's around 556 in the same conditions (see Fig. 10.1). It is safe to say the GIVCN-SP effectively solves the Q2. However, the low proportion of residual edge-weights indicates that the Q1 remain unsolved.

10.3.2 Filtering Edges

It is common in the weighted networks that, even at the local level defined by edges linking to a given node, only a few of those edges carry a disproportionate fraction of its strength, and the remaining ones take a very small percentage left.

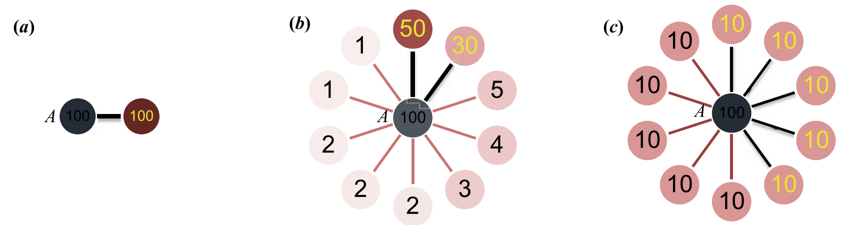
Enlightened by ***H-Index***, the ***Pareto Principle***, and the idea of ***Disparity Filter*** proposed by Vespignani [25], we present a novel heuristic algorithm to effectively prune the dense and weighted GIVCN model, which is named ***X-Index Filtering Algorithm (XIFA)***. As we all know, Hirsch proposed that a scientist has index h if h of his or her N_p papers have at least h citations each and the other $(N_p - h)$ papers have $\leq h$ citations each [32]. Obviously, this mixed quantitative index takes both quantity and quality of papers into account, which can be used as algorithm framework to solve the Q1 by weighing the pros and cons, namely the number and weights of edges. According to the Pareto principle, it makes sense that 80% of consequences come from 20% of the causes, asserting an unequal relationship between inputs and outputs. We hence assume that a minority of edges hold most weights in the network, which are regarded as the so-called important ones as mentioned in the Q2.

XIFA is a sort of mixed quantitative index that takes into account the scope and intensity of industrial sectors and extracts the main topology of ICIO network according to the heterogeneity of IO relations. From the perspective of complex networks, for the nodes owning diversely weighted edges, we only need to retain a small number of them with extremely large weights, while for the nodes owning similarly weighted edges, many but no more than 50% of them will stay, as shown in Fig. 10.2.

In addition to the case in Fig. 10.2b, the larger the X-index, the more even distribution of edge weights, and the more edges are retained; the smaller the X-index, the more concentrated distribution of edge weights, and the fewer edges are retained. The range of the X-index is theoretically (0,0.5]. The core idea of XIFA is as follows: ***An industrial sector has Backward Index x (*** XI^B ***)/Forward Index x (*** XI^F ***) if top x percent of its relations to all upstream/downstream sectors occupy at least*** $(1-x\%)$ ***of its total input/output amount of intermediate goods***. Formula deduction and practical calculation procedures are also presented in Table 10.1.

This algorithm serves a dual purpose. One is to retain the key outward connections from the perspective of provider, and the other is to retain the key inward connections from the perspective of consumer. It should be noted that if all the key export-oriented links cannot touch the industrial sectors of some weak countries as consumers, then these sectors will be separated from the GVC, which undermines the integrity of GVC. Therefore, we carry out the merge after network pruning from the perspective of out-degree and in-degree respectively.

We extract a sub-network from GIVCN model based on the above method and name it the ***GIVCN-FE*** ("FE" means filtering edges) model, and to what extent the left ICIO relations are different from those deleted depending on how heterogeneous the industrial sectors' inputs or outputs are all over the world. We can assume that around 20% of most important input or output relations of a given sector are supposed to cover 80% of its input or output amount of intermediate goods, which addresses the Q1 favorably. Besides, overlapping two subnetworks via input relations (columns) and output relations (rows) pruning process is only a partial solution to the Q2. According to the nature of this algorithm, this pruning method is still based on the



$XI_A = 1/1 = 1$
$100/100 = 1 \geq 1 - XI_A$

$XI_A = 2/10 = 0.2$
$(50+30)/100 = 0.8 \geq 1 - XI_A$

$XI_A = 5/10 = 0.5$
$(10 \times 5)/100 = 0.5 \geq 1 - XI_A$

Fig. 10.2 Three Possible Situations in the Application of XIFA. *Notes* **a** The source node has only one weighted edge connected to it, and 100% of its strength is allocated on it; **b** Top 20% of weighted edges carry 80% of the strength of source node; **c** Any 50% of weighted edges carry 50% of the strength of source node

Table 10.1 Procedure of Pruning GIVCN Model Based on XIFA

Procedure	Column deletion of input relations	Row deletion of output relations
Network	$W = \left(w_{ij}\right)_{N\times N} i, j \in [1, N]$	
Refactoring	$\overleftarrow{w}_1 = \mathrm{desecend}(w_{11}, w_{21}, \ldots, w_{N1})^T$ $\overleftarrow{w}_2 = \mathrm{descend}(w_{12}, w_{22}, \ldots, w_{N2})^T$ $\overleftarrow{w}_N = \mathrm{descend}(w_{1N}, w_{2N}, \ldots, w_{NN})^T$ $\overleftarrow{W} = \left(\overleftarrow{w}_1, \overleftarrow{w}_2, \ldots, \overleftarrow{w}_N\right) = \left(\overleftarrow{w}_{hj}\right)_{N\times N}$ $h, j \in [1, N]$	$\overrightarrow{w}_1 = \mathrm{desecend}(w_{11}, w_{12}, \ldots, w_{1N})$ $\overrightarrow{w}_2 = \mathrm{descend}(w_{21}, w_{22}, \ldots, w_{2N})$ $\overrightarrow{w}_N = \mathrm{descend}(w_{N1}, w_{N2}, \ldots, w_{NN})$ $\overrightarrow{w} = \begin{pmatrix} \overrightarrow{w}_1 \\ \overrightarrow{w}_2 \\ \ldots \\ \overrightarrow{w}_N \end{pmatrix} = \left(\overrightarrow{w}_{ik}\right)_{N\times N}$ $i, k \in [1, N]$
Conditions	$\forall a_1, a_2, \ldots, a_j \in [1, N]$ $\begin{cases} \frac{\sum_{h=1}^{a_j} \overleftarrow{w}_{hj}}{\sum_{h=1}^{N} \overleftarrow{w}_{hj}} \geq 1 - \frac{a_j}{N} \\ \frac{\sum_{h=1}^{a_j-1} \overleftarrow{w}_{hj}}{\sum_{h=1}^{N} \overleftarrow{w}_{hj}} < 1 - \frac{a_j-1}{N} \end{cases}$	$\forall b_1, b_2, \ldots, b_i \in [1, N]$ $\begin{cases} \frac{\sum_{k=1}^{b_i} \overrightarrow{w}_{ik}}{\sum_{k=1}^{N} \overrightarrow{w}_{ik}} \geq 1 - \frac{b_i}{N} \\ \frac{\sum_{k=1}^{b_i-1} \overrightarrow{w}_{ik}}{\sum_{k=1}^{N} \overrightarrow{w}_{ik}} < 1 - \frac{b_i-1}{N} \end{cases}$
Definition	$XI_j^B = \frac{a_j}{N}$ $XI^B = \left(XI_j^B\right)_{N\times 1}$	$XI_i^F = \frac{b_i}{N}$ $XI^F = \left(XI_i^F\right)_{N\times 1}$
Pruning	$\overleftarrow{w}_{ij} = \begin{cases} w_{ij}, & w_{ij} = \overleftarrow{w}_{hj} \text{ and } h \leq a_j \\ 0, & \text{otherwise} \end{cases}$	$\overrightarrow{w}_{ij} = \begin{cases} w_{ij}, & w_{ij} = \overrightarrow{w}_{ik} \text{ and } k \leq b_i \\ 0, & \text{otherwise} \end{cases}$
Merging	$\overleftrightarrow{w}_{ij} = \begin{cases} w_{ij}, & \overleftarrow{w}_{ij} \neq 0 \text{ or } \overrightarrow{w}_{ij} \neq 0 \\ 0, & \text{otherwise} \end{cases}$	
Result	$\overleftrightarrow{W} = \left(\overleftrightarrow{w}_{ij}\right)_{N\times N}$	

relations of adjacent nodes, rather than global information, so it is still possible to ignore the "critical" and "weak" edges.

10.3.3 Mixed Strategy

In consideration of balancing the pruning efficiency (Q1) and effectiveness (Q2), the preferable algorithm for extracting the backbone of GVC with enough structural and functional information has three steps.

Step 1: Find the edges acting as crucial bridges between nodes or communities based on the RFWA;

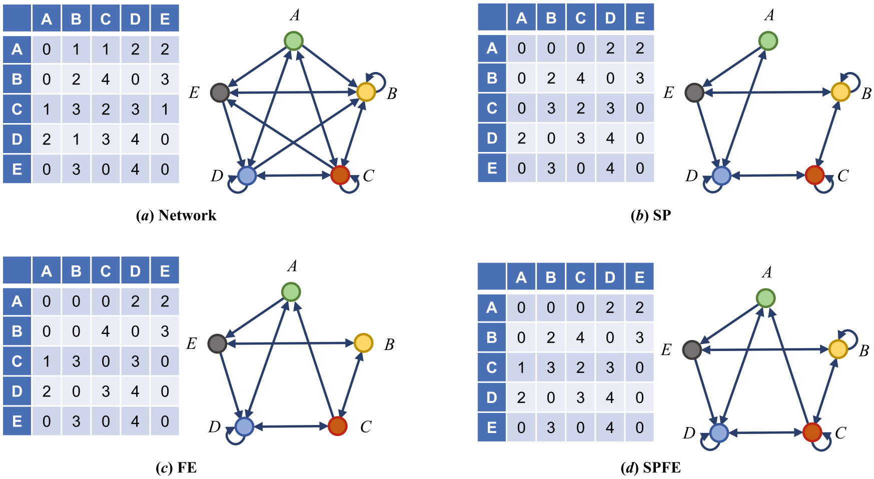


Fig. 10.3 Getting the SPFE from an original network

Step 2: Find the edges retaining the great majority of weights based on the XIFA;

Step 3: Merge the edges of Step 1 and 2 and add their adjacent nodes.

To illustrate this mixed strategy, Fig. 10.3a shows a five-node directed and weighted network with self-loops, in which the larger the edge weight, the closer the asymmetric interactions. When conducting the SP method, we search globally for key chains seeing both the efficiency and effectiveness. An edge will be preserved if it happens to be located on the most direct path between two nodes and the strongest relevance path as well (see Fig. 10.3b). The FE method, from the perspective of local information, retains the pivotal links that play an important role in the adjacent edges of each node, by examining them in two ways according to the XIFA (see Fig. 10.3c). In this case, the mixed strategy increases another two edges on the basis of the FE-based backbone (see Fig. 10.3d). In conclusion, the SPFE method incorporates the theoretical advantages from SP and FE methods and can hence address the Q2 simultaneously.

10.4 Results and Discussions

To compare the effect of network pruning horizontally, we take four sorts of GIVCN models based on the ICIO databases of latest version for example, which are GIVCN-WIOD2016SC4-2014, GIVCN-TiVA2018SC4-2014, GIVCN-Eora26SC4-2014 and GIVCN-ADB2019SC4-2014, and statistics for the structural properties of full networks include ***Number of Edges*** $|E|$, ***Average Distance*** d, ***Mean Node Degree*** K, ***Clustering Coefficient*** C and the ***Degree-Degree Correlation*** from out-degree source nodes to in-degree sink ones $r(out, in)$ are shown in Table 10.2.

Table 10.2 Illustration of Properties of the Original Networks

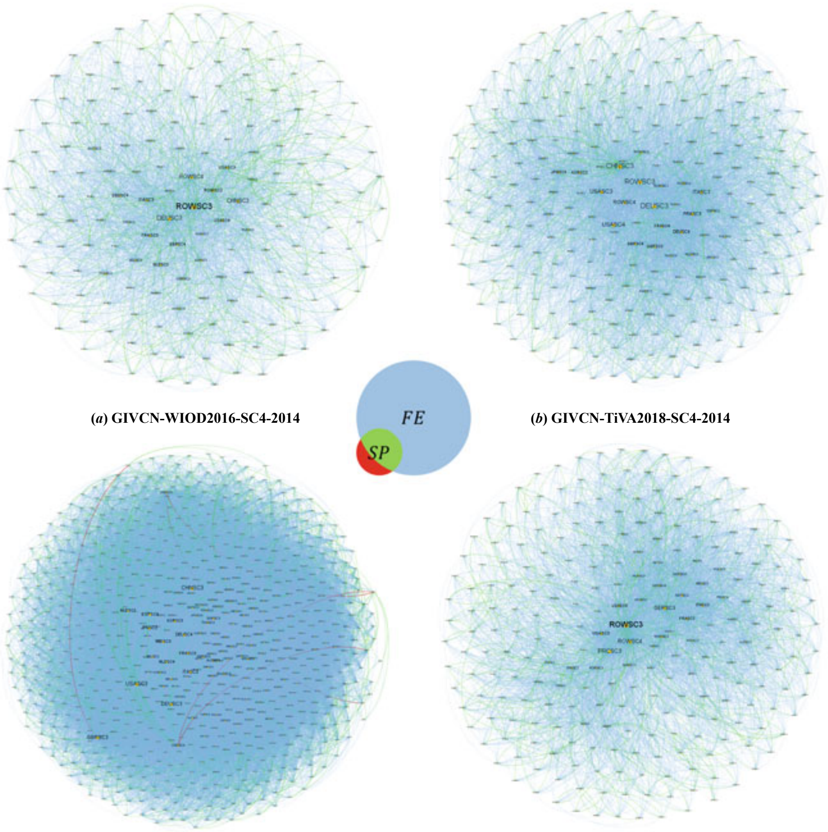
GIVCN of 2014	|E|	⟨d⟩	⟨K⟩	⟨C⟩	r(out, in)
WIOD2016SC4	30,795 (30,976)	1.006 (1.000)	174.972 (176.000)	1.000 (1.000)	-0.002 (0.000)
TiVA2018SC4	66,600 (67,600)	1.007 (1.000)	257.143 (260.000)	0.996 (1.000)	-0.003 (0.000)
Eora26SC4	571,536 (571,536)	1.000 (1.000)	756.000 (756.000)	1.000 (1.000)	0.000 (0.000)
ADB2019SC4	57,761 (63,504)	1.069 (1.000)	231.972 (252.000)	0.971 (1.000)	-0.067 (0.000)

By comparing with the theoretical boundaries marked in brackets, it is not difficult to find that no matter which ICIO database is used as the data source, the GIVCN model is almost a complete connected graph. Obviously, they are too dense to conduct social network and statistical physics analysis, and hence needed to be pruned.

10.4.1 Preservation of Structural Information

Based on the SPFE method, we extract a specific subnetwork and name it the GIVCN-SPFE model. Despite it still looks more like a ball of yarn (see Fig. 10.4), it is possible to analyze the heterogeneous characteristics of global production system based on the simplified topological structure. Given that E_{SP} and E_{FE} are the edge sets of GIVCN-SP model and GIVCN-FE model, respectively, that of the whole one will be $E_{SPFE} = E_{FE} \cup E_{SP}$. We use three sorts of colored lines to differentiate which model the links come from, and Fig. 10.4 shows that GIVCN-SP-2014 model is completely contained in GIVCN-FE-2014 model in most cases. As an exception, GIVCN-Eora26SC4-SPFE-2014 has six edges that only belong to GIVCN- Eora26SC4-SP-2014, which is because the included countries increase the heterogeneity of edge weight. After all, there are always some puny industry sectors or industrial linkages that exist independently, but it is difficult to capture them from the perspective of weight.

Three backbone extraction methods are applied to GIVCN models together with the simplest GT method and the classical DF method. The former is to remove all edges with weight below a certain global threshold and the latter uses the weight fluctuations for each node to identify the edges to be preserved. Take GIVCN-Eora26SC4-2014 as an example, in the GT method, the minimum threshold is one ten-thousandth of the maximum edge weight, which is equal to 9.728E+05, and the second smallest one is 1.946E+06, and so on. Then, each threshold is selected in order from small to large to conduct network pruning. In other words, the parameters in the GT method can be regarded as specific removal rules. DF method computes the probability $p_{ij=\left(1-w_{ij}/s_i\right)^{k_i-1}}$ that such a value is compatible with the null model: if $p_{ij} < \alpha$, where α is a parameter representing the desired significance level, the edge



(a) GIVCN-WIOD2016-SC4-2014

(b) GIVCN-TiVA2018-SC4-2014

(c) GIVCN-Eora26-SC4-2014

(d) GIVCN-ADB2019-SC4-2014

Fig. 10.4 MDS of GIVCN-SPFE-2014 models. *Notes* E_G denoted by the green line is the intersection of E_{SP} and E_{FE}, i.e., $E_G = E_{FE} \cap E_{SP}$; E_B denoted by the blue line is the edge set only belonging to E_{FE} but not E_{SP}, i.e., $E_B = E_{FE} - E_G$; E_R denoted by the red line, contrary to E_G, is the edge set only belonging to E_{SP} but not E_{FE}, i.e., $E_R = E_{SP} - E_G$

is preserved, otherwise it is removed. Lower values of α lead to sparser networks, as fewer edges are preserved. Although an edge is connected to two nodes, its direction determines there exists only one value for p_{ij}, that is, based on the out-degree and out-strength of the source node.

Table 10.3 reports the structural similarity of different backbone networks in terms of the percentage of non-isolated nodes ($N_t\%$) and their ***Quadratic Assignment Procedure (QAP)*** correlation with the original network, where the QAP is an often-used approach to measuring the extent to which two networks are correlated or have a similar pattern of connections. According to the results, the QAP correlations of the five algorithms (all P value < 0.001) are extremely high, that is, they can all maintain

Table 10.3 Structural Similarity of various backbones and original network

GIVCN of 2014	$\mathbf{N_t}$ **%** (no self-loops)					QAP				
	GT	DF	SP	FE	SPFE	GT	DF	SP	FE	SPFE
WIOD2016SC4	88.068	100.000	100.000	100.000	100.000	1.000	0.998	0.994	1.000	1.000
TiVA2018SC4	91.539	99.615	99.615	99.615	99.615	1.000	0.991	0.996	1.000	1.000
Eora26SC4	65.079	100.000	100.000	100.000	100.000	1.000	1.000	0.999	1.000	1.000
ADB2019SC4	77.778	98.413	98.810	98.810	98.810	1.000	0.998	0.996	1.000	1.000

a high similarity with the original network in the overall structure level. Except for GT, other methods can better protect the bridges in the network and hardly make nodes become isolated.

10.4.2 Preservation of Functional Information

The number of residual edges is recorded in the new network and the percentage of the residual edge weights for the original network are shown in the Fig. 10.5. In the network extracted at the global threshold of 9.728E+05 (one ten-thousandth of the maximum edge weight), the number of edges quickly decreases from 571,536 to 2779 and the decline rate reaches 99.510%, while the total edge weight of the network decreases by only 3.370%. Obviously, setting thresholds is acceptable if following the principle of "significantly reducing the number of edges while retaining most of the total edge weight". The edge filtering procedure retains more edges than setting global thresholds, and the proportion of residual edge-weights of the former with $\alpha \geq 0.3$ or $\alpha \leq 0.1$ is higher or lower than the latter. Simplifying the GIVCN model

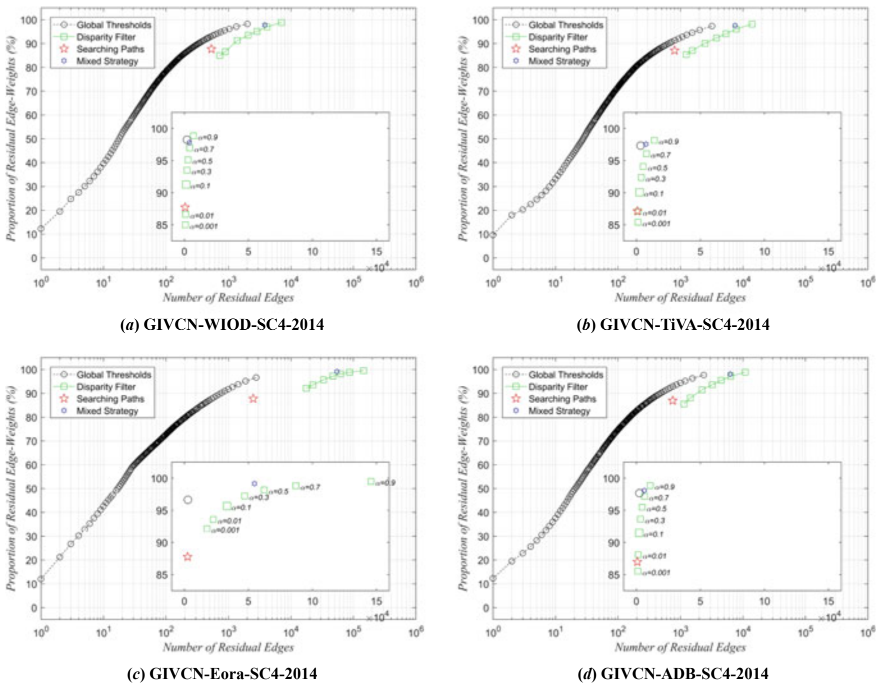


Fig. 10.5 Comparative results of network pruning algorithms in GIVCN models. *Notes* Since the pruning results of SPFE and FE method are almost the same in our models, the FE method is not shown in the figure

by the SP is lower in efficiency than GT even at the level of one ten-thousandth of the maximum edge weight. For instance, in GIVCN-SP model, the proportion of residual edge weights is only 87.758% while the number of residual edges is 2496 which is slightly less than the latter's 2779 in the same conditions. However, with the addition of FE method, GIVCN-SPFE model can retain the weight to the maximum extent, almost reaching 99.154%.

Moreover, we propose the ***Average Edge Weight*** (***AEW***) to measure the weight information included by unit edge:

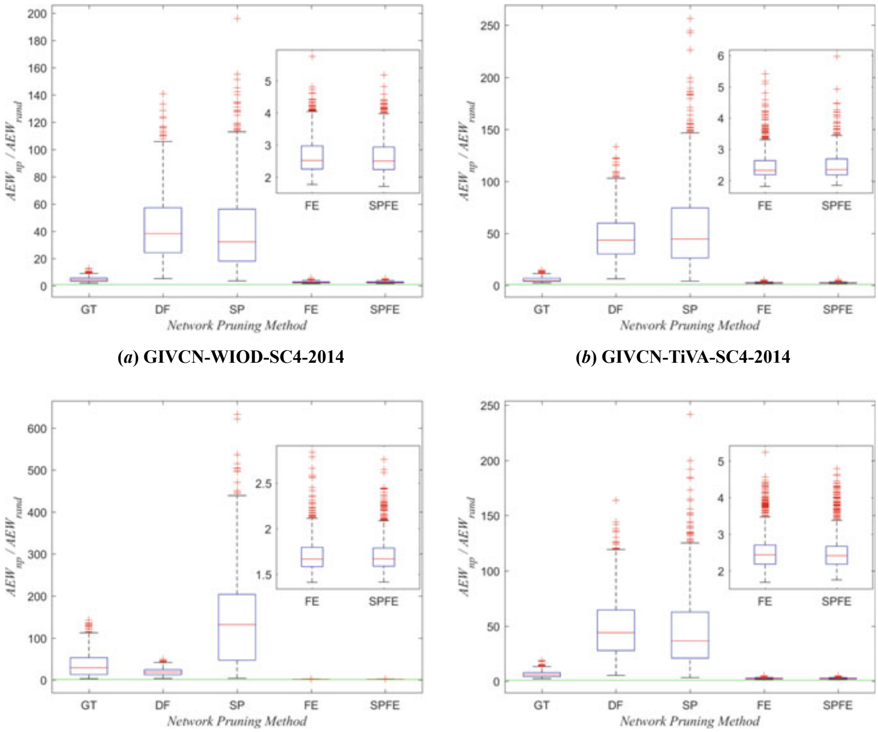
$$AEW = \frac{\sum_{(i,j)\in E} w_{(i,j)}}{|E|} \tag{10.2}$$

where $|E|$ is the number of edges in E and $w_{(i,j)}$ is the weight of edge (i, j). Moreover, given that AEW_{np} represents the average edge weight of the backbones which extracted by pruning methods and AEW_{rand} is the result obtained in a null model where the edges with the same proportion as skeleton networks are randomly removed, then the ratio of them, $AEW_{ratio} = AEW_{np}/AEW_{rand}$, is of great significance to evaluate a specific method's efficiency. Deviations of AEW_{ratio} above or below 1 demonstrate positive or negative pruning result, respectively.

A thousand times comparisons between each method and null model are shown by boxplot graph in Fig. 10.6. Although all of them precede their null models, the SP method as the best and the most consistent one manifests it catches a small number of critical paths but with extremely high edge weights. In conclusion, among the two parameterless methods, the global SP method can preserve the structural integrity of the network well, but the entire robustness and local function of network are inevitably influenced since it yields so few links. FE method can basically embrace SP and supplement more weight information, and thus has more significance in extracting the backbone of ICIO network.

10.5 Summary

Backbone extraction is an adequate tool for studying large networks, which allows for quickly distilling key topological and spatial features. Different from previous works, we consider the economic implication of edge weights in ICIO networks when proposing the new algorithms. The SP algorithm measures the strength of relations across or within sectors from the global perspective of IVC, retaining the links with closer IO relations and lower transaction cost. By combining H-index and Pareto rule, the FE algorithm makes the filtering process at the node local level converge naturally without depending on parameters. Through comparison between the two and existing methods, it is proved that SP algorithm is already an efficient and effective tool, which can not only keep the structural similarity with the original network on the whole level, but also ensure that retained unit edge carry enough information. However,



(*a*) GIVCN-WIOD-SC4-2014

(*b*) GIVCN-TiVA-SC4-2014

(*c*) GIVCN-Eora-SC4-2014

(*d*) GIVCN-ADB-SC4-2014

Fig. 10.6 Ratio of AEW of pruning methods and null model

high-efficiency redundancy removal makes it tortuous to reach some marginal nodes inevitably. The FE algorithm covers the results of SP, while retaining higher weight on the premise of the number of remaining edges is close to other methods, being the best solution for ICIO networks. In the future, the applicability of the algorithm to other dense weighted and directed networks will be explored for generalization.

In addition, the two special network pruning algorithms are useful to explore more possibilities for the study of highly dense and heterogeneously weighted networks, such as information networks, communication networks, citation networks, social media networks, etc. Also, except for visualization and network topology analysis, the obtained sparse network backbone will promote the relevant analyses in terms of community detection, link prediction, spatial econometrics, network embedding edge2eve, etc.

In the left two chapters of Part IV, we will identify the worldwide industrial transfer pattern based on the GIVCN-SP model and depict the nested structure of production system based on the GIVCN-FE model.

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Chapter 11
Identify the Worldwide Industrial Transfer Pattern

11.1 Introduction

Industrial transfer refers to the phenomenon that in market economy, some enterprises in developed regions adapt to the changes in regional comparative advantages and then relocate part of their manufacturing capacity to the developing regions through cross-regional direct investment, resulting in the shift of the spatial distribution of industrial sectors on the GVC from developed regions to developing regions. Let's take the global manufacturing sectors as an example. From the first industrial revolution to the present, three waves of industrial transfers have taken place, each reshaping the global economic layout. The first industrial transfer was in the early twentieth century when the United Kingdom transferred "excessive industries" to the United States, which now turns into the most powerful country in the world. The second wave occurred in the 1950s. The United States' traditional industries, such as textiles and iron and steel industry were relocated to the defeated countries in world War II—Japan and Germany, who then transferred low-value labor-intensive industries to Taiwan, Hong Kong, South Korea, and Singapore, now known as the Four Asian Tigers. The third wave started with China' reform and opening up in the 1980s. At that time, China, as the core of the third industrial transfer, became the destination of various industries from developed countries.

Deriving from theories considering macroscopic factors, including the ***Echelon Theory***, ***Product Life Cycle Theory***, ***Marginal Industry Expansion***, and classical theories like ***Mode Analysis***, the industrial transfer theory transforms from the ***OLI Paradigm*** (OLI stands for Ownership, Location, and Internalization) to microanalysis on transfer effect. Generally speaking, this theory can be classified into three schools: Neoclassical School, Behavioral School, and Institutional School.

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11.1.1 Neoclassical School

On the assumption of perfect competition, perfect rationality, and complete information without considering transfer costs, the neoclassical school, with marginal analysis as a method, considers the root of industrial transfer to be the discrepancy of marginal income in different regions, which will not be affected by factors like natural endowment, market, and traffic [1]. Worthy of note is the school's representative theory—***New Economic Geography***. This theoretical system takes the transaction cost, labor cost, labor intensity, the elastic of substitution, industrial relationship, and knowledge linkages into consideration [2]. The neoclassical school, however, only studies the impacts of regional factors on the industrial transfer from the view of macroeconomics and neglects the factors from industries and enterprises themselves [3]. Especially, its non-discriminatory assumption will undermine the objectivity and scientificity of relevant results [4].

11.1.2 Behavioral School

The behavioral school [5] introduced the ***Location Theory*** into the ***Enterprise Behavior Theory*** [6, 7], and worked on a more general assumption of incomplete information and limited rationality, thus proposing the principle of satisfaction of industrial transfer. In this case, the industrial transfer will be bound by the inertia of industrial development, and its targets will be shifted from being profit-oriented to result-oriented. The behavior school thinks that industrial transfer arises from inside the industries or the enterprises. With case study, statistical analysis, investigation, virtual simulation as research methods, it believes that decision-making about whether an enterprise will transfer from one country to another is determined by itself, especially its ability of tackling with uncertainties [8, 9].

11.1.3 Institutional School

Built on the conclusions of the abovementioned two schools, the institutional school believes that industrial transfer is not only influenced by location factors and internal factors but also constrained by social culture and institutions. Affected by new economic sociology terms like "Embeddedness" and "Network Analysis", some scholars believe that industrial transfer should be regarded as a result of specific social environment and institutions in which the enterprises are embedded [10], rather than that of profit orientation and market equilibrium.

Although opinions vary among different institutional schools [11], they share the common view that industrial transfer results from the equilibrium of essential production factors reached by enterprises and different regions [12]. This equilibrium reflects the nature of dynamic evolution of industrial sectors in the mechanism of "Path Dependence" and "Lock-In Effect", which is an inevitable result of social regulation and control as the GVC, RVCs, and NVCs keep development [13].

11.2 Methodology

11.2.1 Econometric Model in Industrial Economics

In recent years, relevant studies can be divided into two categories. One is to focus on the benefit analysis of industrial transfer, studying positive effects like the industrial structural interaction upgrade, technology spillover and efficiency, and negative effects like industrial hollowing-out, technology dependence, pollution transfer, etc. The other is to research the modes of industrial transfer, such as horizontal and vertical integration, gradient transfer and reverse gradient transfer, industrial transfer network, etc. These studies have covered the concept, motivation, mode, effect, strategy, and policymaking, but few systematically pay attention to the mechanism and path of industrial transfer. The three mainstream schools base their research methods on the data structure [14]—***Discrete Choice Model*** and ***Count Model*** are mainly adopted for the data from enterprises, ***Concentration Ratio Model*** and ***IRIO Model*** for the data from industrial sectors, and ***ICIO/MRIO Model*** upgrading the research perspective from the industrial or regional scale to the global scale.

We summarize four theoretical frameworks as follows:

(1) **Discrete Choice Model and Count Model**

Industrial transfer, as a small probability event occurred in the production and operation of enterprises, is characterized by discretely distributed data, which are not in conformity with normal distribution or homogeneity of variance. Hence, it should be studied with the discrete choice model and count model, instead of the traditional multiple linear regression method [15]. Discrete choice model, represented by the ***Logit Model*** (a type of probabilistic statistical classification model), is used to deal with the results of enterprises' location decisions and study the impact of spatial factors on the location decision. However, it is difficult to solve the likelihood function with excessive explanatory variables [16], and the results would be affected by the model's preference randomness, as well as the linear correlation between factors and irrelevant non-observable factors [17]. The count model, represented by the ***Poisson Model***, is used to analyze the influence of location factors, firm characteristics, policies, etc., and the results would be, however, affected by its assumption on the equality of sample mean and variance.

(2) **Concentration Ratio Model**

Concentration ratio model judges the state of industrial transfer by calculating the industrial share or concentration ratio, and solve its difference from the time series, with gross industrial production, industrial value-added and the total number of employees [18].

(3) **IRIO Model**

IRIO model analyzes the IO data between regions and builds the ***Gravity Model*** to estimate the inter-regional trade volume. It holds this review that the industrial transfer usually occurs when the net outputs of regional industrial sectors increase [19]. But this model assumes that other industries or relevant industries in other regions remain unchanged, limiting the result to the emergence of absolute transfer. Therefore, this model can hardly work when the relative transfer or the intra-industry autocorrelation appears.

(4) **ICIO/MRIO Model**

ICIO/MRIO model is good at depicting the process of inter-country industrial transfer since the industry-level linkages incorporate all the possibilities of where value stream goes. For instance, Gao et al. proposed an accounting method for tracking the flow of value during the process of industrial transfer based on the IOA framework [20]. But this model assumes that other industries or related industries in other regions remain unchanged, limiting the result to the emergence of absolute transfer. However, there are currently few empirical studies in this area, and the lag in the release of ICIO/MRIO data also limits the timeliness.

11.2.2 Link Prediction in Complex Networks

With the development of science and technology, as well as the improvement of the industry classification, inter-industry connections are becoming more and more complex and close. Some characteristics of the global production system are thus needed to be studies by examining the detailed inter-sectoral IO relations, in order to avoid the adverse effect on the industrial transfer mechanism relying on separately studying one industrial sector after another. The complex network theory is the most effective of all research tools for the global production system with high nonlinearity.

In recent years, link prediction, as an analytical tool for complex networks, has become an important method in the research of network evolution. It predicts the possibility of the connection between the two nodes with the information about the already known topological structure of network, including the unknown links in the static network and the forthcoming links in the dynamic network [21].

Link prediction is a method of data mining from the field of computer science. Early studies mainly focused on network link prediction and path analysis based on node attributes, Markov chains, and machine learning. For example, Zhu, et al. used Markov chain prediction methods to help the Internet users to navigate online [22]; Popescuul and Ungar used the scientific literature to refer to the author's information, the periodical information as well as the content of the article [23]; Madadhain'O et al. used the node attributes to establish the conditional probability forecast model for the local area of the network [24].

Link prediction methods based on the node attributes are effective but difficult to implement, because it is difficult to collect such kind of information in the actual network, especially the large-scale networks. As a compromise, more easily available and more reliable network structure can be used as the basis for prediction. In recent years, link prediction methods based on network structure have become the reliable alternative. For example, Liben-Nowell and Kleinberg proposed the similarity algorithm based on the network topology and analyzed the effect of link prediction from node similarity and path similarity [25]; according to the structural similarity index of local information, Zhou et al. analyzed the link prediction accuracy of the real network and put forward resource allocation index with higher accuracy and local path index [26]; Guimera and Sales-Pardo used stochastic block model to predict the missing edge of the network and then identifies the error link, and unprecedentedly put forward the concept of "Spurious Links" [27]. In addition, some of the more complex physical processes are used to estimate the likelihood of the existence of edges between nodes, such as the local random walk, which further improve the accuracy of link prediction.

More importantly, no matter GVC or RVC is evolving all the time. Described by a complex network model, the so-called industrial transfer can be reduced into network evolution. As we often observed, some new nodes appear in the network, new links between nodes are built, or the weights on the original links have changed, all of which can be used to explain the changes in the industrial layout. That is why we say it with confidence that, revealing the mechanism of network evolution from the perspective of econophysics can solve the problems of industrial transfer, thus better applying complex network theory to the study of industrial economics. In sum, studies on the worldwide industrial transfer pattern based on link prediction theory are at the leading edge.

11.3 Framework

11.3.1 GISRN Model

In this chapter, there is an important premise lying ahead of link prediction. That is, the GIVCN model is too dense to embody the main topological structure of an economic system, which means useful forecasting results with existing methods are unavailable. No matter how we plan to do, the first mission is to prune the network.

Since the GIVCN-SP model proposed in Sect. 10.3.1 has retained the crucial linkages between industrial sectors, we name it as the ***Global Industrial Strongest Relevant Network (GISRN)*** model and use it to better understand and find the worldwide industrial transfer pattern. In addition, the self-loops, standing for the intra-industry consumption, become useless to predict the inter-industry relations. Relevant analyses will, therefore, be carried out in the binary GISRN models.

On the one hand, in Sect. 11.4, three network-level indicators are adopted to reveal the evolutionary characteristics of GVC backbone. And we choose the ICIO tables in WIOD2016 as the modeling data since it is rooted in official statistics.

On the other hand, in Sect. 11.5 we establish an analytical framework based on link prediction to observe the evolutionary mechanism of globalization. For this purpose, we choose the ICIO tables in Eora26 as the modeling data since it covers the largest number of countries/regions and the longest period among all the ICIO databases.

11.3.2 Training and Evaluation Metrics

Consider an undirected graph $G = (V, E)$, V is node set and E is edge set while multiple links and self-loops are not allowed. Also, the universal set, denoted by U, contains $|V| \times (|V| - 1)/2$ possible edges, where $|V|$ is the number of edges in set V In order to test the accuracy of algorithms, the known edge set E is generally divided into two parts: the training set E^T and the test set E^P When calculating certain score value, we can only use the information of the training set. By definition, $E = E^T \cup E^P$ and $E^T \cap E^P = \emptyset$ Here, we name the edges which belong to U but not E as non-existing edges (form the edge set E^N and those belong to U but not E^T as unknown edges (form the edge set E^U).

As shown in Fig. 11.1a, a complete network contains 13 nodes and 19 edges. The universal set includes 78 edges, so 59 edges do not exist. Select 4 of the 19 known edges as E^P as shown by dashed lines in Fig. 11.1b, and the rest of the 15 will constitute a E^T Given a certain prediction algorithm, it will give valuations to 63 edges in E^U including 4 test edges and 59 non-existing edges. Then the 63 edges will be sorted in accordance with the score value in descending order. If taking more

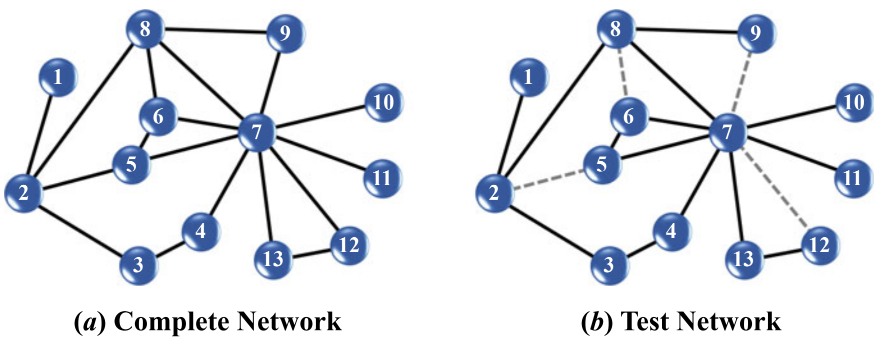


Fig. 11.1 Sketch map of network link prediction. *Notes* In the test network, the dotted lines represent the test set, and the rest the training set

test sides (4 in total) in the front of the non-existing edges (59 in total), it means we have achieved higher prediction accuracy with this algorithm.

For a given network, to test and compare the performance of algorithms, we need to select one part from the known data as the test set. Division methods of E^T and E^P are in different kinds, including random sampling, itemized traversal, K-fold cross-validation, rolling snowball sampling, acquaintances sampling, random walk sampling, sampling based on path, etc. One of the most common methods is random sampling. Given network G, containing n nodes, m edges, if the edges with the ratio $p(p \in (0, 1))$ are needed to be assigned to the test set, the random sampling method will select pM edges randomly from E to form E^{P} This method ensures that the probability of each edge being selected into E^{P} is the same. Sometimes, we must give some necessary constraints, such as to ensure the connectivity of the network after being sampling, during which the nature of the sample space will become very complex.

11.3.3 Link Prediction Indices

An important prerequisite of link prediction by using the similarity of nodes is that the more similar the nodes are, the more possibly will they have links between each other. There are many ways to describe the similarity of the nodes, among which the simplest and most direct one is to use the attributes of nodes—that is, the nodes in the network with similar attributes are more likely to be connected. Although node attributes and external information lead to satisfying predictive effect, the information is not easily accessible in most cases, and even if the node attribute information is available, its reliability can not be guaranteed. Besides, how to identify information useful to the network link prediction remains unsolved. Compared with the node attribute information, the information of the network structure or users' past behaviors is more accessible and accountable. The similarity defined based on the structural information of the network is called structural similarity. The accuracy of link prediction based on structural similarity is determined by whether the structural similarity can capture the structural features of the targeted network. We selected from three types of existing structural similarity indices and used those that fit binary GISRN model's features to carry out the link prediction.

(1) **Similarity Index Based on Local Information**

The similarity index based on local information can be calculated according to certain features of node and its surrounding ones. The advantage of this index is low computational complexity, which is suitable for large scale network applications. But because of its limited information, the prediction accuracy is slightly lower than the global index.

Common Neighbors

The simplest similarity index based on local information is the ***Common Neighbors (CN)*** index. *CN* similarity, or Structural Equivalence, refers to the condition that two similar nodes have a lot of common neighbors. The structural equivalence concerns whether the two nodes are in the same environment. The basic assumption of the application of *CN* in the link prediction is that two of the non-connected nodes tend to be connected if they have a lot of common neighbors. *CN* index is defined as: for the nodes i in the network, its neighbor set is $\Gamma(i)$, and then the similarity of nodes i and j will be defined as the number of their common neighbors. That is:

$$S_{ij} = |\Gamma(i) \cap \Gamma(j)| \tag{11.1}$$

where the right side of the equation represents the potency of set. Obviously, the number of their common neighbors is equal to the number of two-order paths between nodes i and j which is $S_{ij} = \left(A^2\right)_{ij}$

Adamic-Adar

If we consider the information about the degree of two nodes' common neighbors, the ***Adamic-Adar (AA)*** index will be a good choice. The idea of *AA* index is: the common neighbor nodes with a small degree will contribute more than those with a larger degree. That is to say, if two nodes are both linked with nodes of large degree, instead of believing in high probability that there is a link between the two, we'd better conclude that they are more likely to be connected with each other when they are both linked with a node of small degree. *AA* index gives, according to the degree of the *CN* nodes, each node a weight, which is equal to the reciprocal of the log of the node's degree. In this manner, the *AA* index is defined as:

$$S_{ij} = \sum_{k \in |\Gamma(i) \cap \Gamma(j)|} \frac{1}{\log K(k)} \tag{11.2}$$

Resource Allocation

The definition of ***Resource Allocation (RA)*** index is that, given that there is no directly connected nodes i and j in the network, some resources can be allocated from node i to j during which their common neighbors will become the transmission medium. If each medium has a unit of resources and allocates them to its neighbors, the number of resources accessible to node j can be defined as the similarity between nodes i and j i.e.:

$$S_{ij} = \sum_{k \in |\Gamma(i) \cap \Gamma(j)|} \frac{1}{K(k)} \tag{11.3}$$

The difference between the *RA* index and the *AA* index is how the weights of adjacent nodes are attached. *RA* index declines in the form of $1/K$, and *AA* index declines in the form of $1/\log K$. The variance of the two will not exist when the average degree of network is small but will emerge when the average degree is large.

Preferential Attachment

The scale-free network structure can be generated with the method of ***Preferential Attachment (PA)***, in which the probability of a new edge connected to a node i is proportional to $K(i)$. This mechanism has also been applied to the network without consideration of growth, for instance, a link is removed at the first step, with another link added. The probability of the new edge connecting nodes i and j is directly proportional to the product of the degree of two nodes. From this, we can define the *PA* index as:

$$S_{ij} = K(i)K(j) \tag{11.4}$$

(2) **Similarity Index Based on Path**

Considering the potential influence of the three-order path range based on *CN* index, we can define the similarity index based on ***Local Path (LP)*** as:

$$S = A^2 + \alpha A^3 \tag{11.5}$$

where α is an adjustable parameter, A represents the adjacency matrix of the network, and $\left(A^3\right)_{ij}$ represents the number of paths whose length between nodes i and j is 3. When $\alpha = 0$, the *LP* index will be degraded to *CN* index. In other words, *CN* index can be regarded as an index based on the path in nature, but it only considers the number of two-order paths. *LP* index can be extended to cases of higher-order, i.e. the case of n-order:

$$S^n = A^2 + \alpha \cdot A^3 + \alpha^2 \cdot A^4 + \cdots + \alpha^{n-2} \cdot A^n \tag{11.6}$$

As n increases, the computational complexity of the *LP* index will be increasing. In general, the computational complexity of n-order path is $O(NK^n)$. But when $n \to \infty$, the *LP* index is equivalent to the *Katz* index concerning all the paths of the network.

(3) **Similarity Index Based on Random Walk**

Many kinds of similarity indices are defined based on the random walk process, including ***Average Commute Time (ACT)***, ***Cos +*** , ***Random Walk with Restart***, ***SimRank***, etc. Considering the binary GISRN-Eora26 model is a small-scale network, the *ACT* index is selected as the representative of this sort of index.

Average Commute Time

From the view of the whole network, the Mean First Passage Time (MFPT), denoted by $E(i, j)$, is the expected number of steps when a random walk starts at source node

i needs to reach sink node j for the first time, see Eq. (5.2) in Sect. 5.3.1. Then the *ACT* between nodes i and j is:

$$n(i,j) = E(i,j) + E(j,i) \tag{11.7}$$

The smaller the *ACT* of the two nodes is, the closer the two nodes will be. Then we can define the similarity based on the *ACT*:

$$S_{ij} = \frac{1}{E(i,j) + E(j,i)} \tag{11.8}$$

In directed but unweighted network, $E(i,j)$ probably not equals to $E(j,i)$, which means *ACT* index depends on bidirectional MFPT.

In sum, from the performance of link prediction algorithms, we can divide the 6 indices into four categories: the first one includes the *LP* index and the *CN* index, the prediction accuracy of which are both proportional to the importance of common neighbors of given nodes, and the latter is the special case of the former (i.e. the adjustable parameter of *LP* index is zero); the second one that is based on the opposite assumption of the first one includes the *RA* index and the *AA* index, and the difference between them is that the *RA* index is more sensitive to the heterogeneity of network and thus prior to the *AA* index in the case of higher average degree centrality; the third one is the *ACT* index, which measures the distance of inter-node information transfer path from two directions; the fourth category is the *PA* index, which is correlated to certain importance of the nodes themselves, not to the path between them.

According to the law of gravity, we can further explain the econophysics significance of the *ACT* index and the *PA* index. The former only relates to the inter-node distance (the expected number of steps) is a concept in the sense of probability during the random walk, which is probably not equal in the forward and backward directions. Therefore, the premise of *ACT* index is that inter-industry closeness is inversely proportional to their integrated round-trip distance on the GVC. The latter, on the other hand, ignores the influence of distance and is only related to certain importance of a node (just like the mass of matter), which means the bigger the local influence of two industrial sectors, the closer the relationship between them. In other words, they respectively concern about the denominator and numerator of the formula for gravity, and their econophysics hypothesis are as follow: the influence of industrial sector in the backbone network of GVC can promote industrial transfer, and the length of inter-industry IVC is one of the factors hindering industrial transfer.

11.3.4 Accuracy of Prediction Algorithms

The main methods to measure the accuracy of link prediction algorithms include ***Area under the Receiver Operating Characteristic Curve (AUC)***, ***Precision***, and ***Ranking Score***. They differ in their emphasis on prediction accuracy. Among them,

AUC is the most commonly used, measuring the overall accuracy. Precision only focuses on whether the prediction to the top L edges is accurate, and the ranking score has more consideration about the edges' order.

AUC refers to the area under the ***Receiver Operating Characteristic Curve (ROC)***. In the theory of signal detection, ROC is used to evaluate the classification effect of a certain classifier. This can be used to measure the accuracy of link prediction algorithms too.

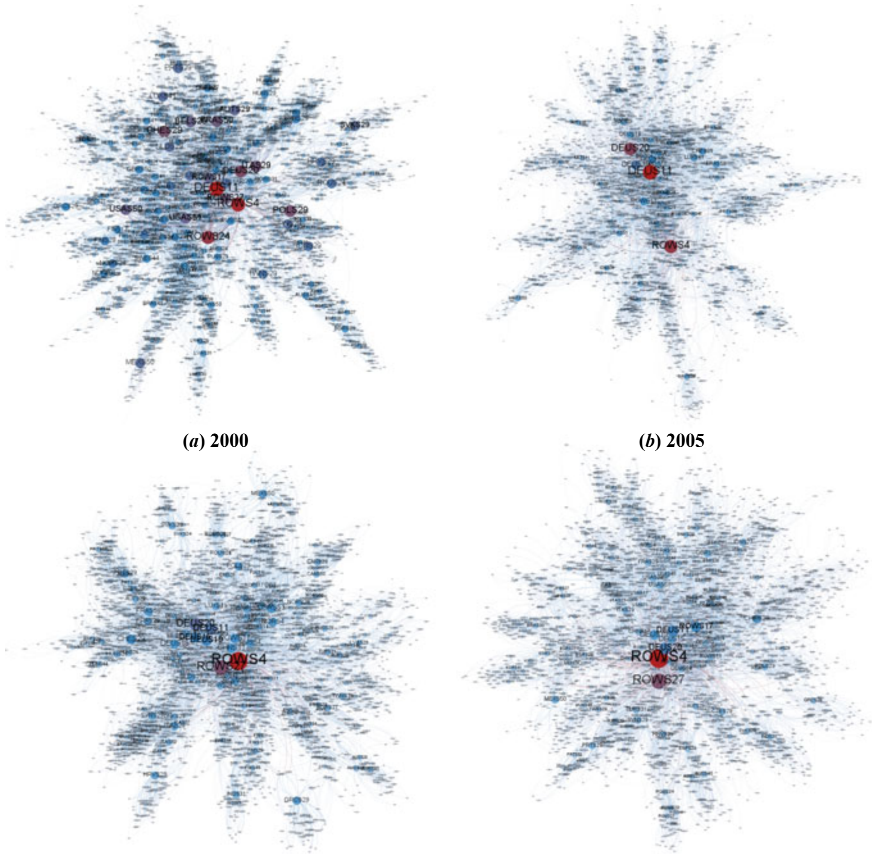
Given a prediction algorithm, for each unknown edge, we will give a value or a value which is called the probability of existence. The unknown edge can be classified into two types: one is the non-existing edge in E^N, and another is the test edge in E^P, each of which will have a distribution of values. The first distribution should be on the left side of the second one, and the farther the distance between the two distributions is, the better prediction results of the algorithm will be. The actual calculation does not need to draw a specific ROC. Especially, when the samples are excessive, the sampling comparison can be employed to get the approximate value. In fact, AUC can be regarded as a higher probability to randomly choose an edge from E^P than the from E^N, i.e., each time we choose one edge from E^P and another one from E^N. If the value of the edge from E^P is larger than that from E^N, one point will be added into the value. But if the two have equal value, 0.5 point will be added. After n times of independent comparison, if the value of the edge from E^P is larger than that from E^N for n' times, and their value equal with each other for n'' times, then AUC will be defined as:

$$AUC = \frac{n' + 0.5n''}{n} \tag{11.9}$$

If all the values are randomly generated, $AUC \approx 0.5$, so the degree of AUC larger than 0.5 indicates to what extent the algorithm is more accurate than the random sampling. AUC in form is equal to Mann–Whitney U statistical test and Wilcoxon rank-sum test, and its whole process is just like the Bernoulli experiment.

11.4 Empirical Analysis I: Evolutionary Characteristics of Globalization

In this section, we adopt three network-level indicators to reveal the evolutionary characteristics of GVC backbone. The topological structure of binary GISRN-WIOD2016 models, which contains 2464 industrial sectors in 44 countries/regions, is as shown in Fig. 11.2.



(*a*) **2000** (*b*) **2005**

(*c*) **2010** (*d*) **2014**

Fig. 11.2 Binary GISRN-WIOD2016 models

11.4.1 Density of GVC Backbone

Network Density, referred to as *ND*, reflects the overall cohesion level of a network and the closeness various nodes associated with each other, and is defined as the ratio of the actual number of edges in the network to the potentially maximum number of edges. The potentially maximum number of edges a directed network may contain is equal to the total number of pairs it contains, which is, $N(N-1)$, and therefore the formula of density is:

$$ND = \frac{L}{N(N-1)} \times 100\% \tag{11.10}$$

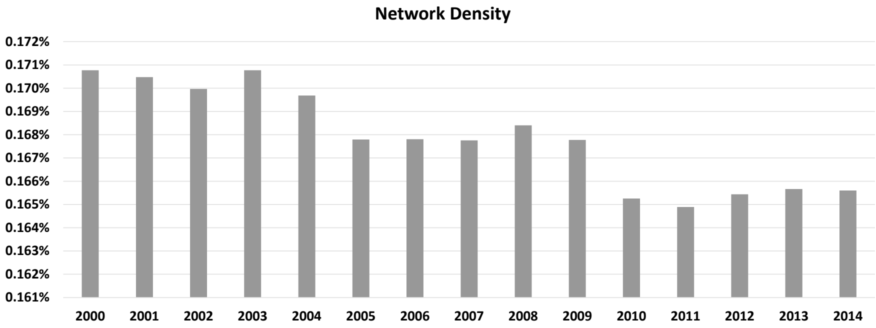


Fig. 11.3 Density of GVC backbone

where L represents the actual number of directed edges in the network. Obviously, the value range of ND is [0, 1].

In the backbone part of the GVC, the network density is in a downward trend as shown in Fig. 11.3, generally with five years as a stage. 2004–2005 and 2009–2010 are two adjustment stages, and in the latter stage, the decline rate is more significant, indicating that the U.S. subprime mortgage crisis has greatly impacted and changed the original structure of international trade. Countries and their industrial sectors will make trade choices that maximize their own interests by weighing the world economic situation, and thus reshape the topological structure of GVC. We therefore believe that the shrinkage of the GVC backbone part reflects that the optimization of global economy is essentially a protection mechanism, which allocates limited production resources to the GVC segments that can best avoid risks and create value.

11.4.2 Centralization of GVC Backbone

Degree Centralization mainly measures the dependency of the network on the hub nodes, reflecting how centralized the network is. Given that the directional edges between nodes reflect the value stream between industrial sectors, which is the micro foundation of network evolution, we use the relative central tendency of in-degree and that of out-degree as the measurements:

$$C_{RD}^{IN} = \frac{\sum_{i=1}^{N}\left(C_{RDmax}^{IN} - C_{RD}^{IN}(i)\right)}{N-2} \times 100\% \tag{11.11}$$

$$C_{RD}^{OUT} = \frac{\sum_{i=1}^{N}\left(C_{RDmax}^{OUT} - C_{RD}^{OUT}(i)\right)}{N-2} \times 100\% \tag{11.12}$$

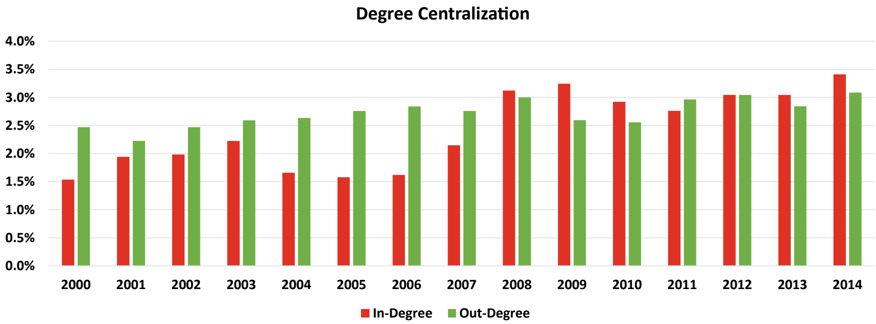


Fig. 11.4 Centralization of GVC backbone

where C_{RDmax}^{IN} and C_{RDmax}^{OUT} are the maximum values of relative degree in two directions.

C_{RD}^{IN} and C_{RD}^{OUT} quantify the breadth of the network's overall inward and outward value streams, and also reflect the industry transfer trend in the GVC backbone part. When $C_{RD}^{OUT} > C_{RD}^{IN}$, global industrial expansion is greater than industrial agglomeration, the international division of labor is further developed, and the global economy is in the stage of globalization; when $C_{RD}^{OUT} < C_{RD}^{IN}$, the situation is just the opposite: the global economy will be facing the trend of de-globalization. We compare the two in Fig. 11.4.

According to our hypothesis, before 2008, driven by the wave of globalization, GVC continuously evolved towards the direction of global economic integration. For instance, China's accession to the WTO in 2000 exert positive influences on globalization; after 2008, the U.S. Subprime Crisis has increased the resistance of many countries in trade and industrial transfer and dwarfed the international division of labor, which has led to the orientation of industrial policy in various countries changed into the adjustment and optimization of domestic industrial structures, in order to respond to the risks which may occur during the process of globalization.

11.4.3 Global Efficiency of GVC Backbone

Global Efficiency, or *GE* for short, quantitatively reflects the average efficiency of sending information between nodes in the network [28], which is introduced to measure the overall capacity of the turnover value stream of industrial sectors that form the backbone of GVC. Its definition in a directed network is the Harmonic Mean of the distance between two nodes:

$$GE = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}} \times 100\% \tag{11.13}$$

According to Eq. (11.4), when the distance between two nodes is infinite, the reciprocal will be zero, and the *GE* will always have a finite value, i.e., $0 \leq GE \leq 1$; when $GE = 0$, there are only isolated nodes in the network, without any edge in between; when $GE = 1$, all node pairs are directly connected; the larger the *GE*, the better the connectivity between the nodes, the stronger the ability of the network to spread information.

From Fig. 11.5, the *GE* in the GVC backbone part has steadily increased before 2009, gone through a sharp decline between 2009 and 2010, and then entered a recovery phase. After five years of adjustments,*GE* in 2014 finally recovered and surpassed that in 2009. The decrease in *ND*, as shown in Fig. 11.3, indicates that the number of edges in sequential networks is decreasing, and the disappearing edges may cause two situations. One is that these edges are redundant existing inside many communities, and the *GE* increases due to the downsizing scale of network, that is, inversely proportional to $N(N-1)$. On the other hand, the situation is diametrically opposite. The disappearing edges act as the bridge linking different communities in the original network, so the decrease in *ND* is also accompanied by a decrease in *GE*, because the shortest paths of the network are lengthened, making the part of $\sum_{i \neq j} \frac{1}{d_{ij}}$ smaller. We therefore believe that 2009 is a watershed for the evolution of GVC. Prior to this, the adjustment of global industrial structure and the changes in international division of labor sufficed to be proactive and positive, and the overall efficiency of the global economy was improving; for some time after the U.S. Subprime Crisis, the above-mentioned change became passive and negative, because the collapse of some industrial linkages playing the role of pivotability in the world impeded it.

All in all, globalization is a double-edged sword, and one of its negative effects is that local turbulence may spread at a faster rate. At present, the COVID-19 pandemic has caused a rapid global economic recession, in that the value stream on various segments of the GVC backbone part has been hindered or even blocked. Moreover, the impact caused by the Coronavirus Recession will be more serious and far-reaching, because it occurred simultaneously in many countries and regions around the world, being different from the Subprime Crisis just from the United States gradually affecting the world through the cascade effect.

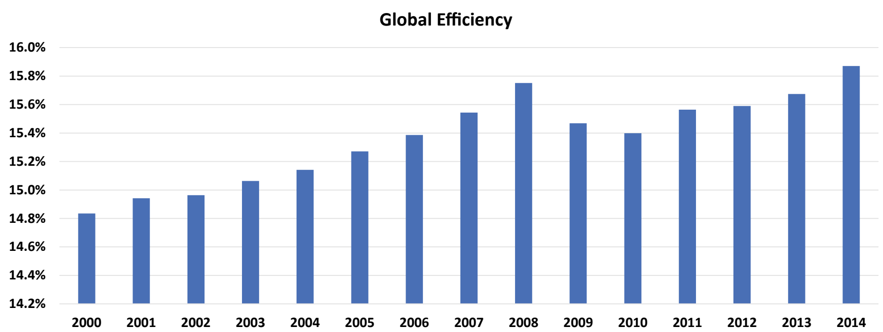


Fig. 11.5 Global efficiency of GVC backbone

11.5 Empirical Analysis II: Evolutionary Mechanism of Globalization

The topological structure of binary GISRN-Eora26-2015, which contains 4914 industrial sectors and 18,085 inter-industry IO relations in 189 countries/regions (much less than the square number of industrial sectors), is as shown in Fig. 11.6.

Although there are almost 5000 nodes in Fig. 11.6, it's easy to find that Switzerland's "Re-export & Re-import" (CHES26), China's "Recycling" (CHNS12), and the United States' "Financial Intermediation and Business Activities" (USAS21) are the top 3 sectors with the biggest node degree.

Binary GISRN-Eora26-2015 is a scale-free network according to its out-degree and in-degree distribution as shown in Figs. 11.7 and 11.8, and its average path length and clustering coefficient are respectively 5.343 and 0.511, which means it presents both strong heterogeneity and obvious small-world feature in the topological structure.

After a large-scale industrial transfer, the relationship between the relevant industry sector (whether it is transferred or not) and its neighboring ones will change significantly. For example, if Foxconn moves its iPhone assembly plant from China to India or Vietnam, all relevant multinational supply chains will also relocate, reshaping the topological structure of regional or even global economic system. In the era of globalization, the pace of industrial transfer is also accelerating, either by "going global" strategy (i.e., Xi's BRI) or by "going back" strategy (i.e., Trump's "America First" policy). In fact, despite of the various political factors, all kinds of the possibility at the economic level have long been embedded in the topological structure of GVC. Therefore, based on the Binary GISRN model, an attempt has been made to

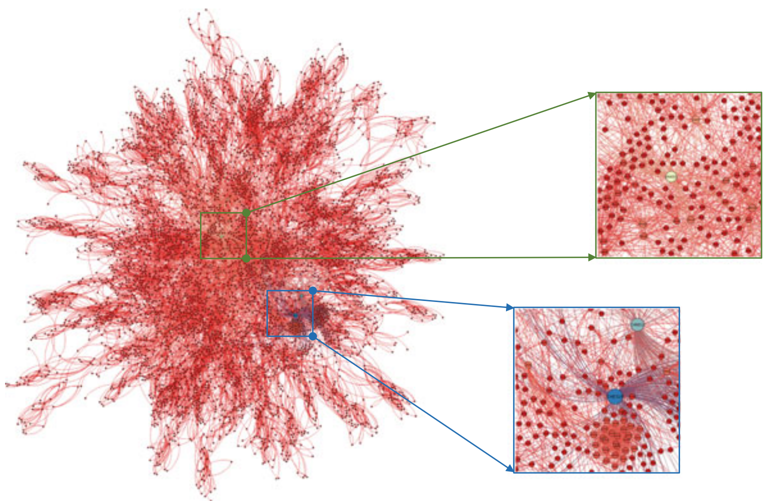


Fig. 11.6 Binary GISRN-Eora26-2015

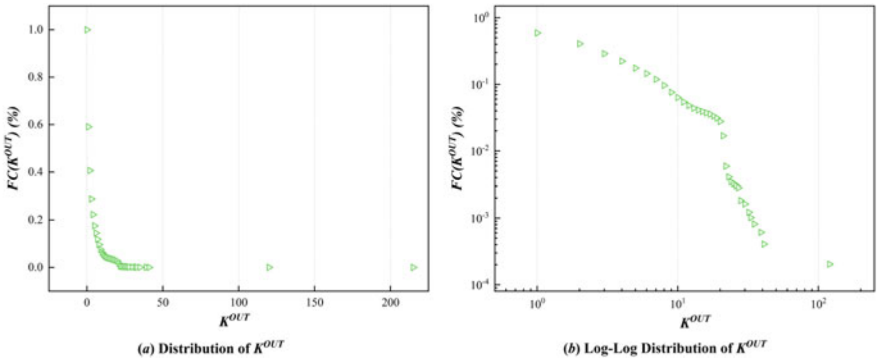


Fig. 11.7 Distribution and log–log distribution of $\mathbf{K}^{\mathbf{OUT}}$ in binary GISRN-Eora26-2015

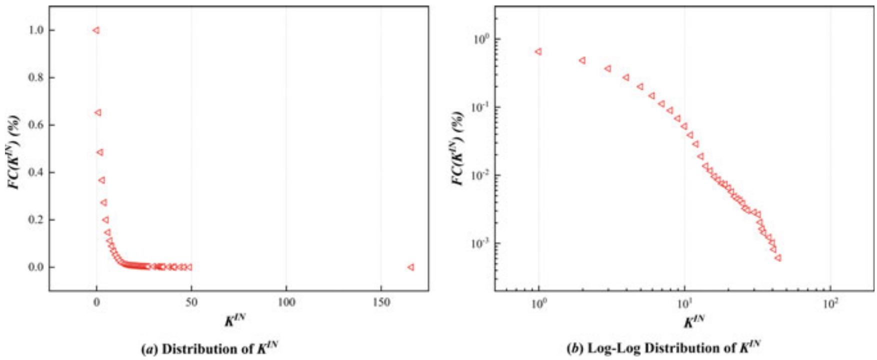


Fig. 11.8 Distribution and log–log distribution of $\mathbf{K}^{\mathbf{IN}}$ in binary GISRN-Eora26-2015

restore the dynamic mechanism of industrial transfer at the global level through the link prediction algorithms, which is also the evolutionary mechanism of GVC.

11.5.1 Overall Statistics

Considering the relative stability of the industrial structure in a short period, the proportion of E^P is set as 10%. In the simulation, the *LP* index sets the weight calculated in the second step as 0.5. That is to say, the indirect influence caused by the adjacent nodes is attenuated to 50%. During the accuracy calculation of *AUC*, the more the number of samplings, the closer the result is to the accurate value, so each algorithm sets the sampling frequency to 10,000 times in this step. Finally, the link prediction simulation results from 26 binary GISRN-Eora26 models are shown in Table 11.1.

Table 11.1 Accuracy of link prediction results in binary GISRN-Eora26 models based on similarity algorithm

Year	CN	AA	RA	PA	LP	ACT
1990	0.717	0.689	0.711	0.792	0.827	0.746
1991	0.713	0.696	0.711	0.785	0.835	0.748
1992	0.714	0.680	0.716	0.791	0.834	0.750
1993	0.731	0.688	0.715	0.781	0.829	0.752
1994	0.725	0.681	0.722	0.769	0.826	0.762
1995	0.712	0.689	0.700	0.802	0.826	0.788
1996	0.724	0.678	0.722	0.798	0.824	0.787
1997	0.707	0.687	0.706	0.783	0.821	0.796
1998	0.703	0.675	0.717	0.763	0.832	0.798
1999	0.707	0.671	0.688	0.764	0.820	0.771
2000	0.715	0.681	0.711	0.775	0.822	0.791
2001	0.711	0.674	0.707	0.769	0.826	0.784
2002	0.708	0.681	0.709	0.779	0.822	0.758
2003	0.731	0.678	0.718	0.790	0.836	0.785
2004	0.705	0.674	0.719	0.789	0.810	0.776
2005	0.708	0.684	0.693	0.775	0.816	0.760
2006	0.718	0.680	0.711	0.802	0.815	0.778
2007	0.723	0.673	0.695	0.782	0.824	0.782
2008	0.717	0.673	0.699	0.794	0.835	0.790
2009	0.709	0.696	0.722	0.794	0.830	0.775
2010	0.719	0.662	0.725	0.797	0.801	0.777
2011	0.686	0.670	0.696	0.798	0.809	0.783
2012	0.709	0.665	0.719	0.785	0.823	0.773
2013	0.725	0.692	0.736	0.796	0.818	0.798
2014	0.701	0.677	0.713	0.797	0.822	0.794
2015	0.708	0.682	0.708	0.786	0.826	0.749

In Table 11.1, the *LP* index represents the highest accuracy, and the *AA* index the lowest. From the results, it can be concluded that there is a discrepancy shown in the conditions and tendencies of industrial transfer on the GVC and within regions. In the following parts, we explicate what characteristics each index can reflect on the industrial transfer at a global level.

11.5.2 Industrial Convergence

The *LP* index, derived from the *CN* index, takes into consideration the relationship between industrial sectors and global upstream and downstream sectors, as well as direct trading with other countries. Moreover, it expands the study on industrial transfer possibility, along the value chain and the supply chain, to a broader GVC level. However, higher-order local path algorithms (for example, the *Katz* index when $n \to \infty$) do not apply to the binary GISRN model. This is because most of industrial sectors on the GVC only have strong connection to their neighboring sectors (they may be the different sectors in the same country/region, or the similar sectors in other countries/regions), and the internal relationship of the industrial sector will be compromised if the assessment of industrial transfer trends is expanded to the GVC level. This is just like predicting the distribution of sectors close to the production end through changes in close-to-market-end sectors (the retail industry), not to mention that industrial sectors in binary GISRN models spread all over the global economic system.

When the *LP* index has been calculated in the foregoing discussion, the second-order is weighted at 0.5, meaning that the indirect influence of neighboring nodes declined to 50%. To scrutinize how changing edge weight affect *AUC*, its values are calculated at a 10% weighting interval, and the results are listed in Table 11.2.

According to the results, the *LP* index is better than the *CN* index in all situations. This shows that industrial transfer on the GVC, driven by economic globalization, gradually develops toward the goal of ***Industrial Convergence***. From the perspective of the information and communication industry, industrial convergence means that the industrial boundaries blur based on technical and digital convergence. From the perspective of its causes and process, industrial convergence is regarded as a process that gradually completes technical convergence, product and business convergence, market convergence, and finally industrial convergence. From the perspective of product services and industrial organization structure, as the function of a product changes, the boundaries of the institutes or corporate organizations start to blur. From the perspective of industrial innovation and development, it refers to the dynamic development process wherein different or the same industries, based on technological and regulatory innovation, interpenetrate, interweave and in the end blend into one, gradually acquiring new industrial forms.

11.5.3 Mega-Merger Tendency

The *PA* Index, with the second-best predictive effect in binary GIRSN-Eora26 model, gives rise to a crucial economic problem: industrial production specialization on the GVC brings greater influence on some industrial sectors, and between the two, the close IO relations are more likely to be established, thus creating the so-called ***Mega-Merger Tendency*** in the global economic system.

Table 11.2 LP index precisions with different weightings in binary GISRN-Eora26 models

Year	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
1990	0.722	0.847	0.850	0.850	0.847	0.847	0.844	0.845	0.848	0.845	0.850
1991	0.705	0.826	0.832	0.828	0.830	0.822	0.823	0.828	0.826	0.829	0.828
1992	0.720	0.851	0.854	0.851	0.853	0.850	0.853	0.854	0.851	0.854	0.856
1993	0.734	0.845	0.842	0.845	0.850	0.846	0.849	0.846	0.846	0.848	0.843
1994	0.713	0.841	0.842	0.841	0.845	0.844	0.840	0.843	0.842	0.843	0.843
1995	0.717	0.831	0.831	0.822	0.832	0.826	0.826	0.828	0.827	0.826	0.826
1996	0.722	0.839	0.836	0.837	0.836	0.839	0.833	0.838	0.841	0.835	0.836
1997	0.698	0.813	0.817	0.815	0.818	0.814	0.821	0.811	0.816	0.819	0.814
1998	0.699	0.817	0.819	0.820	0.820	0.820	0.819	0.823	0.821	0.821	0.816
1999	0.706	0.819	0.819	0.817	0.818	0.816	0.816	0.816	0.820	0.818	0.818
2000	0.713	0.811	0.812	0.814	0.812	0.817	0.816	0.811	0.811	0.813	0.817
2001	0.716	0.828	0.825	0.833	0.829	0.829	0.830	0.833	0.829	0.831	0.832
2002	0.708	0.814	0.814	0.816	0.816	0.815	0.814	0.814	0.813	0.816	0.814
2003	0.717	0.836	0.835	0.830	0.834	0.835	0.837	0.832	0.838	0.832	0.832
2004	0.709	0.827	0.824	0.829	0.829	0.832	0.832	0.833	0.830	0.831	0.831
2005	0.697	0.824	0.821	0.818	0.815	0.820	0.821	0.817	0.823	0.820	0.820
2006	0.704	0.828	0.825	0.828	0.828	0.830	0.829	0.824	0.826	0.827	0.826
2007	0.691	0.820	0.821	0.825	0.823	0.822	0.825	0.819	0.822	0.823	0.819
2008	0.702	0.808	0.807	0.806	0.808	0.806	0.810	0.810	0.806	0.814	0.813
2009	0.720	0.840	0.840	0.838	0.843	0.836	0.840	0.835	0.838	0.836	0.839
2010	0.708	0.824	0.825	0.828	0.824	0.827	0.825	0.817	0.824	0.823	0.825
2011	0.710	0.812	0.816	0.815	0.817	0.821	0.815	0.819	0.815	0.816	0.813
2012	0.709	0.824	0.823	0.826	0.827	0.830	0.823	0.822	0.822	0.828	0.822
2013	0.717	0.831	0.835	0.828	0.831	0.832	0.832	0.831	0.827	0.830	0.825
2014	0.721	0.839	0.845	0.843	0.843	0.841	0.842	0.841	0.839	0.843	0.843
2015	0.700	0.823	0.825	0.819	0.822	0.821	0.823	0.820	0.817	0.821	0.820

According to Ohlin's Factor Endowment Theory, presuming that two countries are at the same technological level of making a product, the discrepancy of prices would be due to different costs which arises from different prices of production factors. Further, prices of production factors depend on a country's relative abundance of factors, referred to as the endowment differences, and the price difference that consequently follows results in international trade and international division of labor [29]. The theory assumes that factors are homogeneous, having no difference, and can be transferred. Nevertheless, factor endowments of countries/regions are different in both quantity and quality, so it is difficult to plausibly explain the emergence of strong industrial sectors in a certain region if quality differences of factors are ignored.

Nowadays, vertical specialization can be found in every country worldwide. Differences in technological and capital factors have promoted industrial transfer on a global scale. At the same time, various multilateral trade agreements have removed barriers to market entry in many countries, and the technology diffusion effect is constantly increasing overall. As a result, competitive industrial sectors tentacles extend from domestic to international. According to the gravity model, this process can be described like that the breadth of the industrial sectors' impact (measured by the degree of corresponding nodes in the network model) may undermine the impact of location factors on the possibility of establishing relevance between sectors. However, in recent years, political games (e.g., British Brexit) and trade friction (e.g., China-US Trade War) between some countries/regions have impeded the flow of production factors from one country to another.

11.5.4 Industrial Agglomeration

As defined in the ACT index, if the adjacency matrix is asymmetric, the prediction accuracy of this index is inversely proportional to the sum of MFPTs in both directions. In the Binary GISRN model, this means if two industrial sectors are both upstream and downstream sector to one another with few medium sectors connecting them, the possibility of establishing direct linkages between them will be higher. In other words, industrial sectors will possibly form a kind of symbiotic relationship in the economic sense when that does happen, eventually resulting in the phenomenon of ***Industrial Agglomeration***. In the high-tech parks with a high degree of openness, thousands of domestic and foreign enterprises on the same IVCs stay together, significantly reducing the transaction costs and promoting the flow of various production materials and innovation elements. It is therefore reasonable to assume that the ACT index has the capability of interpreting the development mechanism of regional economic system from the perspective of industrial economics.

However, the ACT index still needs to be improved due to its application only in the unweighted network. If the common neighbors of two given nodes incorporate important hub nodes in the network, the possibility of shortcuts between them will notably increase, which also works for LP index and ACT index. Their real difference lies in whether the transfer efficiency after the first step will go down or not. Obviously, since the prediction accuracy of the ACT index is lower than the LP index in the Binary GISRN model, one should not ignore the attenuation of value transfer efficiency, which will even be aggravated with the extension of IVCs. In the follow-up study, the ACT index will be applied to the weighted and directed GIVCN model, because each IO relation embodies the local heterogeneity of GVC and constitutes the source of information asymmetry.

11.5.5 Niche Advantage

Both RA index and AA index are used to find pairs of nodes with weaker common neighbors and give them a higher chance of being connected. In the Binary GISRN model, this means if there are some structural holes on the GVC, i.e., the IO relations between some industrial sectors and their upstream and downstream ones appear to be weak, their peripheral sectors will establish direct supply chain beyond them. According to the analysis on the LP index, as the industrial boundaries become increasingly blurred, some medium sectors face the result of being marginalized or even eliminated. As a result, there is the inevitability that the industrial classification for the ICIO database be updated to better reflect GVC. In addition, the simulation result that the prediction accuracy of the RA index is higher than the AA index again justifies that the backbone of GVC is unbalanced, even though the average degree centrality K of Binary GISRN models is merely between 3 and 4.

By comparison, the prediction accuracy of these two indices turns out to be the lowest, because the IO structure reflects the relatively stable counterbalance between the industrial sectors after the economic system has evolved over a long period of time, and it is contrary to the general law of the value-added process that certain industrial sectors bypass the weak production links to directly connect each other. But some industrial transfer phenomena do occur between two countries/regions of considerable geographical distance or weak direct and indirect industrial relevance. Part of this is due to policy changes at the national macro-level (e.g., the Marshall Plan after World War II), and more importantly, the transferee of industrial transfer often has ***Niche Advantage***[1] that the transferor lacks (e.g., China' large amounts of cheap labor and the huge consumer market in the 1980s). In the follow-up study, research ideas from spatial econometrics will be drawn on, relevant data of a country's niche advantage beyond ICIO data collected, and the link prediction algorithms by combining graph embedding methods optimized.

11.6 Summary

After a year-by-year discovery on the GVC, how to predict the evolution trend of the industrial structure still captures the interest of scholars and policymakers. The reason for such enduring fascination is that when a wide consensus was finally reached on the importance of geographical proximity, agglomeration and local spillovers, the industrial globalization from breadth to depth had already made the GVC evolve into a complex economic system with mobile boundaries. It is the transformation that undermines the traditional perspectives and forces us to critically think over why

[1] Niche advantage is the comprehensive resource advantage of a region, i.e., the favorable condition or superior position in terms of economic growth. It mainly comprises natural resources, geographical location, and social, economic, scientific, management, political, cultural, educational, and tourism factors.

clusters and districts exist, extend, exhaust, or expand finally. From the econophysics angle, we try to simulate this process by link prediction [30], and hence give economic meanings to the most practical results. Some conclusions based on link prediction in binary GISRN models are as follows:

(1) The existing studies can't catch up with the rapid socio-economic development due to its lack of understanding and experience of the mechanism of industrial transfer—a large-scale and interdisciplinary system. This chapter, to analyze the basic laws and mechanisms of regional industrial transfer and the prediction methods of transfer paths, is of great practical value and has provided strong theoretical guidance for the formulation of relevant policies.
(2) The industrial transfer is a branch of regional economics, but its research methods should not be limited to that of economics. The regional industrial structure is an explicitly defined complex system, in which the internal relationships can be described in detail by IO data, and the tools and methods developed in statistical mechanics and theoretical physics can be used effectively to model and analyze the complex system of regional industries. This method reflects the research prospects, for it spans multiple disciplines including economics, management, physics, and statistics.
(3) Traditional theories and methods can't fulfill the needs of the regional industrial transfer. The IO-based system study on the regional industrial complex network and industrial transfer is a holistic research theory, and the application of link prediction and accuracy analysis to this field is a breakthrough in this research method. The integration of new theories and new methods fundamentally guarantees the integrity and systematization of the research.
(4) The application of link prediction obtains index accuracy on different levels, because the government agencies of countries/regions will promote the upgrading of industrial structure through macro-control means, while the global economic system lacks division of labor by overall planning. Besides, complicated factors in international trade aggravate the development imbalance between countries/regions.

However, there is still a lot of room for improvement in the research content covered in this chapter. The Binary GISRN model ignores the edge weight of network and thus loses a lot of information that can reflect its heterogeneity, resulting in that the prediction results are difficult to accurately reflect the actual industrial transfer trend. To solve this problem, each link prediction algorithm must be further refined to be applied to a weighted and directed GISRN network or even more dense GIVCN model. In the optimization, we can use the dynamic mechanism behind many economic phenomena as the basis for designing the link prediction algorithm, such as the dissipative structure theory and the law of gravity. In the follow-up study, we will also compare and analyze the industrial transfer patterns of various regional economic organizations, countries/regions from the historical view.

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Chapter 12
Depict the Nested Structure of Production System

In theoretical ecology and evolutionary biology, ***"Nestedness"*** refers to a structural measure of the overall stability in the ecosystems [1–3]. The structure is an optimal system state conducive to both sides, which is the result of a mutual benefit mechanism established between species and between species and the environment through evolutionary games [4, 5]. Mutualistic species strengthen cooperation through network reciprocity, and weaken competition by reducing niche overlap, so as to promote the system to an evolutionary equilibrium. This concept has, in recent years, also begun to be applied by sociologists and economists to analyze various phenomena related to human society. Just like the ecosystem, the economic system seeks an evolutionary equilibrium in the process of dynamic evolution. In today's highly developed globalization, cooperation among economies has reached an unprecedented level. Through dynamic games to allocating scarce resources, economies in the global value chain can maximize their relative interests. The role of network reciprocity in emerging cooperation is an important mechanism for the global economic system to achieve dynamic balance [6]. As the leading link in the global value chain, the flow of intermediate products depends on the cooperation between various industrial sectors. Considering that the industrial sector on the GVC has a dual identity, i.e., provider and consumer of intermediate products, it can be represented by a bipartite graph to separate the two attributes of a node, and thus the mutualistic relationship between upstream and downstream industries can be clearly depicted. In fact, the ecosystem and the global production system have some common grounds. For instance, the flow of energy between species and the flow of intermediate goods between industrial sectors both reflect the mutually beneficial symbiosis relationship produced through the competition and cooperation game, as shown in Fig. 12.1. With the nested structure being identified among industrial sectors in the GVC network, nestedness can be applied to measure the topological stability of both the whole and local parts of the global industrial ecosystem.

Ecological metaphor is not ecological reductionism or ecological imperialism, and it is not to simply reduce the phenomenon of macroeconomic evolution (industrial transfer between countries and adjustment of industrial structure within countries) to

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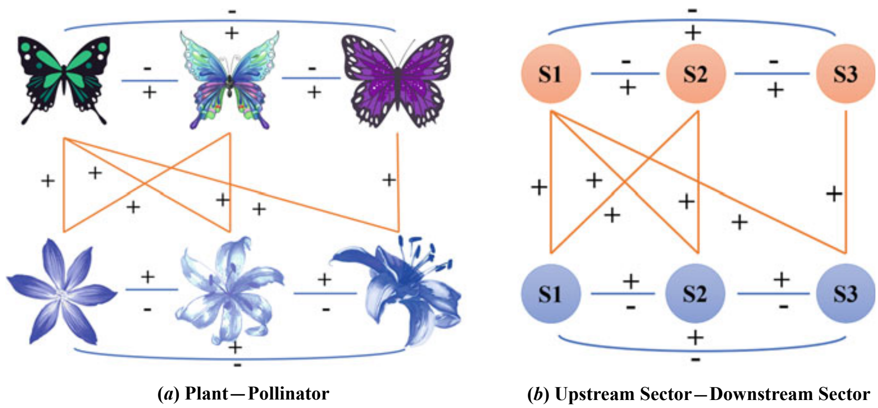


Fig. 12.1 Comparison between mutualistic system and global production system. *Notes* **a** there exists a mutually beneficial symbiosis relationship between plants and pollinators. In simple terms, pollinators pollinate plants to promote the formation of their fruits and take in the nutrients they need at the same time. Among pollinators, there is not only competition for plants but also collaboration to complete the process of collecting pollination, which will be beneficial to both sides as their population grows. **b** refers to the global production system where the orange circles represent the upstream sectors and the blue circles the downstream ones. The numerous upstream and downstream sectors on the GVC cooperate to complete the industrial division of labor, while the upstream ones not only compete for the same buyers but also collaborate to make true these buyers can get what they need in the production process

ecological evolution [7]. Moreover, Chase and Leibold's research on ecological niche is only an abstract milieu interne adjustment mechanism and does not describe the specific evolution process [8]. The complex system theory must be embedded in it to accurately explain the law of the evolution of economic system. Therefore, the evolutionary game theory of biological populations in ecology has certain enlightening significance to the theory of economic development.

12.1 Introduction

Nestedness, derived from theoretical ecology and evolutionary biology, is an important structural feature of complex networks. In 1957, Darlington mentioned this concept in his book Zoogeography, in which he noticed that the spatial distribution of species displayed the nested feature [9]. Building on Darlington's discovery, in 1986, Patterson and Atmar formulated the precise concept of nestedness, i.e., in a fully nested network, the neighborhood of a node with lower node degree is a subset of the neighborhood of a node with higher node degree [10]. In 2003, Bascompte, et al. analyzed 25 plant-pollinator networks and 27 plant-frugivore networks and found that most of the networks exhibited nested features [11]. The nested structure reflects the mutualistic relationship between species. In a mutualistic network, specialist species tend to relate to generalist species who have higher adaptability to the environment, thus mitigating the risk of extinction. Niche overlap decreasing in nested structure helps weaken competition and improve species diversity [12], and the greater the nestedness, the stronger the recovery ability of the system after external shocks, and the stabler the network structure [13–15].

Inspired by this discovery in ecological networks, scholars in socioeconomic networks began to devote themselves to the study of nestedness. As early as 1965, when studying the U.S. economic structure using ICIO data, Leontief identified obvious nestedness of the U.S. industrial network [16]. Subsequently, a large number of theoretical and empirical studies have emerged, which has greatly enriched the interdisciplinary research in the field of economics. The world trade network [17], the arms trading network [18], the inter-bank capital flow network [19], the manufacturer-supplier network [20] and the product export network [21–23] also show nested features. The network heterogeneity caused by the dynamic evolution of social economic system is the main reason for its nested structure. Taking the world trade network as an example, the coexistence of competition and cooperation among countries leads to unbalanced economic development, which makes the world trade network show a center-periphery structure. That is, the generalist sectors are connected with most counterparts, form the core of the network and specialist sectors are at the periphery and dependent on the center [24, 25]. This highly connected center makes the links of the network replaceable. Even if the supply or demand of some sectors disappears, the existence of other replaceable sectors can make the products flow normally. At the same time, these studies reflect that the nested structure is of great significance for maintaining the stability of the economic system [26, 27]. For example, in the 2008 global financial crisis, the reason for the decrease in inter-bank transactions was that the core banks reduced the number of externally active sides [28].

This chapter is organized as follows. In the first section, the application and development of nested structure theory in the field of ecology and economics are systematically introduced. In the second section, a GVC network is built based on ICIO database to embody the flow of intermediate goods between industrial sectors. In the third section, nested structure is embodied by sorting algorithm and measured by *NODF* method. In the fourth section, analyses on the divergence, trend, and stability are made to explain the complex relations between industrial sectors and the global production system, and then the economically evolutionary mechanism is proposed. In the fifth section, the econometric models are used to analyze the relations between the nestedness-based indicators and the level of economic development. Finally, some countermeasures are put forward for economies to achieve a much more stable and healthy state [29].

12.2 Modeling

In order to represent the nested structure of global production system and its economic significance, we build an analytical framework in this section, as shown in Fig. 12.2.

As proposed in Sect. 8.3.3, the GIVCNBG model is constructed in the form of a bipartite graph $G = (O, P, E, W)$. In the G, all upstream industrial sectors form the set of object nodes O, and all downstream industrial sectors form the set of participant nodes P; edges pointing from upstream to downstream form the set of edges E in competition with other N-1 sectors as a consumption sector, downstream industry sector i obtains from its upstream industry sector j intermediate goods input, the amount of which is w_{ji} ($j = i$ indicates that the upstream and downstream are the same sector), constituting the weight set W.

While the GIVCNBG model applies the weight set W to substitute the adjacency matrix, each row refers to the distribution of intermediate goods output of upstream sector and each column the intermediate goods input of a downstream sector. In spite of being the same mechanism as the one-mode GIVCN model, a two-mode network is able to identify the underlying cooperative relationships between industrial sectors. That is, there is cooperation between upstream sectors to promote the production of their common downstream ones [30]. We believe that the flow of intermediate goods in production systems (expressed in the IO table as value or currency flow) is similar to the flow of energy in ecosystems, and that both systems converge to a steady state after a complex game. As mentioned above, ecological studies have found that ecosystems in a steady state are characterized by nested structures and a more stable mutualistic relationship between species. Therefore, we believe such features can also be found for in the topology of production systems due to the same evolutionary mechanism.

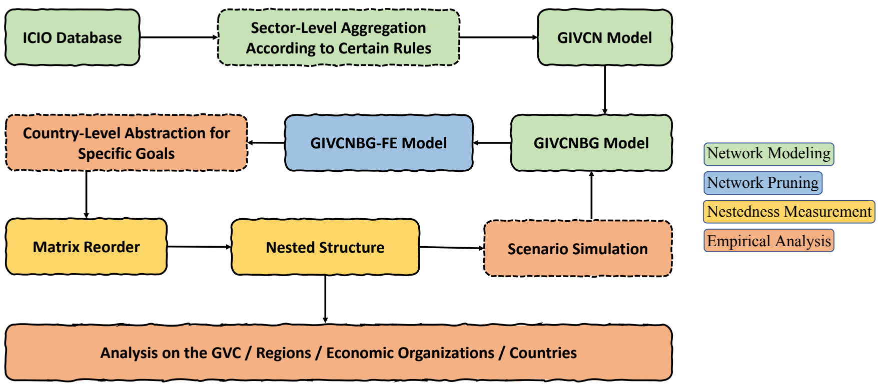


Fig. 12.2 Modeling and analytical procedures in this section. *Notes* The dotted box means that the step in it is optional. In the last two sections, we make preliminary predictions on the GVC reconfiguration and proposes countermeasures for the future industrial optimization and stable economic development of the world, taking Brexit and RCEP for example

GIVCNBG model is an extremely dense weighted network with highly heterogeneous material flows between each upstream sector and downstream sector. Thus, it needs to be pruned in search of the backbone part before nested structure analysis. In Sect. 10.3.2, we introduce the heuristic algorithm—XIFA, and hence a special subgraph $G^{'} = \left(O, P, E^{'}, W^{'}\right)$ is extracted from the GIVCNBG, named as ***GIVCNBG-FE*** model. GIVCNBG-FE model compresses the size of the edge set E to a large extent, For example, after pruning the GIVCNBG-Eora26SC4-2015 model by XIFA, $\left|E^{'}\right| = 8.95\% \times |E|$, while $\sum w_{ij}^{'} = 99.15\% \times \sum w_{ij}$, which means more than 90% of the deleted edges carry less than 1% of the network information, leaving less than 10% of the edges carrying more than 99%. In sum, the bipartite graph $G^{'} = \left(O, P, E^{'}\right)$, with the weight information removed and all edges left being important, is sufficient to portray the nested structure of the network.

12.3 Measurement

Nested structure is determined by the distribution of edges in the network and can be influenced by the network connectivity. The higher the connectivity of the network, the more likely it is to exhibit nested characteristics. In ecosystems, nested structure is established when ecological niches of different species adapt to each other and thus achieve dynamic equilibrium. It is a network structure characteristic formed by species adapting to the natural environment in pursuit of homeostasis. Nestedness in an ecological network is therefore a measure of the stability and sustainability of ecological environment. From the perspective of bionomics, there are many similarities between GVC network and ecological network in terms of topological characteristics. Just like the biological species, the industrial sectors on the GVC form a complex association of mutual benefit and the trade and economic cycles between them make GVC an organic whole. Higher nestedness of GVC network indicates a more mature industrial trade mechanism, a more regular and orderly industrial trade network, and the deeper integration between industries. Hence, research on the nested structure of GVC network has fundamental implications for the economic development of countries, regions and even the world [14, 31].

12.3.1 Sorting Methods

Prior to the analysis, the adjacency matrix needs to be reordered to maximize the degree of network nestedness. Several classical sorting algorithms are introduced below.

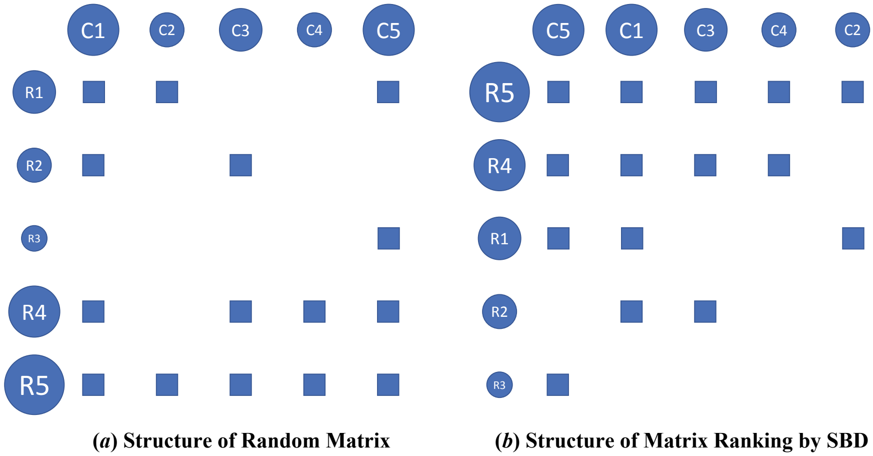


Fig. 12.3 Sorting adjacency matrix based on SBD algorithm. *Notes* This is a schematic diagram of the process of ordering nodes by degree. The solid blue circles represent each industrial sector, the rows represent the upstream industrial sectors, the columns represent the downstream industry sectors, the blue squares represent the existence of interdependence between upstream and downstream industries, and the size of the solid circles is proportion-al to the node's degree

Sorted by Degree (SBD Algorithm), based on the concept of nestedness, sorts the adjacency matrix according to the degree of the network node (see Fig. 12.3). It is prescribed in the nested structure that the neighborhood of lower-degree nodes is a subset of the neighborhood of higher-degree nodes. Accordingly, the SBD algorithm basically rearranges the adjacency matrix's rows and columns in the descending order of the node's degree from top to bottom and from left to right respectively. In the rearranged network adjacency matrix, the topmost upstream sector boasts the largest number of downstream sectors, while the leftmost downstream sector boasts the largest number of the most upstream sectors.

Nestedness Temperature Calculator (NTC Algorithm) is a thermodynamics-based algorithm proposed by Atmar, focusing on the degree of disorder of the measurement matrix [32]. The nested structure features ordered arrangement of nodes, therefore, the more disordered the adjacency matrix, the higher its temperature, and the lower the level of nestedness. NTC Algorithm lines out a perfect nested region at the top left of the adjacency matrix, and the unexpected absence of any element above the line and the unexpected appearance of any element below the line would result in an increase in the temperature of the adjacency matrix.

BINMATNEST Algorithm (BIN Algorithm) was proposed by Rodrı´guez-Girone´s, et al., which compensates for the shortcomings of NTC, e. g. the non-uniqueness of the perfect order line and the inadequacy of null model selection [33]. In design, BIN Algorithm is a genetic algorithm that minimizes the matrix temperature by rearranging the rows and columns. It first generates some alternative solutions and then lets the well-performing matrix generate "Offspring", thus, iteratively filtering out the best-performing solution. Unlike the NTC algorithm, BIN algorithm is capable of screening out the optimal matrix with lower temperature. The matrix reaches the lowest temperature after reordering and is therefore more well-organized, with stabler connections between industrial sectors concentrated at the upper left corner. Under the circumstances, NTC algorithm is not be worth discussing anymore.

Fitness-Complexity Algorithm (FCA Algorithm) applies a non-linear iterative method originally designed to measure economic complexity [34]. The mechanism is that the higher the fitness of a country, the higher its productive capacity or competitiveness; the higher the complexity of certain product, and thus the higher the productive capacity required from other countries producing that product. In the adjacency matrix of the country-product network, the rows represent countries and the columns the export products. After reordering the matrix in the descending order of fitness from top to bottom and product complexity from left to right, the new matrix will exhibit distinct nestedness. FCA therefore can be used to explore the maximum nestedness of a network.

12.3.2 Nestedness Quantification

Once a nested network structure is obtained, the nestedness of the network needs to be further quantified to compare the sorting algorithms. The ***Nested Overlap and Decreasing Fill (NODF)*** metric proposed by Almeida-Neto, et al. is applied to calculate the nestedness of the network based on two basic properties: ***Decreasing Fill (DF)*** and ***Paired Overlap (PO)*** [35].

Given that a matrix has m rows and n columns, and MT is the number of elements valued at 1 in any row or column. For any pair of rows $(i, j)(i < j)$, if $MT_i > MT_j$, then $DF_{ij} = 100$, otherwise $DF_{ij} = 0$. Similarly, for any pair of columns $(h, k)(h < k)$, if $MT_h > MT_k$, then $DF_{hk} = 100$, otherwise $DF_{hk} = 0$.

For any pair of rows $(i, j)(i < j)$, PO_{ij} refers to the percentage of 1's in a given row j that is located at identical column positions to the 1's observed in a row i. Similarly, for any pair of columns $(h, k)(h < k)$, PO_{hk} refers to the percentage of 1's in a given column k that is located at identical row positions to those in a column h. Therefore, for any up-to-down row pair, or any left-to-right column pair, the degree of paired nestedness (N_{paired}) can be expressed as follows:

$$N_{paired} = \begin{cases} 0, & if \quad DF_{paired} = 0 \\ PO, & if \quad DF_{paired} = 100 \end{cases} \tag{12.1}$$

There are $m(m-1)/2$ row pairs in row m, and $n(n-1)/2$ column pairs in column n. Thus, the nestedness of the entire network can be calculated by "averaging all paired values of rows and columns":

$$NODF = \frac{\sum N_{paired}}{\left[\frac{m(m-1)}{2}\right] + \left[\frac{n(n-1)}{2}\right]} \tag{12.2}$$

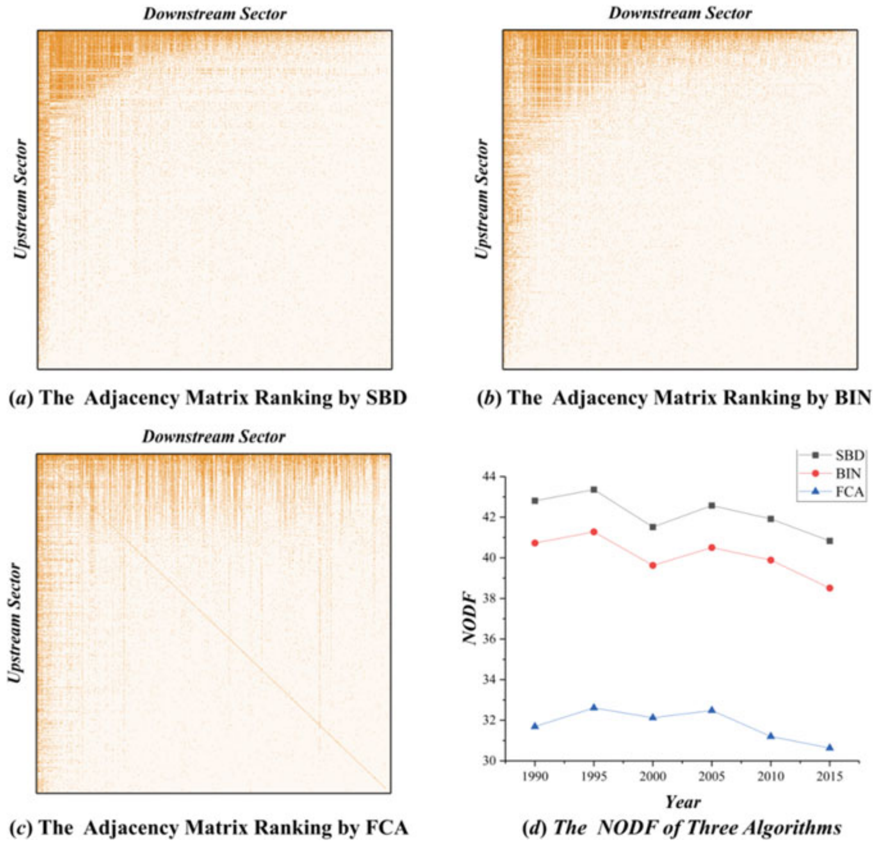


Fig. 12.4 Sorting adjacency matrix of GVC network based on three algorithms and its corresponding NODF variation trend. *Notes* **a**, **b**, and **c** are the adjacency matrix ranking results obtained according to the SBD, BIN, and FCA algorithms, respectively. Where the vertical axis represents the upstream sector and the horizontal axis represents the downstream sector, and each non-empty position reflects the transfer of intermediate products from the upstream sector to the downstream sector. This input–output relationship between industrial sectors resembles predation in an ecosystem: the upstream sector, as the provider of energy (products and services), can be regarded as the prey; the downstream sector, as the consumer of energy (products and services), can be regarded as the predator. And each industry sector plays dual role in the industrial ecosystem

where the *NODF* value ranges from 0 to 100, with $NODF = 0$ indicating non-nested network structure and $NODF = 100$ indicating a fully nested network structure.

We apply the GIVCNBG-FE-Eora26SC4 model to calculate the nestedness of GVC network at intervals of five years, and compare the sorting results of SBD, BIN and FCA algorithms and their *NODF* metrics, as shown in Fig. 12.4.

The SBD algorithm sorts adjacency matrix in the way that most of the non-zero elements are clustered at the upper left corner. The results obtained by the BIN algorithm resemble that of the SBD algorithm, with the upper left corner being sparser. The results obtained by the FCA algorithm are computationally weaker than the other two algorithms. Given the above analysis (see Fig. 12.4d), the SBD algorithm is thus used to sort the nested structure of adjacency matrix. The overall smooth *NODF* values indicate temporal stability of the nested structure, which means the topology of GVC network does not change drastically during a normal economic cycle.

12.4 Statistical Analysis

Globalization is both an opportunity and a threat for the economic development of each country. On the one hand, the industrial sectors of each country have their comparative advantages, thus forming a relatively stable international industrial division of labor. On the other hand, they also fiercely compete in the global market, seeking for a place on the GVC. It is under the impetus of both cooperation and competition that the global economic system evolves and shows nested structural characteristics in the process of convergence to homeostasis.

12.4.1 Divergence Analysis

If the economic system is compared to an ecosystem, the generalist feature of an industrial sector can be measured by the number of important IO relations they establish with the other sectors. In this chapter, the larger-degree industrial sectors are defined as Generalist Sector, featuring higher involvement on the GVC, widely distributed outputs/inputs, and broader industrial ecological niche. In the opposite would be the Specialist Sector. Viewed by rows, the nodes in the upper part of the nested area have higher outdegree and stronger supply-side generalist degree, while those in the lower part have lower outdegree and weaker supply-side generalist degree. Viewed by columns, the nodes on the left side have higher indegree and stronger demand-side generalist degree, while those on the right side have lower indegree and weaker demand-side generalist degree.

Due to the vertical specialization, product manufacturing and its related services exists through all stages of the global production process. Each country takes advantage of its own and the others' comparative advantages in technology, capital and/or labor, jointly shaping the main structure of GVC. As a result, the manufacturing and services sectors own a higher degree of external dependence, i.e., higher generalist degree. In contrast, agriculture and mining, sector only affect a limited number of sectors. They mainly trade with the domestic sectors for self-sufficiency, and seldom establish international trade channels with the manufacturing sectors of a few developed economies. In short, most of them have low involvement on the GVC, resulting in lower generalist degree.

To further analyze the features of nested structure of GVC, we select four representative areas consisting of the top twenty and bottom twenty sectors on the supply and demand sides respectively, as shown in Fig. 12.5. The comparative results reveal significant differences in the generalist degree of industrial sectors in developed and developing countries.

Area (a) on the top left shows the IO relations between the upstream and downstream generalist sectors. This rearranged local network consisting of manufacturing and services sectors in advanced economies is very dense, indicating that intense competition occurs because of overlapping ecological niches. The NODF value of Area (a) is 76.165, due to the empty elements of the upper triangle and the non-empty elements of the lower triangle, which indicate the insufficient collaboration

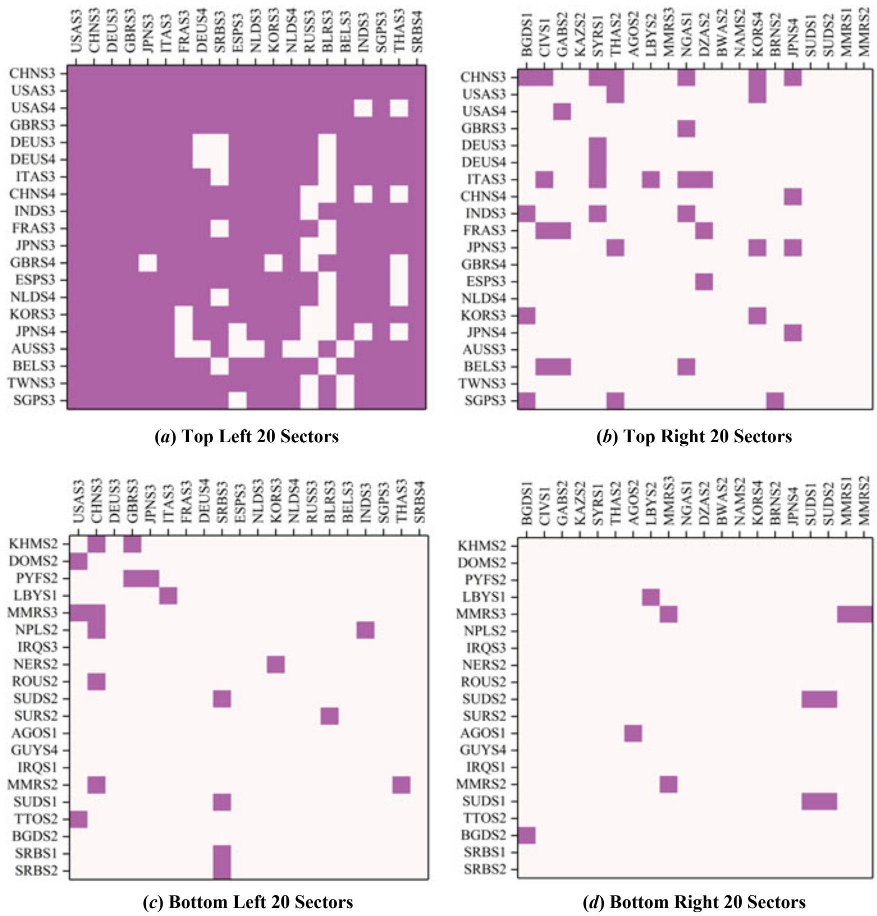


Fig. 12.5 Topological structure of different areas after sorting the adjacency matrix of GVC network based on SBD algorithm

and excessive competition among these generalist sectors and hence negatively affect the stability of the industrial structure.

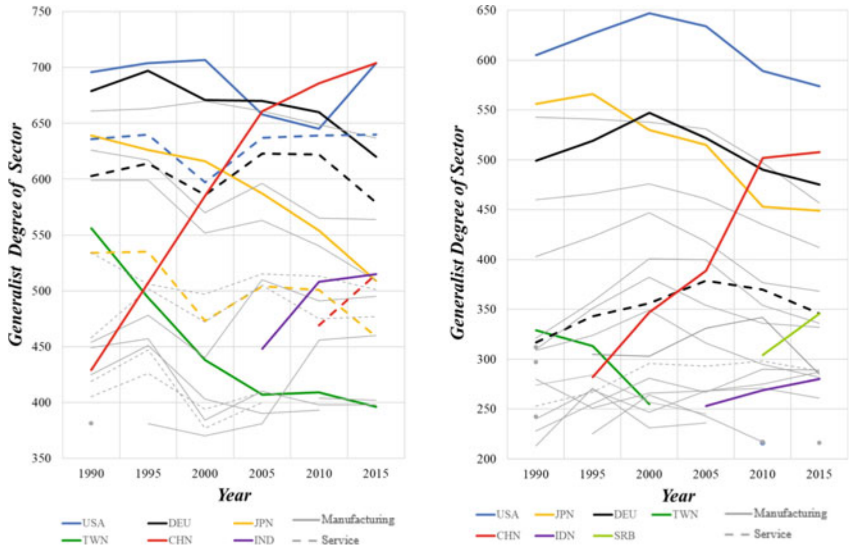
Area (b) in the top right shows the IO relations between the upstream generalist sectors and the downstream specialist sectors. It is found that Japan's services belong to generalist sector in the upstream, whose trade in services exports to most countries around the world, while they have very low generalist degree in the downstream. On the one hand, Japan's services sectors are highly developed and mainly in the form of outsourcing. Along with the progress of economic globalization and division of labor, they penetrate every aspect of the global market. On the other hand, Japan's market remains relatively closed. Since the World War II, the industrial structure of Japan has been continuously upgraded, and various industries, especially the services sectors, have entered a relative mature stage and become the dominant industry. As for other countries, it is difficult to compete with Japanese companies because of the high trade barriers.

From the bottom two regions, the agriculture and mining sectors in underdeveloped countries have lower generalist degree—except for achieving self-sufficiency [Area (d)], they only open international trade channels with the manufacturing sectors of a few developed economies [Area (c)]. On one hand, as the multilateral trading system is frequently challenged by unilateralism, agriculture sectors often passively become an important bargaining chip for balancing bilateral economic and trade relations, together with the presence of invisible barriers to agricultural trade, posing obstacles to the globalization process of the agricultural sector. On the other hand, since the globalization of the mining sectors depend on resource endowment and geographical factors, only a few countries are able to achieve significant exports of mineral resources, upon which most other countries have to rely.

12.4.2 Trend Analysis

To observe the dynamic trend, this section puts together the top twenty industrial sectors in terms of generalist degree on both sides as shown in Fig. 12.6. Overall, the major generalist sectors did not change significantly between 1990 and 2015, with the absolute generalist value fluctuating in a small scale. In particular, the manufacturing and services sectors of the United States and Germany in the export sectors, and the manufacturing sectors of them in the import sectors, have always maintained a high generalist degree, which means these sectors are deeply integrated into all parts of the global economic cycle. In addition, some variation trends also deserve more attention.

First, on matter the export trade reflected by the upstream sector's generalist degree or the import trade reflected by the downstream sector's generalist degree tend to wax and wane. It is clear that, with the scaling-up influence exerted by China's manufacturing export trade, the generalist degree distribution of the upstream manufacturing sector has evolved from a "U.S.-Germany-Japan" tripolar pattern to



(*a*) **Variation Trend of Upstream Generalist Sectors** (*b*) **Variation Trend of Downstream Generalist Sectors**

Fig. 12.6 Generalist degree variation trends of the upstream and downstream industrial sectors

a "China-U.S.-Germany" one [36]. In the meanwhile, Chinese exports of trade in services have begun to narrow the gap with developed countries and surpassed Japan.

Second, the rise of manufacturing sectors in Chinese mainland and India have brought impact to Taiwan. As one of the once "Four Asian Dragons", Taiwan used to be a supply chain hub in Asia, except for Germany and Japan for western countries. However, with the advent of dividends of Chinese reform and opening up, productive enterprises in Taiwan began to move to Chinese mainland and overseas, leading to the significantly shrunk influence of Taiwan's manufacturing industry. Besides, in order to accelerate the development of the manufacturing industry, the Indian government has introduced a batch of relevant measures to stimulate investment and ease market access for foreign investment. Due to the blockade and restrictions imposed by the European and American markets on the Chinese market, a huge market like India is taken as the preferred place for partial industrial transfer, which provides favorable conditions for the development of manufacturing industry in India [37].

Third, Serbia has become a new "European Factory" by virtue of its unique location and started to play an important role in the import and export trade of manufacturing industry in recent years. Located at the junction of the East and the West, Serbia is an important hub connecting the major corridors of Europe and Asia and boasts strong connectivity. Besides, it has signed free trade agreements with the European Union and Central and Eastern Europe, and enjoys the most-favored-nation treatment of the United States With the progress of the BRI, Chinese enterprises also brings it infrastructure construction, creating a favorable environment for the development of

Serbian manufacturing industry. All these positive factors make Serbia an important intermediate goods processing link on the GVC.

The vertical international division of labor and the continuous development of the global production network have played an unprecedented role in promoting the economy and trade of all countries in the world. The dynamic exchange of resources across the world is also an important guarantee for the stable and orderly progress of GVC network. Through static and dynamic analysis of the generalist degree of the industrial sectors, the phenomenon is found that most of the generalist sectors come from more developed economies which are in the most closely nested areas, and their internal competition is fierce. Due to the rapid increase in the generalist degree of China's manufacturing industry, the manufacturing and services sectors in Japan and Taiwan have shown a downward trend, which paved the way for changes in the global supply chain pattern. These advanced economies, as well as their industrial sectors have also played a decisive role in maintaining the stability of GVC network and promoting the process of global economic integration. In addition, there is still a lot of room for optimization of the industrial layout on the GVC. Encouraging specialist sectors to actively integrate into global trade system is an effective way to realize that.

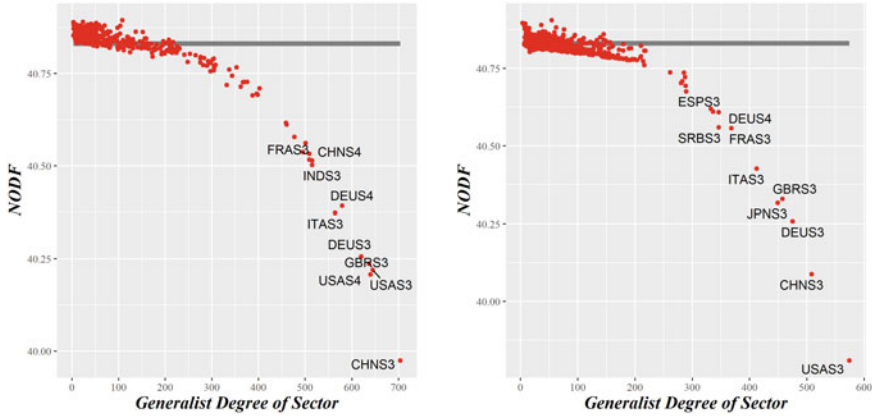
12.4.3 Robustness Analysis

It is necessary to quantify the influence of generalist and specialist sectors on the nestedness of GVC network, two control tests are designed to examine the influence of a certain sector and the cumulative influence of multiple sectors respectively. The results are shown in Figs. 12.7 and 12.8.

After removing a generalist sector (see Fig. 12.7), the *NODF* of the nested network significantly decreases, indicating that the higher the industry sector's generalist degree, the more positive its effect on maintaining the stability of GVC network. In contrast, after removing a specialist sector, the *NODF* slightly increases, which means that industrial sector with lower degree of generalist would weaken the stability. With the deepening of globalization, these industrial sectors will entail the risk of being marginalized or even eliminated if they do not actively participate in international competition and cooperation.

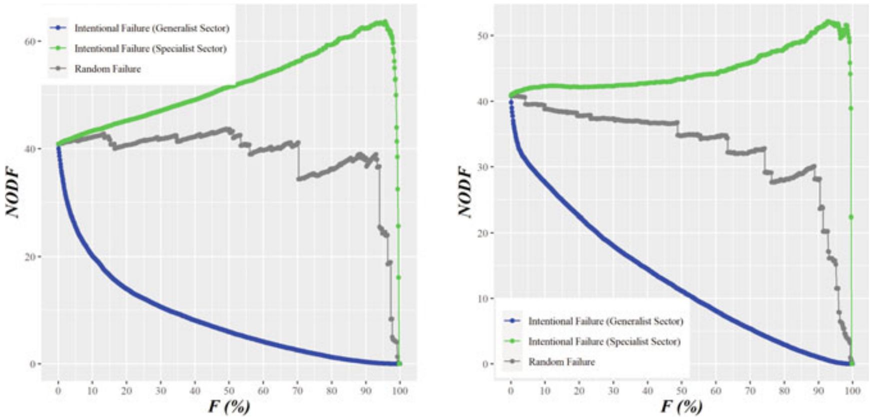
Figure 12.8 further confirms the above findings. After removing a small proportion of industrial sectors with the highest generalist degree, the *NODF* of the nested network fall drastically, i.e., the stability of GVC network deteriorates rapidly, indicating that a few generalist sectors are important hubs to maintain the functioning of GVC. In contrast, when the industrial sectors with the lowest generalist degree are removed, *NODF* display an increasing trend which does not start to decline until only 10% of the industry sectors are left. This reinforces the importance of the generalist sectors to the stability.

By comparison, we further find that there is difference between generalist and specialist sectors on in terms of impact. Given the same proportion of removed



(*a*) **Remove the Upstream Sectors Respectively** (*b*) **Remove the Downstream Sectors Respectively**

Fig. 12.7 NODF of GVC backbone by removing a certain industrial sector. *Notes* The horizontal gray lines represent the NODF of the nested network sorted by the SBD algorithm, and the red scatter points represent the correspondence between the generalist degree after removing a certain industrial sector (the size of the outdegree or indegree) and the new NODF of the nested network



(*a*) **Remove the Upstream Sectors Proportionally** (*b*) **Remove the Downstream Sectors Proportionally**

Fig. 12.8 NODF of GVC backbone by proportionally removing industry sectors. *Notes*: The gray lines represent the variation in the value of network nestedness after randomly removing a certain proportion of industrial sectors from the aligned adjacency matrix; the blue lines represent the variation in the value of network nestedness after removing industrial sectors from the aligned adjacency matrix in the descending order of generalist degree; the green lines represent the variation in the value of network nestedness after removing industrial sectors from the aligned adjacency matrix in the descending order of specialist generalist sectors (e.g. 10%), the removal of upstream sectors would exert greater negative impact on the nestedness of GVC network than that of downstream sectors. In other words, the global demand network of intermediate goods (consisting of downstream sectors) is sturdier than the supply network (consisting of upstream sectors). Considering this, when the global economy faces systematic risks, in order to cope with the resulting pressure or even disruptions of supply chains and reduce economic dependence on external resources, many countries have explored alternatives for supply chain management and import dependency. For example, they usually move their supply chains to countries less affected by the pandemic, pull some of the production capacity back from overseas, or accelerate the industrialization process.

12.4.4 Evolutionary Mechanism

In the early 1970s, American scholar Wallerstein proposed the **World System Theory** and believed that: in terms of the distribution pattern of capital, technology, and wealth, North America and Europe located at the "core" of the world, while the vast Asian, African and Latin American regions scattered around the "periphery" [38]. The "core" countries dominate the direction of the entire world economy and international strategic pattern. Accordingly, the structure of "core-half-periphery-periphery" will not change, but the status of a country or society in the world system can be changed. A peripheral country can be upgraded to a half-peripheral one or even the "core". The central countries, similarly, may also fall into half-peripheral or even peripheral ones. The few countries in the "half-periphery" position can successfully achieve dependent development.

Dependency Theory, also known as **Core-Periphery Theory**, is established on the world trade pattern and the resulting unequal international division of labor. It is powerful to explains the differences between developed and developing economies. The simple explanation is that developed countries gather at the core of the world economic system, while developing ones scatter at the periphery. Functionally, the central countries transfer the production of primary products to peripheral countries through capital import and transnational corporations, exploiting the peripheral countries' cheap labor resources to develop labor-intensive industries and thus optimizing their own industrial structure. Being subject to the external constraints of the central countries, peripheral countries form dependence on the central countries and the surplus value keeps flowing from the periphery to the core, thus leading to the rich countries getting richer and the poor countries getting poorer [39–42]. For example, after the World War II, the Asian, African and, especially, Latin American countries did not embark on the road to affluence after their attainment of independence, but instead, became even more dependent on and formed the neo-colonialist industrial affiliation with the economy of capitalist countries in Europe and North

America. Given that, the advocates of the dependency theory call for trade protection and import substitution in the peripheral countries and, with a strong nationalist tendency, encourage them to develop their own industries. However, this theory puts the peripheral countries in a passive position and attributes their economic distress on external factors, taking no consideration of the drawbacks in their domestic economic structures, which is to some extent pessimistic and biased.

Despite the similar nested structures of the mutualistic ecosystem and the global economic system at the topological level, their formation mechanisms are not identical. Species enhance their ecological benefits by continuously adjusting their interactions with other species, and the nested structure evolves through their dynamic games and active adaptation to the environment. On the other hand, the driving force behind the formation of the core-periphery model of the global economic system lies in the international division of labor based on the countries' comparative advantages, and therefore features historical inevitability. However, from the perspective of dynamic development, peripheral countries are not always stuck in a position of being exploited and unable to develop their economies. On the contrary, the industrial transfer of the central countries creates opportunities for the peripheral countries to make full use of the capital and technology of developed countries to promote their own industrial development and technological innovation, thereby achieving the so-called "Corner Overtaking". With the increased depth and breadth of GVC, by transferring many industrial production processes to developing countries, developed countries have completed the transition from a production-based society to a consumption-based society and need to rely on the supply of goods from developing countries. This has inevitably led to the emergence of Industrial Hollowing-Out in some developed countries, increasing their dependency on the developing countries as the world factories. Figure 12.9 briefly shows the movement of peripheral countries to the core of the industrial landscape, which is also the formation process of the nested structure of the global production network. From the perspective of evolutionary economics, the continuously flattened world is derived by the evolutionarily stable equilibrium of global production system.

Of course, the heterogeneity of economic development is still prevalent and increasingly serious. Even if the peripheral countries in the global industrial pattern achieve their economic growth targets, they are still at the end of high-tech diffusion, lacking core technologies and high value-added products, and are often subject to economic sanctions and technological blockade by the central countries. In other words, the dependence of peripheral countries on the central countries is much stronger than that in the reverse. Developing countries therefore need to face up to the gap with developed countries in various aspects, transform economic growth mode, so as to become the beneficiaries of economic globalization rather than just the contributors.

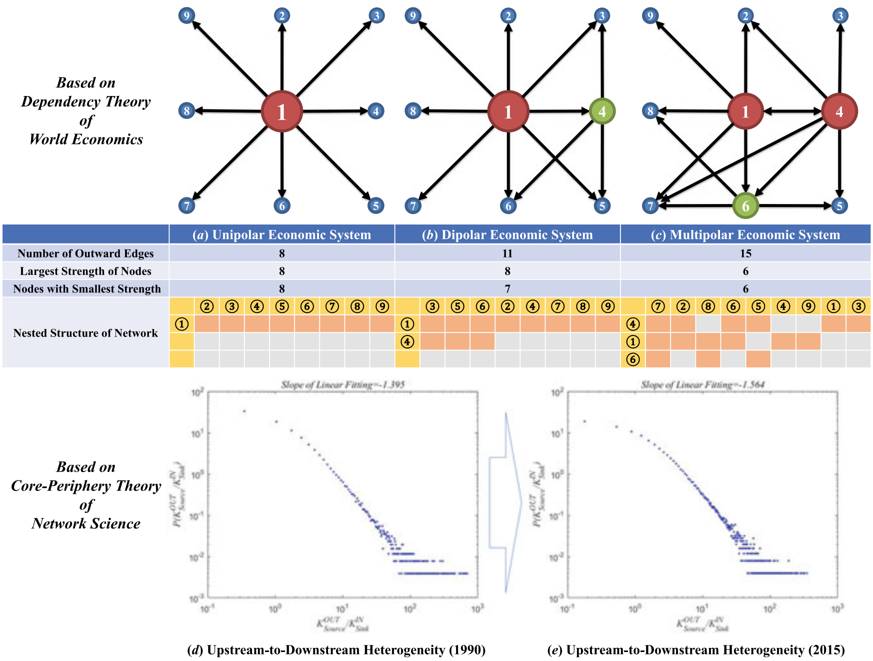


Fig. 12.9 Formation process of nested structure of GVC backbone. *Notes* The orange circle 1 in **a** represents the developed countries initially at the core of the world economic system, while the yellow circles are the developing ones at the periphery, and the size of the circles reflects the degree of centrality of the countries; **b**, **c** indicate the gradual migration process of peripheral country 4 and peripheral country 6 to the central position, respectively. Besides, the ratio of out-degree of upstream sectors to in-degree of downstream ones is designed to reflect the heterogeneity of development level of economies. Accordingly, the absolute value of slope of linear fitting increasing in (**d**) and **e** means our world is flattened by the economic integration

12.5 Econometric Analysis

Based on the above analysis, it is found that the generalist degree of a country's industrial sectors is closely related to its economic status and productive capacity. So, the focus of the following section is going to be whether a country's economic condition is affected by the nested structure of GVC network, or in other words, how a country's macroeconomic performance is related to the microstructure of trade networks.

12.5.1 Correlation Between Variables

In some empirical studies [43, 44], the in-block nestedness is worthy to be computed if the modularity is considerable. Obviously, GIVCN model incorporates many communities mainly consisting of industrial sectors and IO relations related to a country or region. Considering that a country's macroeconomic performance is affected by both domestic and international trade cycles, we design three *NODF*-based indicators to measure the nestedness of the local network in terms of economies, as shown in Fig. 12.10. Firstly, ***DTN-NODF*** measures the nestedness of ***Home Trade Network (HTN)***, which consists of trade activities of intermediate products between industrial sectors within a country. Secondly, ***ETN-NODF*** measures the nestedness of ***Export Trade Network (ETN)***, which is formed when industrial sectors of a country, as upstream sectors (supply side), trades intermediate products with other countries. Thirdly, ***ITN-NODF*** measures the nestedness of the ***Import Trade Network (ITN)*** formed when a country's industry, as a downstream sector (demand side), trades intermediate goods with other countries. Their formulas are as follows:

$$DTN - NODF(u) = NODF(HTN\, of\, Country/Region\, u) \tag{12.3}$$

$$ETN - NODF(u) = NODF(ETN\, of\, Country/Region\, u) \tag{12.4}$$

$$ITN - NODF(u) = NODF(ITN\, of\, Country/Region\, u) \tag{12.5}$$

In terms of macroeconomic performance, we use GDP data provided by the World Bank. The correlation diagrams of them are plotted at intervals of five years, as shown in Fig. 12.11.

First, in all countries, the values of *DTN-NODF* are larger (mostly between 50 and 80), and those of *ETN-NODF* and *ITN-NODF* are smaller (mostly between 0 and 20). This is because, compared with international trade networks, most countries have relatively mature domestic trade networks, in which domestic industrial sectors can also form synergy. Hence, it is much less difficult and risky to form a domestic trade cycle of IVC, moving the original country-to-country trade to province-to-province and city-to-city economic cycle. Certainly, the premise is that the country's domestic market is sufficiently huge and the industrial system is complete.

Second, no matter a domestic trade network or an international trade network, economies with better macroeconomic performance usually have higher the nestedness. We believe it is the relatively mature trade mechanisms that bring them with economic benefits and avoided risks. Hence, both domestic and international market are equally important for a country's economic development. How to better connect and utilize them will be the key for countries to gain new advantage in international cooperation and competition.

Third, the *ETN-NODF* and *ITN-NODF* of the United States show a negative correlation with its GDP. In recent years, the United States has integrated a large amount of capital into the highly lucrative consumption side and shifted low-end manufacturing to countries with cheap labor costs, thus leading to the advent of manufacturing hollowing-out. Combined with industrial shocks from many developed (e.g., Germany and Japan) and developing countries (e.g., China), the international trade cycle does not seem to be contributing to the macroeconomic performance of the

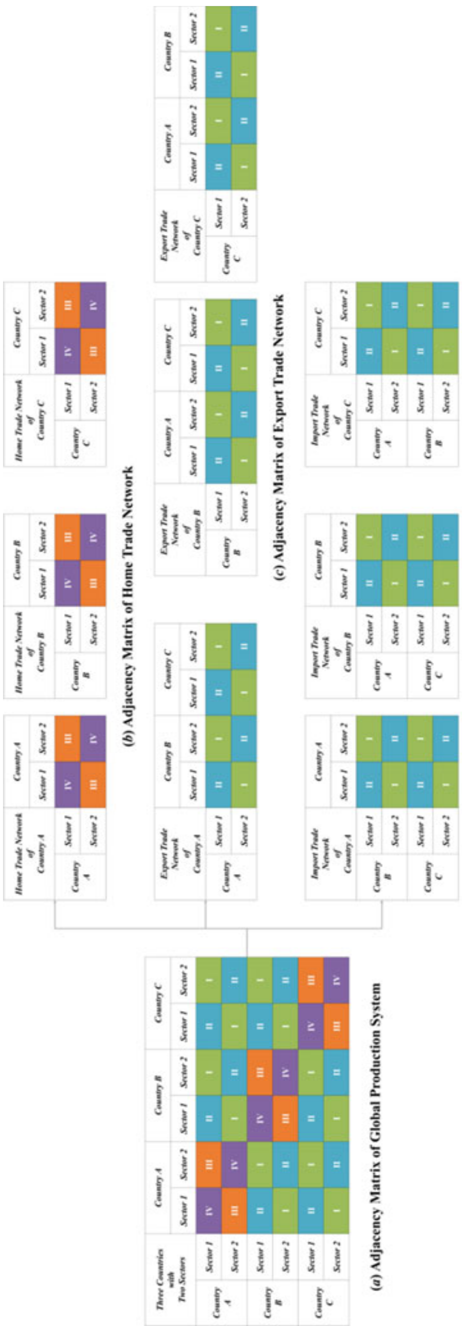
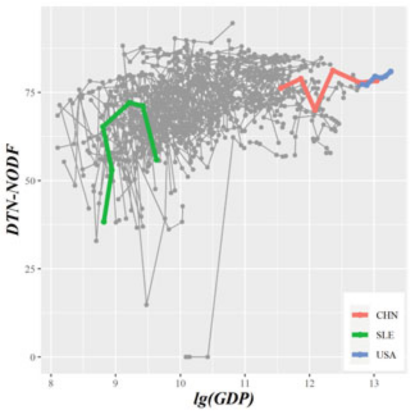
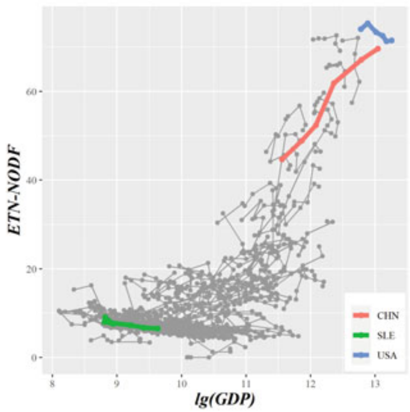


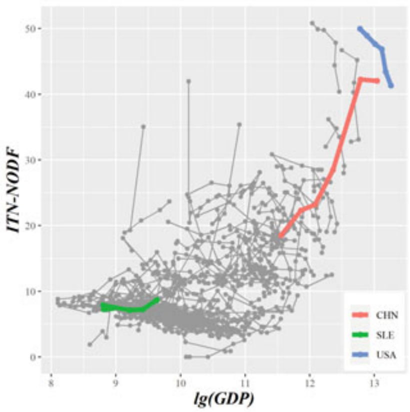
Fig. 12.10 Decomposition of ICIO table according to the nature of trade. *Notes* **a** shows the ICIO table composed of three countries and their three industrial sectors; **b**, **c**, **d** are three types of adjacency matrix of country A



(*a*) DTN-NODF and GDP



(*b*) ETN-NODF and GDP



(*c*) ITN-NODF and GDP

Fig. 12.11 Correlation of DTN-NODF, ETN-NODF, ITN-NODF and GDP. *Notes* Three countries with large differences in GDP are selected, with red representing China, blue the United States, and green Sierra Leone. Data source: World Bank—https://data.worldbank.org.cn/indicator

United States as expected. Such U.S. industrial layout undermines its stability when encountering the rare but severe systematic risk. For instance, it is impressive that the White House could not obtain enough prevention and control supplies at the beginning of the COVID-19 pandemic.

12.5.2 Regression Model

To describe the quantitative relationship between GDP and the *NODF*-based indicators accurately, this section applies regression analysis on these variables. First and foremost, a ***Mixed Effect Regression (MER)*** model is established by taking GDP of each country as the dependent variable and *DTN-NODF*, *ETN-NODF* and *ITN-NODF* as the independent variables, as shown in Table 12.1.

The correlation coefficients between the three independent variables are examined to check the existence of multicollinearity problems in the above model, so as to avoid spurious regression and ensure the validity of the model. The results show that the two variables, *ETN-NODF* and *ITN-NODF*, are significantly correlated, with correlation coefficients as high as 0.8608 (0.2631 for *DTN-NODF* and *ETN-NODF*, and 0.3289 for *DTN-NODF* and *ITN-NODF*).

The ***Ridge Regression (RR)*** model (see Table 12.2) is applied to find the penalization term and proven that the coefficients and conclusions are robust. The results of FE, RE, and LSDV models are also provided (see Tables 12.3, 12.4, 12.5). In sum, we concluded that the pooled regression (i.e., MER model) with PCA is the optimal solution.

To avoid multicollinearity problems in the following regression, PCA is performed between *ETN-NODF* and *ITN-NODF* to investigate the components that constitute their covariance and ensure the orthogonality of the independent variables [45]. The

Table 12.1 Results of the MER Model

Variables	Coeff.	Robust Std. Err	t	P	95% Confidence interval
DTN-NODF	−9.49	2.64	−3.60	0.000	[−14.67, −4.32]
ETN-NODF	44.27	3.88	11.40	0.000	[36.65, 51.90]
ITN-NODF	21.03	6.88	3.06	0.002	[7.54, 34.52]
Intercept term	71.97	180.36	0.40	0.690	[−281.95, 425.89]
R^2(adjusted)	0.411		**Root MSE**	867.68	

Table 12.2 Results of the RR model

Variables	Coeff.	Robust Std. Err	t	P	95% Confidence interval
DTN-NODF	−9.49	2.64	−3.60	0.000***	[−14.67, −4.32]
ETN-NODF	44.27	3.88	11.40	0.000***	[36.65, 51.90]
ITN-NODF	21.03	6.88	3.06	0.002*	[7.54, 34.52]
Intercept term	71.97	180.36	0.40	0.690	[−281.95, 425.89]
R^2(adjusted)	0.411		Root MSE	867.68	

Notes There is basically no difference between the coefficient of ridge regression and the mixed regression with PCA. For example, the coefficients of *DTN-NODF* and *ETN-NODF* in ridge regression are −9.49 and 44.27, and the mixed regression are −9.63, 48.99 × 0.8824 = 43.23. Thus, the regression coefficients and related conclusions of the mixed regression model are robust

Table 12.3 Results of the FE model

Variables	Coeff.	Robust Std. Err	t	P	95% Confidence interval
DTN-NODF	0.40	1.99	0.20	0.840	[−3.52, 4.33]
Comp	43.27	45.56	0.95	0.343	[−46.62, 133.17]
Intercept term	−538.56	712.27	−0.76	0.451	[-1943.92, 866.80]

Notes All coefficients in the fixed effects model failed the test

ranked components with their loadings are listed in Table 12.6, turning out that both the KMO and the SMC confirm the correctness of PCA. The first principal components of PCA results are retained.

As shown in Table 12.7, the model exhibits a relatively good fit with a large R^2 and all the independent variables (DTN-NODF and Component variable) pass the P-value test at the significance level of 0.01.

From the above results, *DTN-NODF* displays a weak negative correlation with GDP. It is believed that an excessively nested domestic trade network may hinder a country's economic development. Although a highly nested industrial layout can enhance the stability of the production system, it can also bring about problems such as lack of effective competition, path dependence in innovation, and blocked channels for international cooperation, thereby hampering the country's macroeconomic performance. On the other hand, *ETN-NODF* and *ITN-NODF* show a significant positive correlation with GDP. This can be attributed to the fact that for those who actively participates in the international trade cycle, they can complement each other by their own advantages and efficiently leverage resources in the international market, which leads to domestic socio-economic development.

Besides, the regression model indicates that the positive effect of *ETN-NODF* on GDP is about two times greater than that of *ITN-NODF*. This is also a self-evident phenomenon. Larger *ETN-NODF* means higher degree of nestedness in the export trade network structure, more orderly export mechanism, and more stable relevant channels, which together help to increase the trade surplus and boost domestic economic growth. At the same time, export growth drives import growth, secures the source of raw materials for the normal functioning of a country's production system. As a result, promotes the healthy development of the import trade network in turn, along with the increase of *ITN-NODF*. However, compared to the export trade network which can be unstoppably expanded, the expansion of the import trade network is limited by the relatively homogenous source of raw materials. That is why *ETN-NODF* is higher in value than *ITN-NODF*.

Table 12.4 Results of the LSDV model

Variables	Coeff.	Robust Std. Err	t	P	95% Confidence interval
DTN-NODF	0.40	2.19	0.18	0.854	[−3.91, 4.72]
Comp	43.27	50.14	0.86	0.389	[-55.65, 142.20]
Economies					
AFG	346.87	353.84	0.98	0.328	[−351.2987, 1045.033]
AGO	281.05	257.66	1.09	0.277	[−227.3288, 789.4262]
ALB	216.71	218.33	0.99	0.322	[−214.0759, 647.4973]
AND	236.70	238.52	0.99	0.322	[−233.9195, 707.3123]
ARE	422.05	276.65	1.53	0.129	[−123.7993, 967.9091]
ARG	−346.32	749.44	−0.46	0.645	[−1825.031, 1132.375]
ARM	214.61	231.28	0.93	0.355	[−241.7304, 670.9555]
ATG	202.95	188.93	1.07	0.284	[−169.8275, 575.7282]
AUS	−477.86	1384.80	−0.35	0.73	[−3210.196, 2254.469]
AUT	−134.15	501.67	−0.27	0.789	[−1123.986, 855.6903]
AZE	211.72	206.19	1.03	0.306	[−195.0985, 618.5441]
BDI	197.72	179.91	1.1	0.273	[−157.2522, 552.6847]
BEL	−1179.98	1749.33	−0.67	0.501	[−4631.553, 2271.592]
BEN	266.94	276.91	0.96	0.336	[−279.4249, 813.3128]
BFA	197.92	209.44	0.94	0.346	[−215.324, 611.1616]
BGD	463.47	441.16	1.05	0.295	[−406.9706, 1333.907]
BGR	322.55	330.76	0.98	0.331	[−330.0761, 975.1704]
BHR	321.21	341.12	0.94	0.348	[−351.8472, 994.2654]
BHS	263.53	275.51	0.96	0.34	[−280.0784, 807.1395]
BIH	303.62	310.98	0.98	0.33	[−309.9727, 917.2204]
BLR	109.25	102.04	1.07	0.286	[−92.07386, 310.582]
BLZ	142.7	156.80	0.91	0.364	[−166.6857, 452.0805]
BMU	163.46	161.68	1.01	0.313	[−155.5533, 482.4662]
BOL	80.53	84.62	0.95	0.343	[−86.4349, 247.4872]
BRA	527.65	715.03	0.74	0.462	[−883.1721, 1938.471]
BRB	282.83	291.34	0.97	0.333	[−292.0029, 857.6546]
BRN	334.04	351.24	0.95	0.343	[−358.9823, 1027.066]
BTN	79.27	88.60	0.89	0.372	[−95.53579, 254.075]
BWA	285.04	305.34	0.93	0.352	[−317.4236, 887.4988]
CAF	265.57	260.87	1.02	0.31	[−249.161, 780.2916]
CAN	770.19	341.90	2.25	0.025*	[95.58298, 1444.791]
CHE	−909.9	1534.75	−0.59	0.554	[−3938.092, 2118.301]
CHL	−60.5	228.66	−0.26	0.792	[−511.6715, 390.6751]

(continued)

Table 12.4 (continued)

Variables	Coeff.	Robust Std. Err	t	P	95% Confidence interval
CHN	1503.19	2459.50	0.61	0.542	[−3349.617, 6355.998]
CIV	346.24	367.63	0.94	0.348	[−379.13, 1071.614]
CMR	360.41	378.99	0.95	0.343	[−387.3771, 1108.196]
COD	265.26	265.10	1	0.318	[−257.8036, 788.316]
COG	290.82	307.71	0.95	0.346	[−316.319, 897.9642]
COL	81.02	76.04	1.07	0.288	[−69.00603, 231.0458]
CPV	219	208.95	1.05	0.296	[−193.2711, 631.2752]
CRI	390.24	414.36	0.94	0.348	[−427.3227, 1207.812]
CUB	381.23	369.91	1.03	0.304	[−348.6375, 1111.096]
CYP	342.62	366.80	0.93	0.352	[−381.1153, 1066.35]
CZE	−172.23	317.34	−0.54	0.588	[−798.369, 453.9041]
DEU	198.25	2855.59	0.07	0.945	[−5436.072, 5832.577]
DJI	163.01	138.96	1.17	0.242	[−111.1765, 437.1888]
DNK	−703.72	1088.11	−0.65	0.519	[−2850.657, 1443.218]
DOM	416.84	427.58	0.97	0.331	[−426.8171, 1260.502]
DZA	408.18	350.16	1.17	0.245	[−282.7166, 1099.085]
ECU	−118.3	175.10	−0.68	0.5	[−463.7915, 227.1998]
EGY	511.76	410.13	1.25	0.214	[−297.4581, 1320.971]
ERI	235.58	222.08	1.06	0.29	[−202.6103, 673.7649]
ESP	−609.87	1790.20	−0.34	0.734	[−4142.082, 2922.346]
EST	−48.19	69.35	−0.69	0.488	[−185.0211, 88.64208]
ETH	−107.18	134.83	−0.79	0.428	[−373.2024, 158.8407]
FIN	−20.37	245.53	−0.08	0.934	[−504.8219, 464.0865]
FJI	276.83	299.98	0.92	0.357	[−315.0676, 868.72]
FRA	−1.51	2245.24	0	0.999	[−4431.562, 4428.534]
GAB	314.42	332.34	0.95	0.345	[−341.3062, 970.1512]
GBR	−1022.55	3512.17	−0.29	0.771	[−7952.356, 5907.252]
GEO	−178.73	200.24	−0.89	0.373	[−573.8264, 216.3583]
GHA	323.03	336.75	0.96	0.339	[−341.3976, 987.4673]
GIN	264.45	280.28	0.94	0.347	[−288.5671, 817.4742]
GMB	203.94	205.10	0.99	0.321	[−200.7466, 608.6262]
GRC	100.46	91.75	1.09	0.275	[−80.57459, 281.495]
GRL	375.57	432.99	0.87	0.387	[−478.7589, 1229.897]
GTM	400.99	420.56	0.95	0.342	[−428.8063, 1230.781]
GUY	403.69	444.55	0.91	0.365	[−473.4424, 1280.816]
HKG	−172.88	417.98	−0.41	0.68	[−997.5889, 651.824]

(continued)

Table 12.4 (continued)

Variables	Coeff.	Robust Std. Err	t	P	95% Confidence interval
HND	351.7	384.12	0.92	0.361	[−406.2073, 1109.612]
HRV	393.84	411.64	0.96	0.34	[−418.3654, 1206.055]
HTI	322.38	338.26	0.95	0.342	[−345.0331, 989.8003]
HUN	−39.7	165.92	−0.24	0.811	[−367.0765, 287.6826]
IDN	−204.47	695.67	−0.29	0.769	[−1577.078, 1168.141]
IND	−405.95	1554.43	−0.26	0.794	[−3472.961, 2661.06]
IRL	61.82	107.64	0.57	0.566	[−150.5622, 274.2033]
IRN	−367.70	704.14	−0.52	0.602	[−1757.034, 1021.625]
IRQ	287.09	163.82	1.75	0.081	[−36.13326, 610.32]
ISL	336.34	362.54	0.93	0.355	[−378.9751, 1051.662]
ISR	−403.11	647.93	−0.62	0.535	[−1681.534, 875.3045]
ITA	−358.7	2247.07	−0.16	0.873	[−4792.36, 4074.952]
JAM	351.8	378.13	0.93	0.353	[−394.2818, 1097.891]
JOR	325.8	359.43	0.91	0.366	[−383.3841, 1034.987]
JPN	2047.56	3094.29	0.66	0.509	[−4057.734, 8152.856]
KAZ	−244.62	362.13	−0.68	0.5	[−959.1294, 469.8803]
KEN	−197.97	244.35	−0.81	0.419	[−680.0901, 284.1591]
KGZ	−455.86	512.61	−0.89	0.375	[−1467.283, 555.5592]
KHM	289.57	316.28	0.92	0.361	[−334.4798, 913.6205]
KOR	−313.24	1286.85	−0.24	0.808	[−2852.31, 2225.822]
KWT	−154.41	235.90	−0.65	0.514	[−619.8692, 311.0498]
LAO	270.07	289.50	0.93	0.352	[−301.147, 841.2839]
LBN	323.88	326.75	0.99	0.323	[−320.815, 968.5826]
LBR	184.38	192.94	0.96	0.341	[−196.318, 565.0694]
LBY	365.12	357.11	1.02	0.308	[−339.4948, 1069.737]
LIE	302.74	309.76	0.98	0.33	[−308.4337, 913.9225]
LKA	355.78	375.62	0.95	0.345	[−385.3557, 1096.923]
LSO	134.13	131.54	1.02	0.309	[−125.4121, 393.6786]
LTU	−77.57	124.47	−0.62	0.534	[−323.162, 168.0136]
LUX	3.05	33.70	0.09	0.928	[−63.45578, 69.54905]
LVA	−70.4	97.66	−0.72	0.472	[−263.0863, 122.2896]
MAC	235.37	247.68	0.95	0.343	[−253.3254, 724.0649]
MAR	426.86	415.58	1.03	0.306	[−393.1085, 1246.832]
MCO	228.67	228.95	1	0.319	[−223.0632, 680.4089]
MDA	26.78	37.72	0.71	0.479	[−47.63299, 101.1987]
MDG	293.64	318.76	0.92	0.358	[−335.2989, 922.5689]

(continued)

Table 12.4 (continued)

Variables	Coeff.	Robust Std. Err	t	P	95% Confidence interval
MDV	88.83	87.04	1.02	0.309	[−82.90518, 260.5718]
MEX	374.19	398.69	0.94	0.349	[−412.467, 1160.84]
MKD	−157.69	179.44	−0.88	0.381	[−511.7428, 196.361]
MLI	275.04	271.87	1.01	0.313	[−261.3773, 811.4663]
MLT	−125.21	149.46	−0.84	0.403	[−420.1182, 169.6895]
MMR	456.09	479.59	0.95	0.343	[−490.168, 1402.357]
MNE	32.86	22.77	1.44	0.151	[−12.06697, 77.78323]
MNG	209.38	216.84	0.97	0.336	[−218.4693, 637.2248]
MOZ	277.65	287.27	0.97	0.335	[−289.1506, 844.4498]
MRT	136.57	144.52	0.94	0.346	[−148.5807, 421.7112]
MUS	−221.78	246.34	−0.9	0.369	[−707.8259, 264.269]
MWI	265.54	286.68	0.93	0.356	[−300.1154, 831.1903]
MYS	−432.16	665.46	−0.65	0.517	[−1745.172, 880.8547]
NAM	282.94	314.23	0.9	0.369	[−337.0612, 902.9311]
NCL	285.79	312.88	0.91	0.362	[−331.5583, 903.1301]
NER	211.67	211.31	1	0.318	[−205.2679, 628.5985]
NGA	462.42	328.72	1.41	0.161	[−186.1661, 1111.009]
NIC	298.84	323.29	0.92	0.357	[−339.0496, 936.7254]
NLD	−1257.85	2128.45	−0.59	0.555	[−5457.455, 2941.764]
NOR	171.77	144.10	1.19	0.235	[−112.5632, 456.0975]
NPL	322.12	342.61	0.94	0.348	[−353.8727, 998.1114]
NZL	−324.92	491.89	−0.66	0.51	[−1295.46, 645.6192]
OMN	306.8	306.43	1	0.318	[−297.7998, 911.4071]
PAK	493.49	426.25	1.16	0.248	[−347.5393, 1334.529]
PAN	366.84	392.24	0.94	0.351	[−407.0808, 1140.766]
PER	271.73	222.84	1.22	0.224	[−167.9554, 711.4218]
PHL	−104.64	262.64	−0.4	0.691	[−622.8616, 413.5793]
PNG	297.34	316.28	0.94	0.348	[−326.6992, 921.381]
POL	297.22	20.63	14.4	0***	[256.5053, 337.9304]
PRT	−41.92	222.84	−0.19	0.851	[−481.6021, 397.7661]
PRY	−60.38	68.79	−0.88	0.381	[−196.1178, 75.3495]
PSE	250.98	256.15	0.98	0.328	[−254.4312, 756.3853]
PYF	300.49	308.45	0.97	0.331	[−308.1146, 909.092]
QAT	207.47	166.47	1.25	0.214	[−120.9961, 535.9267]
ROU	−172.6	299.78	−0.58	0.565	[−764.0896, 418.8857]
RUS	55.24	861.24	0.06	0.949	[−1644.06, 1754.53]

(continued)

Table 12.4 (continued)

Variables	Coeff.	Robust Std. Err	t	P	95% Confidence interval
RWA	205.69	207.25	0.99	0.322	[−−203.2454, 614.611]
SAU	678.99	400.19	1.7	0.091	[−−110.6093, 1468.596]
SDN	678.37	630.08	1.08	0.283	[−564.8316, 1921.575]
SEN	213.10	229.29	0.93	0.354	[−239.313, 665.5046]
SGP	−1055.88	1389.32	−0.76	0.448	[−3797.131, 1685.373]
SLE	236.47	236.93	1	0.32	[−231.0028, 703.9444]
SLV	371.88	399.40	0.93	0.353	[−416.1667, 1159.925]
SMR	211.90	195.89	1.08	0.281	[−174.6041, 598.398]
SOM	300.16	297.33	1.01	0.314	[−286.5072, 886.8234]
SRB	94.44	55.08	1.71	0.088	[−14.23795, 203.1249]
SSD	400.82	407.84	0.98	0.327	[−403.8719, 1205.521]
STP	193.51	198.63	0.97	0.331	[−198.4036, 585.4259]
SUR	243.73	262.98	0.93	0.355	[−275.149, 762.6014]
SVK	−247.02	326.19	−0.76	0.45	[−890.6272, 396.5884]
SVN	19.56	13.68	1.43	0.155	[−7.434995, 46.55195]
SWE	−393.60	866.62	−0.45	0.65	[−2103.527, 1316.32]
SWZ	242.6	251.98	0.96	0.337	[−254.5818, 739.7901]
SYC	132.13	125.70	1.05	0.295	[−115.8824, 380.1409]
SYR	359.9	377.63	0.95	0.342	[−385.2012, 1104.996]
TCD	188.54	157.18	1.2	0.232	[−121.5861, 498.6678]
TGO	238.09	240.84	0.99	0.324	[−237.107, 713.2928]
THA	−888.23	1271.91	−0.7	0.486	[−3397.813, 1621.363]
TJK	244.53	256.35	0.95	0.341	[−261.2624, 750.32]
TKM	241.53	249.09	0.97	0.334	[−249.9408, 732.9929]
TTO	233.84	258.47	0.9	0.367	[−276.1362, 743.8105]
TUN	390.26	415.38	0.94	0.349	[−429.3194, 1209.847]
TUR	151.52	355.53	0.43	0.67	[−549.9788, 853.0178]
TZA	363.15	384.23	0.95	0.346	[−394.9798, 1121.274]
UGA	338.52	352.60	0.96	0.338	[−357.1915, 1034.23]
UKR	−625.16	818.54	−0.76	0.446	[−2240.213, 989.8846]
URY	−251.19	310.16	−0.81	0.419	[−863.1708, 360.7852]
USA	8620.85	3545.36	2.43	0.016*	[1625.561, 15,616.13]
UZB	−500.93	603.00	−0.83	0.407	[−1690.688, 688.8321]
VEN	−229.32	437.64	−0.52	0.601	[−1092.822, 634.1773]
VNM	−357.61	489.28	−0.73	0.466	[−1323.01, 607.7872]
VUT	180.37	171.08	1.05	0.293	[−157.189, 517.9312]

(continued)

Table 12.4 (continued)

Variables	Coeff.	Robust Std. Err	t	P	95% Confidence interval
WSM	146.34	140.63	1.04	0.299	[−131.1335, 423.8183]
YEM	343.20	357.33	0.96	0.338	[−361.8306, 1048.234]
ZAF	−490.76	832.22	−0.59	0.556	[−2132.81, 1151.288]
ZMB	194.33	185.64	1.05	0.297	[−171.9579, 560.6236]
ZWE	272.31	291.27	0.93	0.351	[−302.3891, 847.0155]
_cons	−701.87	663.58	−1.06	0.292	[−2011.17, 607.42]

Notes The intercept term of each country basically fails the test, which further shows that the individual effect between countries is not significant, and the mixed regression model is thus better

Table 12.5 Results of the RE model

Variables	Coeff.	Robust Std. Err	Z	P	95% Confidence interval
DTN-NODF	−1.89	1.33	−1.42	0.156	[-−4.50, 0.72]
Comp	46.55	13.81	3.37	0.001**	[19.49, 73.61]
Intercept term	−430.93	188.57	−2.29	0.022*	[−800.53, -−61.33]

Notes ITN-NODF fails the test, indicating that the fitting effect of random effects is not good

Table 12.6 Principal component analysis of ETN-NODF and ITN-NODF

Component	Eigenvalue	Difference	Proportion	Cumulative	KMO	SMC
ETN-NODF	233.326	220.745	0.9488	0.9488	0.9999	0.7410
ITN-NODF	12.581	–	0.0512	1.0000	0.9999	0.7410

Table 12.7 Results of MER model after PCA

Variables	Coeff.	Robust Std. Err	t	P	95% Confidence interval
DTN-NODF	−9.63	2.60	−3.71	0.000	[−14.72, −4.54]
Comp	48.99	1.83	26.74	0.000	[45.39, 52.58]
Intercept term	74.09	180.14	0.41	0.681	[−279.40, 427.57]
R^2(adjusted)	0.411		**Root MSE**	867.3	

Notes Comp. = 0.8824*ETN-NODF* + 0.4705*ITN-NODF*

12.6 Empirical Analysis II: Brexit's Impact on European Nations

12.6.1 Brexit

On December 24, 2020, the ***European Union (EU)*** and the ***United Kingdom (UK)*** reached an agreement on a series of cooperative relations (including economic and trade fields) after several rounds of negotiations, which further promoted the process of "Brexit". This British exodus event, which began in 2013 and was fermented by the referendum in 2016, was finally getting close to an end. This seven-year tug of war reflects not only the hindrance of the European integration process, but also the difficulty of global economic integration. On the one hand, Brexit stem from Salisbury's "Splendid Isolation" policy. Regarding the European debt crisis, refugees and immigration issues, the United Kingdom has always opposed and resolutely stayed out of the matter [46]. On the other hand, the social and economic roots of Brexit are due to the fact that the global flow of value promotes the unprecedented prosperity of the world economy and weakens the country's ability to distribute as the main body at the same time. The imbalance in the distribution of all kinds of productive resources has made the heterogeneity of the development of various countries continue to increase, the factors of social instability have multiplied, and the extreme anti-elitism and populist sentiments have been unprecedentedly high [47, 48]. This is exactly why the richer elites advocated Britain staying in Europe in the referendum. Obviously, the European integration has brought greater benefits to them [49].

For a long time, there exists mutually beneficial business partnership between the UK and the EU because the two sides have a high degree of consistency in economic and political aspects. As a huge change in the economic and social structure of Europe, Brexit will not only break the EU's internal balance in the short term, damage its international status, but will also promote changes in the world economic system and political structure to a certain extent [50]. In a word, the relationship between the UK and the EU must be revisit. Therefore, scholars have drawn many conclusions that are worth learning from around the impact of Brexit on both, mainly focused on the social and historical motivations and economic consequences. Related studies include, but not be limited to, the exploration of the deep-seated causes of European populism [46, 47]; the analysis of the reasons for Brexit and its impact on Europe and the world [48–50], the direct and indirect influence on economic factors such as investment, production and budget [51–54], and the factors affecting the outcome of the Brexit vote [55, 56], etc.

12.6.2 Simulation Setting

In order to further quantify the impact of Brexit, we design a Randomized Controlled Trial (RCT) and proposed the ***Nestedness Disturbance Index (NDI)***. Firstly, the sub-network (named GIVCN-ADB2019-EU) consisting of 28 EU members (including the UK) is separate out of the pruned network. Secondly, the contribution of countries to the stability of EU's trade network can be measured one by one, by removing all the sectors within a country once at a time and calculating the *NODF* of the rest network (formed by the remaining 27 members). Thirdly, NDI can be used to measure the contribution of nodes or communities to the overall nestedness of network:

$$NDI(u) = \frac{\left(NODF_{Original} - NODF_{Remove}\right)}{NODF_{Original}} \times 100 \tag{12.6}$$

where $NDI(u)$ represents the contribution of country u to the nestedness of the economic system in which it is located, $NODF_{Original}$ the initial *NODF* of corresponding economic network, and $NODF_{Remove}$ its subsequent *NODF* after removing an economy. $NDI > 0$ means the *NODF* of network is reduced after the removal of certain economy, that is, this country or region has a positive effect on maintaining the industrial stability of the whole economic system. Otherwise, $NDI < 0$ indicates this economy bring a negative effect.

12.6.3 Results and Discussions

Based on the NDI, we want to know what kind of influence that Brexit may have on the European economy. For this purpose, we calculate all the EU members' (including UK) contribution to the nestedness of GIVCN-ADB2019-EU in three periods (2010 is the timing before the idea of Brexit came up, 2015 is just before Brexit referendum, and 2019 is after that). MDS of three networks are shown in Fig. 12.12, and the results of trend and correlation are shown in Fig. 12.13.

The *NDIs* of countries such as Germany, France, Italy, and UK are positive all the time, as they play an important role in maintaining the stability of the EU economic system. While the removal of countries such as Greece, Estonia, and Latvia can increase that of this alliance organization. Therefore, the impact of breaking the link between a single country and the entire regionally economic system cannot be easily summed up. So, can we find a macroeconomic indicator that is highly related to *NDI* and interpret the importance of the economy from another dimension? Yes, it is GDP. As shown in Fig. 12.13d, e, and f, NDI is obviously proportional to GDP, which explains the strong relationship between the country's industrial status and its economic development level from one side. That is, a country's role in the stability

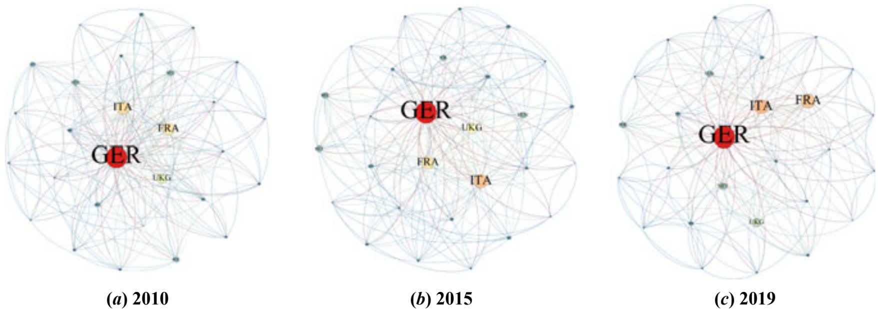
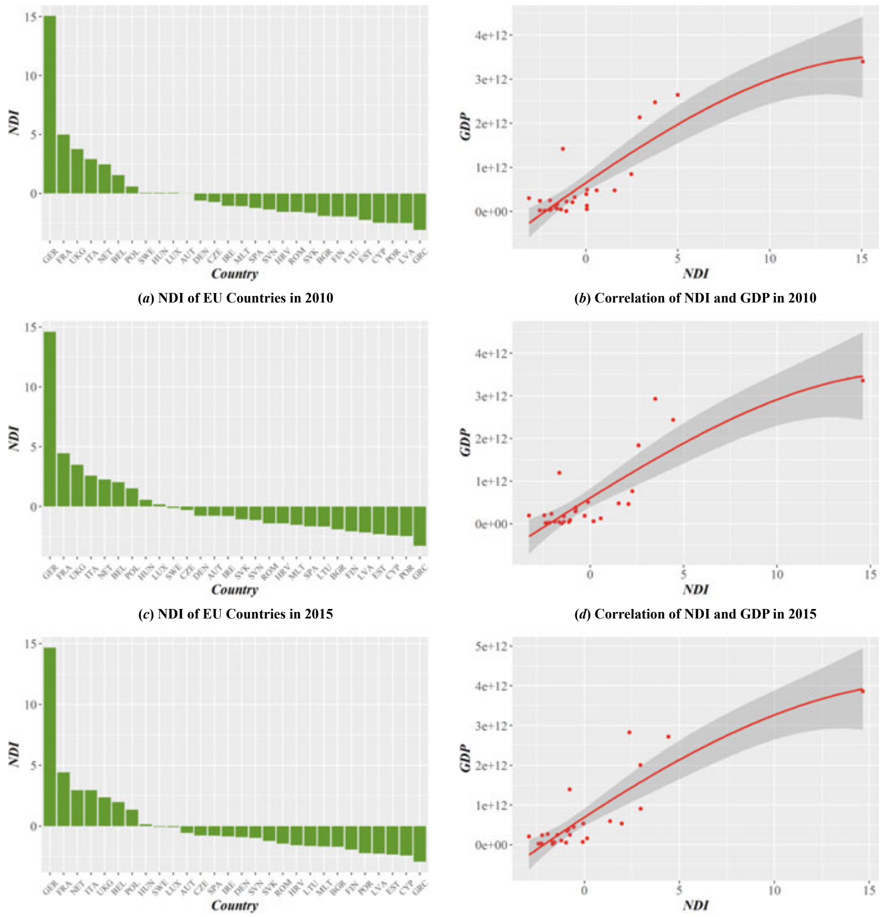


Fig. 12.12 GIVCN-ADB2019-EU models

of economic organization system is closely related to its economic conditions. The greater the economic power, the wider the distribution of trade, and the stronger the dependence of other countries. Once this country is suddenly separated from the existing economic community, the unbalanced product supply system will cause immeasurable losses to other member states.

The *NDI* of Germany is the largest in recent decades, far beyond the second one, which means it is the very core of European economic development. We know that, as the largest economy of EU, Germany ranks among the best in the world with strong sales in many industrial fields, such as automobile manufacturing, machinery and equipment manufacturing, chemical and medical technology. Along with its status of industrial power, a Germany-centered trade network of intermediate goods is already formed in the Europe. Under the perspective of nested structure, Germany is an indispensable hub for maintaining European economic development. At another end, Greece's *NDI* is the smallest since at least 2010. Compared with other countries in the Eurozone, its economic foundation is weaker, and especially the manufacturing sectors are far behind the international level, while its national economic income mainly comes from tourism and shipping. This fragile internal industrial structure makes Greece unable to withstand external shocks when facing the financial crisis happened in 2009. No surprise, those countries deeply affected by the European debt crisis, such as Greece, Portugal, Ireland, and Spain, are the unstable factors in the regional industrial system.

As for the UK, it is the second largest in real but not the second most important economy of EU under the perspective of nestedness. The UK's *NDI* used to rank behind Germany and France, however, drops to the fifth place after Brexit was announced in 2016. Since its *NDI* is positive all the time, we believe an EU containing UK is benefit for all the other countries. In other words, Brexit initiated by the UK not only undermines the integrity of the EU, but also disrupts the balance of industrial structure inside it. In essence, Brexit is a process of decoupling an economy from its original RVC, which will inevitably lead to the RVC's restructuring and may also bring the opportunity to some relevant countries on their IVC climbing. In fact, the EU members have taken a series of measures to reduce the systemic and



(*a*) NDI of EU Countries in 2010

(*b*) Correlation of NDI and GDP in 2010

(*c*) NDI of EU Countries in 2015

(*d*) Correlation of NDI and GDP in 2015

(*e*) NDI of EU Countries in 2019

(*f*) Correlation of NDI and GDP in 2019

Fig. 12.13 NDI and its relationship with GDP. *Notes* **a**, **c**, and **e** are the rankings of EU member states' *NDI* in 2010, 2015 and 2019, respectively; **b**, **d**, and **f** are the corresponding relationship between *NDI* and GDP

structural risks of the UK's no-deal Brexit. For example, after the Brexit referendum, the senior EU members, led by Germany and France, supported the implementation of the "Multi-Speed Europe" program to promote reforms and resolve crises, because of European outstanding diversity of both economic development level and political will. In sum, Brexit has caused certain obstacles to the integration of the EU in the short term, but in the long run, it may not be the thrust of European transformation.

12.7 Empirical Analysis II: RCEP's Economic Significance to Relevant Nations

12.7.1 Rcep

On November 15, 2020, fifteen countries—the ten member states of the ASEAN (including Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, Vietnam) and its five FTA partners (i.e., Australia, China, Japan, New Zealand and Republic of Korea)—signed the RCEP, arguably the largest free trade agreement in history. RCEP and the CPTPP, which concluded in 2018 and is also dominated by East Asian members, are the only major multilateral free trade agreements signed in the Trump era. India and the United States were to be members of RCEP and the CPTPP, respectively, but withdrew under the Modi and Trump governments. As the agreements are now configured, they forcefully stimulate intra-East Asian integration around China and Japan. This is partly the result of U.S. policies. The United States needs to rebalance its economic and security strategies to advance not only its economic interests, but also its security goals.

RCEP isn't as comprehensive and doesn't cut tariffs as deeply as CPTPP's successor. But many analysts think RCEP's sheer size makes it more significant. RCEP will cover a market of 2.2 billion people with a combined size of $26.2 trillion or 30% of the world's GDP. In the future, it could add $209 billion annually to world incomes, and $500 billion to world trade by 2030, according to computer simulations published by Petri and Plummer [57]. Benefiting from the RCEP, relevant countries can make full use of the resources from the same economic region for production. For instance, it will be easier for the drugs to obtain the original qualification of the contracting countries, and finally enjoy more preferential tax rates and trade treatment.

ASEAN-centered trade agreements tend to improve over time. Southeast Asia will benefit significantly from RCEP ($19 billion annually by 2030) but less so than Northeast Asia because it already has FTAs with RCEP partners. Negotiations on the trilateral China-South Korea-Japan FTA, which has been stuck for many years, will become active. Of course, RCEP could improve access to Chinese BRI funds, enhancing gains from market access by strengthening transport, energy, and communications links. RCEP's favorable rules of origin will also attract foreign investment.

12.7.2 Simulation Setting

This section will use simulation methods to discuss and analyze the changes in the international trade of relevant countries after the implementation of RCEP. Our aim is to observe how they are embedded in the production system of Southeast Asia, as well as, how to achieve their rise in the RVC network. To this end, we follow

Table 12.8 Rules of scenario simulation

Quantitative relation of each scenario					Trade Volume between ASEAN Member States and Five FTA Partners
High	200%				Doubled
	Medium	167%			Increased by 2/3
		Weak	133%		Increased by 1/3
			Inactive	100%	Remain the same

Notes We treat the ASEAN as a whole during the simulation process, and thus the trade volume between ASEAN member states has not changed, only the import and export parts between them and other FTA partners have been increased

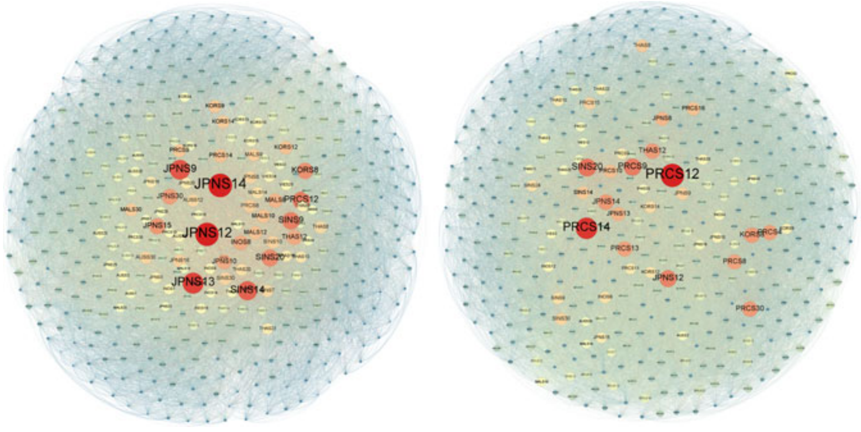
the simulation process in Sect. 12.2 and set the specific scenario simulation rules in Table 12.8.

Firstly, GIVCNBG models including all the countries and sectors in ADB2019 database are established. Secondly, RECP sub-networks are extracted from the pruned GIVCNBG-FE model and labeled as the "Inactive State" of RCEP (denoted by Inactive-RCEP). Thirdly, on the basis of GVICNBG model, the import and export volume of various sectors among RCEP-related countries is increased by 33%, 67%, and 100% respectively, and the RCEP sub-networks are extracted after pruning again and labeled as the "Weak Implementation State" (Weak-RECP), "Medium Implementation State" (Medium-RCEP) and "High Implementation State" (High-RCEP). Finally, statistics on *DTN-NODF*, *ETN-NODF* and *ITN-NODF* of each country is made under various scenarios.

12.7.3 Results and Discussions

By observing the GIVCNBG-FE model based on the ADB-MRIO data in 2000 and 2019 (as shown in Fig. 12.14), we have obtained two basic conclusions. On the one hand, the density of local sub-network formed by RCEP countries is greatly enhanced, from 0.136 in 2000 to 0.141 in 2019. This indicates the importance of intermediate goods trade within and among them in maintaining the robustness of GVC has greatly increased, and therefore the more and more IO relations can be retained after network pruning. On the other hand, the RVC composed of industrial sectors in RCEP countries still presents a "core-periphery" structure, but the core has changed from Japanese "Electrical and Optical Equipment" (S14) and "Basic Metals and Fabricated Metal" (S12) to Chinese the two sectors, which means the core country that promotes economic development in the Asia–Pacific region has also shifted from Japan to China.

According to the results of simulation in Table 12.9 and Fig. 12.15, the increase in trade volume among RCEP-related countries has enhanced the robustness of RVC network, as their *ETN-NODF* and *ITN-NODF* are nearly all on the rise (except for



(*a*) 2000 (*b*) 2019

Fig. 12.14 GIVCN-ADB2019-RCEP models

Malaysia in the medium-RCEP state). This shows that the signing of this agreement has underpinned the import and export channels among the member states. To be sure, RCEP will accelerate Asian economic integration and help countries achieve new economic growth.

The specific analysis conclusions are as follows:

First and foremost, all things considered, the *ETN-NODF* of China, Japan, South Korea and Singapore are significantly higher than their *ITN-NODF* (more than 25). These countries rely on a sound industrial structure and advanced technology and locate at the upstream of Asian-Pacific RVC. In the opposite, Malaysia, Philippines, Brunei, and Laos have lower values of *ETN-NODF* and *ITN-NODF*, and the difference between the two is also small (less than 5), indicating that they are not highly embedded in the GVC. It is difficult for them to achieve a trade surplus by the current industrial layout, resulting in insufficient economic development momentum. Between the previous two cases, although Indonesia, Thailand and Vietnam are all export-oriented economies (ETN-NODF is relatively higher than ITN-NODF), due to the existence of the previous ASEAN "10 + 1" agreements and the overlapping niche markets of the processing and manufacturing industries with China, Japan and Korea, the reconstruction of RVC triggered by RCEP cannot directly bring about obvious changes in their industrial status.

Second, Cambodia is the only country that *ITN-NODF* is greater than *ETN-NODF*, and the reversal can only be achieved in the high-RCEP state. The country's main industries are agriculture, rubber, and clothing, and exports are basically primary products. Therefore, its industrial structure is locked in a low-end state, which is not conducive to the healthy development of its national economy. With the continuous increase of RCEP's influence, if Cambodia can give play to its advantages in labor-intensive industries and establish more stable import and export trade channels,

Table 12.9 Statistics on ETN-NODF and ITN-NODF of RCEP-related nations

Scenario Setting		Inactive-RCEP		Weak-RECP		Medium-RCEP		High-RCEP	
category	country	ETN-NODF	ITN-NODF	ETN-NODF	ITN-NODF	ETN-NODF	ITN-NODF	ETN-NODF	ITN-NODF
ASEAN	INO	20.240	5.212	20.806	5.689	21.252	6.009	21.552	6.152
	MAL	11.649	7.872	11.962	8.273	11.849	8.498	12.314	8.825
	PHI	8.446	5.789	9.375	6.042	10.153	6.193	10.378	6.521
	THA	23.661	8.477	24.756	8.847	24.934	8.907	25.296	9.303
	SIN	28.491	5.889	30.306	6.225	31.456	6.638	31.752	6.655
	BRU	8.941	8.136	9.629	8.347	10.013	8.687	10.076	8.576
	CAM	3.440	3.945	3.719	4.201	4.033	4.272	4.453	4.424
	LAO	4.707	2.566	5.221	2.703	5.669	2.728	6.111	2.769
	VIE	13.858	7.300	14.564	7.673	15.266	7.799	15.805	7.963
Other partners	PRC	41.337	14.982	44.133	17.625	46.066	20.127	47.851	21.730
	JPN	32.857	8.820	36.331	10.358	38.688	11.691	40.677	13.172
	KOR	28.320	5.715	31.366	7.127	33.654	8.221	35.791	9.182
	AUS	10.947	5.895	13.659	7.24	16.166	8.060	17.726	8.876

Notes RCEP-related countries in ADB2019 database include Australia (AUS), People's Republic of China (PRC), Indonesia (INO), India (IND), Japan (JPN), Republic of Korea (KOR), Malaysia (MAL), Philippines (PHI), Thailand (THA), Viet Nam (VIE), Lao People's Democratic Republic (LAO), Brunei Darussalam (BRU), Cambodia (CAM), and Singapore (SIN)

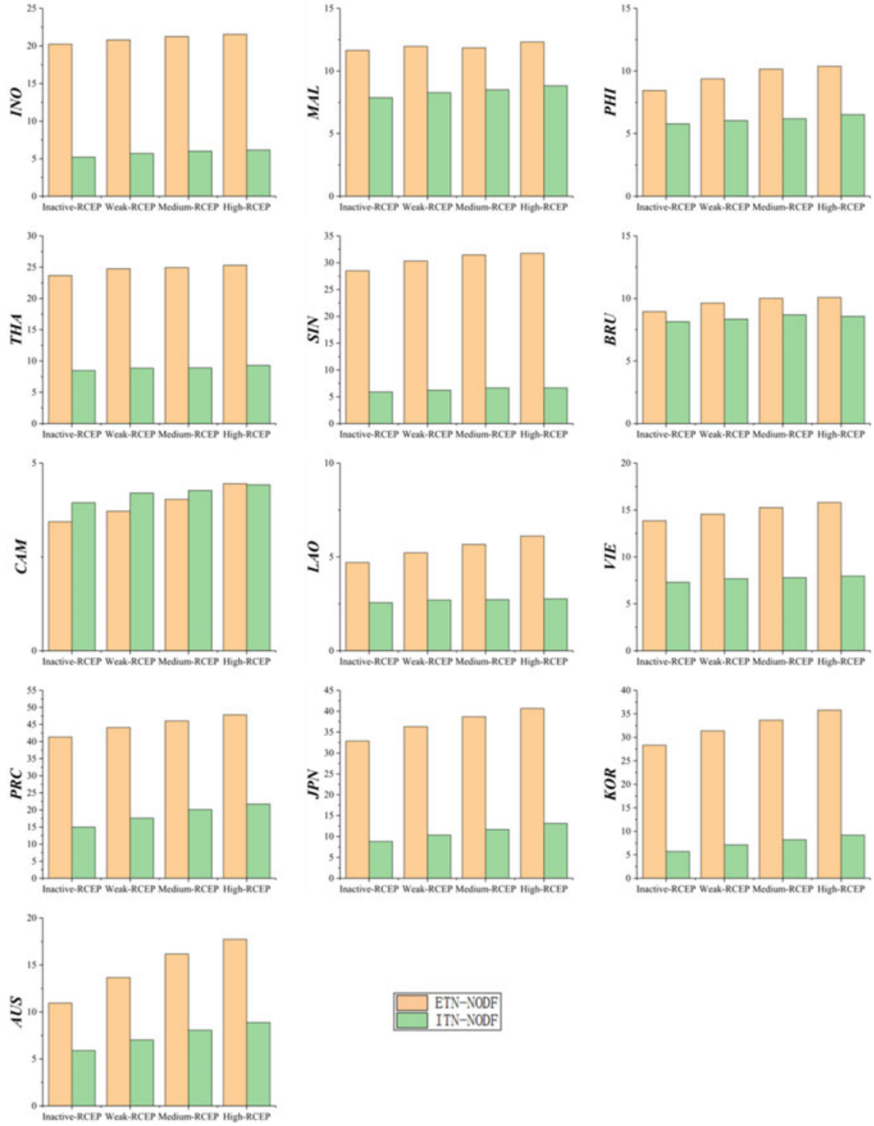


Fig. 12.15 Comparison on RCEP-related nations

then it will be possible to achieve a higher status on the GVC and a new type of industrialization.

Third, Australia's ETN-NODF has risen rapidly with the deepening of RCEP's realization, a large part of which is attributed to the export trade with China. As we all know, Australia's foreign trade dependence on China is extremely high, as the latter has long become its number one trading partner and far exceeds its combined trade with the United States and Japan. The signing of RCEP can further consolidate the economic and trade cooperation ease the political tension between Australia and China. Nowadays, the COVID-19 epidemic has slowed the development of the world economy. Therefore, for a resource-exporting country like Australia, integrating into the Asia–Pacific market through the RCEP agreement is undoubtedly a feasible strategy to maintain the stability of its international trade network.

Fourth, RCEP will further consolidate the foundation of economic and trade cooperation between China, Japan and South Korea, accelerate the pace of China-Japan-Korea free trade area negotiations, and enhance the complementarity between their industrial sectors. At the same time, the industrial structure of the Asia–Pacific region reconstructed by RCEP will also promote the gradient transfer of processing trade from them to ASEAN member states. On the one hand, China, Japan and South Korea will transfer the low-end manufacturing sectors to those economies with imperfect NVC within ASEAN, thereby driving the development of theirs. On the other hand, the three countries can carry out in-depth technology trade and technological innovation cooperation in high-end manufacturing sectors, and pull the entire South Asian region out of the dilemma of "low-end" and "marginalization" via technology spillover effects.

Finally, the severe pandemic has hindered China's supply chain in Europe and the United States, forcing China to explore the vast markets in Asia and countries along the Belt and Road [58, 59]. In Q1 of 2020, ASEAN has become biggest trading partner, which laid a good foundation for the signing of RCEP. Furthermore, although the "Dual Circulation" development pattern is of uppermost priority, China may promote the merger of the RCEP and the CPTPP, since it has given positive consideration to joining the CPTPP and strengthened communications with member countries. As we bear witness, on September 16, 2021, China has filed an application to join the CPTPP. Promoting domestic circulation does not mean that China should close its doors and isolate itself from global trade, but rather, integrate into the global value chain with a higher level of openness and regain new advantages in international competition and cooperation.

12.8 Summary

The ecological metaphor is not ecological reductionism or imperialism, which is not to simply reduce the phenomenon of macroeconomic evolution (industrial transfer between countries and adjustment of industrial structure within countries) to ecological evolution. Moreover, the research on ecological niche by Chase and Leibold is only an abstract steady-state adjustment mechanism in the milieu interne, without describing the specific evolutionary process. Complex system theory must be embedded in it to accurately explain the evolutionary laws of economic systems. Therefore, the evolutionary game idea of species population in ecology has certain enlightening significance to the theory of economic evolution.

The nested structure is a sustainable structural characteristic formed by species seeking ecosystem stability in the long-term development process, which has important implications for studying the functions and status of industrial sectors in the GVC network, as well as the national macro-industrial layout. Unlike previous studies that describe network characteristics through various network indicators, this chapter builds a new theoretical analysis framework, and establishes, through econometric analysis, a bridge between the microstructure of local networks in the global production and countries' macroeconomic performance, directing countries to optimize the international and domestic industrial layout and participate in the international and domestic double cycle.

Under the combined impact of COVID-19 pandemic and the Sino-US trade friction, the generalist industrial sectors, which have contributed greatly to China's economic development, is bound to be damaged, and the import and export trade network hampered. In the short term, China's relevant supply chain may experience a decrease in efficiency or even be disrupted; in the long term, more countries will choose import substitution strategies for the sake of security, which will lead to industrial reshoring and economic downtown. Changes are to be made in terms of China's industrial layout and economic and trade cooperation for adaptation of the systematic reconstruction in the GVC network. In order to smooth the economic cycle, China needs to deepen its supply-side structural reform, and give full play to the advantages of its mega market and the potential of domestic demand, thus building a new development pattern in which the domestic and international cycles reinforce each other. China shall actively participate in global economic integration, build more partnerships on GVC, and optimize the domestic industrial structure through supply-side reform and the BRI, which will all be conducive to the sustainable development of our society and economy.

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Part VI
Causal Inference

Chapter 13
Connect the Structural Features and Economic Status

13.1 Introduction

Economic development usually spirals upward. In recent years, as the trend of deglobalization has become increasingly prevailing, the patterns of world trade and industrial division of labor have undergone major adjustments, coupled with the widespread and far-reaching impact of the COVID-19, leading to the tremendous shocks faced by the global industrial chain and supply chain. In the complex and volatile international environment, more deeds are to be done by countries to achieve steady GDP growth and bigger relative competitive advantage on the GVC. It is necessary not only to optimize domestic industrial layout and improve weak links on the industrial chain and supply chain, but also to give full play to international market resources and their distinctive competitive advantages in international trade. Therefore, it is of significance to study the operating mechanism of the global economic system from the perspective of GVC, so as to enhance the country's relative competitive advantage.

The global economic system is a complex nonlinear system, featuring multiple emergences which will not occur merely through the linear addition of individualities. That is to say, the study of individuals itself may shadow the whole picture. Instead, focuses should be put on the interrelationship and influence mechanism between individuals and the whole from the perspective of systems science. All complex systems have their unique topological structures, and their functions often depend on the characteristics of the microstructures. In other words, the prerequisite of understanding the internal mechanism of an economic system is to gauge the structural complexity of the entire system, which, fortunately, is made easier by the constantly developing complex network technology. It is now an important and trendy research topic to model the global economic system based on complex network theory and analyze the topological characteristics and its evolution.

In order to measure the status and function of a country on the GVC, and study the causal relations between the industrial layout of an economy and its economic development, we introduce six types of network characteristic indicators and summarize

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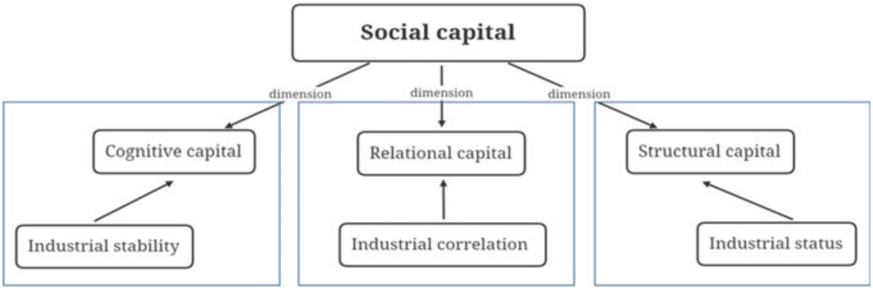

Fig. 13.1 Conceptual map of network-based social capital

them into the analytical framework of Social Capital, which can be explained in three dimensions, i.e., Cognitive Capital, Relational Capital, and Structural Capital according to the research of Nahapiet and Ghoshal [2], as shown in Fig. 13.1.

The purpose of this chapter is to theoretically and empirically enrich the GVC accounting system with the tools from econophysics and econometrics, thus adding up to the existing theoretical framework. It is organized as follows. The related studies are summarized in Sect. 13.2. Section 13.3 introduces the characteristics of econometric model. Section 13.4 builds up the analytical framework from a network-based social capital perspective and carries out the hypothesis testing, which is followed by the discussions of causal relationship among and between dependent and independent variables in Sect. 13.5. Finally, conclusion is provided in Sect. 13.6.

13.2 Literature Review

Social capital originated from the concept of capital in economics. With the deepening of research, scholars in different fields such as sociology and political science have defined social capital from diverse perspectives [3]. Bourdieu was the first scholar to clearly put forward the concept of social capital. From the perspective of social networks, Bourdieu and Wacquant believed that social capital is the sum of resources accumulated by a network composed of individuals or their relationships. Different from the study of social capital theory at the individual level, Burt first extended the theory of social capital to the enterprise level, thinking that social capital is a kind of resource that an enterprise obtains from a social network as a purposeful social actor [4]. Burt's famous Structure Hole Theory emphasizes the importance of entrepreneurs occupying a favorable brokerage position in the relationship network to provide resources for enterprises. More and more scholars pay their attention to the macro-level of social capital, which is to regard it as the resources and wealth possessed by an organization, a community, or even the entire society. Putnam believed that social capital is an organizational feature, such as trust and norms. The economic and democratic development of a society is largely determined by the extent of richness of its social capital [5].

Social capital theory and social network theory are inseparable. Initially, social network theorists represented by Coleman, Lin, and Burt constructed the concept of social capital at the micro and meso analysis levels within the framework of social network theory. Yet the impact of macro-level social capital needs to be further studied [6]. In their in-depth analyses, scholars divide social capital into multiple dimensions accordingly. Coleman emphasized the structural attributes of social capital, and believes that social capital is a social "structural resource" that is determined by its function [7]. Putnam divided social capital into two dimensions: bridging social capital and bonding social capital [5]. Nahapiet and Ghoshal adopted a resource-based organization view to illustrate the relationship between social capital development and organizational performance [8], arguing that social capital has structural, relational, and cognitive dimensions [2]. In this chapter, we explore the internal relations between social capital and its three dimensions represented as the industrial status, industrial correlation, and industrial structure on the GVC.

13.3 Econometric Model

After ***Structural Equation Model (SEM)*** had been used to analyze the causality between latent variables [9], Wold created ***Partial Least Squares (PLS)*** as a complementary approach to factor-based SEM [10]. As a popular research tool, PLS can test hypotheses in an exploratory way, especially in complex path models with relaxed expectations on data [11]. In recent years, PLS-SEM has become popular in management, social sciences, and psychology. According to Ringel and Sarstedt, PLS-SEM is a path model for estimating latent variables based on variance and is especially useful in key interpretation sources of a target structure [12], and in identifying relationships between constructs [13]. However, it is easy to ignore the mediating effect that does not directly influence the complex path models. Nitzl, et al. provided decision tree and high-level mediating effect classification, which helps improve the accuracy [14]. Hair, et al. used the ***Finite Mixture PLS (FIMIX-PLS)*** module of SmartPLS 3 software based on a popular corporate reputation model, identified and processed the unobserved heterogeneity in PLS-SEM [15, 16]. In addition, to evaluate the reliability and validity of higher-order concepts in applied social science research, Sarstedt, et al. used the well-known corporate reputation model to prove and estimate the reflective-reflective and reflective-formative types of higher-order constructs [17].

Since it offers the flexibility needed for the interplay between theory and data [18], PLS-SEM is becoming more and more popular in modeling the causality [19]. For instance, it is usually applied to analyze the secondary data, such as social media data, national statistical bureaus or publicly available survey data. Richter, et al. combined PLS-SEM and ***Necessary Condition Analysis (NCA)*** as complementary views of causality and data analysis [20]. Khan, et al. applied SNA to investigate the knowledge network structure of PLS-SEM and identified the key journals for network knowledge dissemination [21]. The relevant theoretical results of PLS-SEM have fully proved that it has great advantages in causal inference. Hence, combined with the social capital theory, we use the PLS-SEM model and SmartPLS3 software to explore the relationships between various types of capital and the level of national economic development.

13.4 Hypotheses

13.4.1 Hypothesis Formulation

First, *GIIC* and *GDDI* (as structural capital) can effectively reflect the global industrial influence and the participation in worldwide synergic production. The *GIIC* as a part of structural capital, can fully measure one country's competitiveness in gaining information superiority and intermediate interests. A higher *GIIC* often implies a greater GDP level. On the other hand, *GDDI* reflects the cumulative effect of global market demands when directly and indirectly relevant sectors are involved in the global production system. The bigger a country's *GDDI*, the higher its degree of globalization. Accordingly, we propose six hypotheses (see Fig. 13.2).

H1: Structural capital should positively affect social capital.

Next, *NIBC* and *NIFC* (as relational capital) can effectively reflect the impact of industrial correlation on the macroeconomic and industrial status, the greater $C_c^{RFWA-IN}$ (Backward Closeness) and $C_c^{RFWA-OUT}$ (Forward Closeness), the more

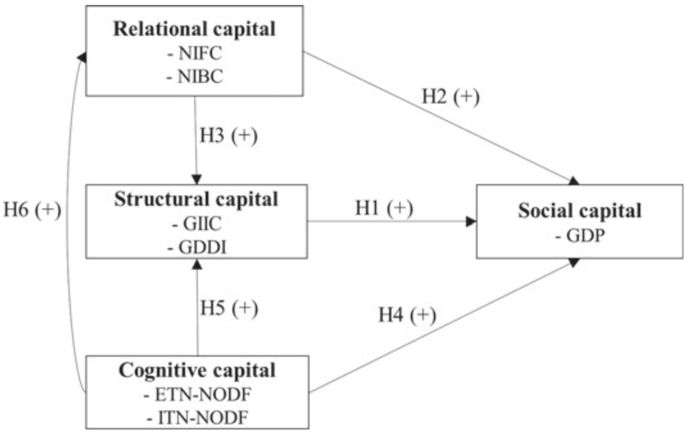

Fig. 13.2 Conceptual framework of hypotheses

it can reflect the closeness of industrial correlation. In other words, if the *NIBC* and *NIFC* become greater, there will be stronger compactness between certain country and its upstream or downstream counterparts. It urges economies to reinforce the ability to integrate upstream or downstream industrial resources. A country with a stronger industrial correlation is more conducive to occupying a dominant industrial status, which is inseparable from the level of national economic development. Similarly, the closer the industrial correlation (relational capital), the higher the level of economic development (social capital) and industrial status (structural capital). From this, we put forward the following hypotheses:

H2: Relational capital should positively affect social capital.
H3: Relational capital should positively affect structural capital.

Finally, *ETN-NODF* and *ITN-NODF* (as cognitive capital) can measure the nestedness of the local network in terms of economies. A Country with better macroeconomic performance generally has higher degree of nestedness, indicating that their trade mechanisms are relatively mature, the global industrial layout is reasonable, and the industrial structure is nearly complete. For the effects of cognitive capital on social capital, the more perfect a country's international trade network operating mechanism, the stronger its economic vitality. In other words, the stability of the export and import structures and the coordinated development of industrial sectors will help develop national economy. For the effects of cognitive capital on structural capital, the completeness of the industrial structure within a country determines its relative competitiveness and influence on the GVC. In addition, regarding the role of cognitive capital in promoting relational capital, a complete and stable industrial structure is also an indispensable prerequisite for close correlation and coordinated development between industries. Thus, the degree of industrial structure perfection (cognitive capital) has a certain impact on the level of macroeconomic development (social capital), industrial status (structural capital), and industrial correlation (relational capital). The more stable the industrial structure, the higher the level of macroeconomic development; the higher the industrial status; the stronger the industrial correlation. Accordingly, we propose the following hypotheses:

H4: Cognitive capital should positively affect social capital.
H5: Cognitive capital should positively affect structural capital.
H6: Cognitive capital should positively affect relational capital.

13.4.2 Hypothesis Testing

In order to reduce data heterogeneity, we take the logarithm of all indicators. Descriptive statistics and the correlation matrix of estimated variables are illustrated in Table 13.1.

According to the research of Hair, Ringle and Sarstedt [22], PLS approach is applicable to evaluate the influence of social capital theory on macroeconomic development [23]. Strictly speaking, the desired level of the ratio is between 15 and 20

Table 13.1 Descriptive statistics and correlation matrix

ID		Mean	S.D.	1	2	3	4	5	6
1	GDP	11.497	0.768	1.000					
2	GDDI	3.706	0.773	0.966	1.000				
3	GIIC	1.615	0.714	0.946	0.969	1.000			
4	NIFC	3.698	0.491	0.959	0.952	0.912	1.000		
5	NIBC	3.710	0.470	0.957	0.956	0.910	0.985	1.000	
6	ETN-NODF	0.815	0.384	0.418	0.449	0.447	0.449	0.421	1.000
7	ITN-NODF	0.435	0.395	0.397	0.476	0.463	0.446	0.415	0.856

observations for each independent variable [24]. However, there are 630 observations and six independent variables in this study, leaving little concern of small-sample bias. To examine the specific effect of each indicator, we first conduct path analysis for all variables as shown in Fig. 13.3.

Overall, structural capital positively affects social capital (H1: $\beta = 0.604$, $p < 0.001$), so H1 is supported. Relational capital positively affects social capital and structural capital (H2: $\beta = 0.382$, $p < 0.001$; H3: $\beta = 0.941$, $p < 0.001$), so H2 and H3 are supported. Cognitive capital positively affects social capital, structural capital and relational capital (H4: $\beta = 0.024$, $p < 0.001$; H5: $\beta = 0.036$, $p < 0.01$; H6: $\beta = 0.426$, $p < 0.001$), so H4, H5, H6 are supported.

Through the bootstrapping operation in the SmartPLS3 software, the data shown in Table 13.2 are obtained. T-statistics are all greater than 1.96, and P-values are all less than 0.05. Therefore, all the three capitals have significant positive effect on social capital.

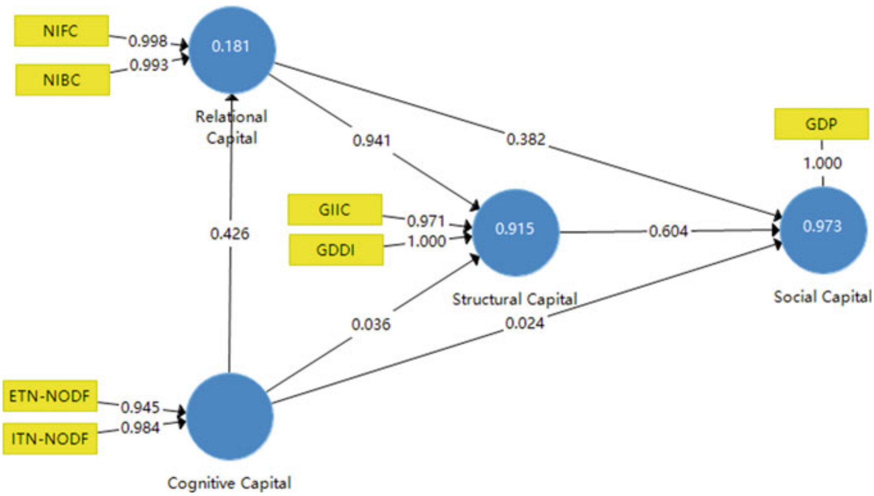

Fig. 13.3 Tests for the hypothesized associations

Table 13.2 Effect sizes of significant hypothesized associations

Hypothesis	β (a)	T-statistic	*p*-values	f^2	Effect size (b)	Decision
H1: structural capital → social capital	0.604	30.028	0.000***	1.142	Large	Supported
H2: relational capital → social capital	0.382	18.560	0.000***	0.464	Large	Supported
H3: relational capital → structural capital	0.941	142.094	0.000***	8.545	Large	Supported
H4: cognitive capital → social capital	0.024	3.525	0.000***	0.017	Small	Supported
H5: Cognitive capital → structural capital	0.036	2.764	0.006**	0.013	Small	Supported
H6: cognitive capital → relational capital	0.426	14.899	0.000***	0.221	Medium	Supported

Notes (*a*) Type II error in hypothesis testing in statistics. Compare the absolute effect or contribution of each coefficient; (*b*) The overall effect sizes $f^2 \geq 0.02, 0.15$, or 0.35 are regarded as small, medium, and large effects, respectively
* $p < 0.05$ (2-tailed), ** $p < 0.01$ (2-tailed), *** $p < 0.001$ (2-tailed)

In order to assess the effect size of a particular independent variable on a dependent variable [22], the squared multiple (or multiple partial) correlation (R^2) is used to calculate Cohen's f^2 [25]. The formula of effect size is as follows.

$$\text{Cohen's } f^2 = \frac{R^2_{full} - R^2_{reduced}}{1 - R^2_{full}} \tag{13.1}$$

where R^2_{full} is the value of R^2 from the least-square model that includes all independent variables; $R^2_{reduced}$ is the value from that includes all but one particular set of independent variables.

As Cohen proposed in his research, an effect size of $0.02 \leq f^2 < 0.15$ is small; $0.15 \leq f^2 < 0.35$ is medium; and $f^2 \geq 0.35$ is large. Table 13.2 also shows the effect sizes of all significant hypothesized associations. It is confirmed that industrial status has a large effect size ($f^2 = 1.142$) on the level of economic development (GDP). For the industrial correlation, it has a large effect size both on GDP ($f^2 = 0.464$) and industrial status ($f^2 = 8.545$). However, for the industrial structure, it has a small effect size on the GDP ($f^2 = 0.017$) and industrial status ($f^2 = 0.013$). Likewise, industrial structure has a medium effect size ($f^2 = 0.221$) on the industrial correlation.

13.5 Results and Discussions

This study regards the level of economic development as social capital, and for the first time uses the three dimensions of social capital theory to examine the impact of each dimension on the level of national economic development. The effects from each dimension are discussed below.

13.5.1 The Effects of Structural Capital

From the results of PLS-SEM model, structural capital (industrial status) positively affects social capital (GDP) with a large beta coefficient and a large effect size ($f^2 = 1.142$). The positive correlation between *GIIC* and GDP indicates that one country's global industrial impact can reveal its international competitive advantage. The stronger the industrial influence, the greater the economic strength and the broader prospects for development. In addition, the higher the degree of participation in worldwide synergic production (*GDDI*), the higher the degree of globalization. Specifically, focusing on industrial sustainability, expanding industrial influence, and increasing participation in worldwide synergic production can enable a country to occupy a favorable industrial status on the GVC. This can not only contribute to the GVC, but also stimulate the macroeconomic growth. In other words, strengthening the accumulation of structural capital can promote the development of social capital.

As the world's largest economy, the United States provides developing countries with high-value-added intermediate goods, and integrates domestic value chains to enhance its internationalization. It is precisely because of the dominant position of the United States and the high connectivity of economic activities that the subprime mortgage crisis quickly spread to other economies worldwide and trigger the global economic tsunami. This fully indicates that in the process of global integration, once a crisis occurs in a country with high global industrial influence and high industrial status, the global economic system will be severely affected.

13.5.2 The Effects of Relational Capital

Relational capital composed of *NIBC* and *NIFC* well explains the internal mechanism forming the competitiveness of country. The greater the both, the stronger the ability of the economy to connect with the supply side or the demand side, and the more prominent its competitive advantage on the GVC. We further optimize the model and find that *NIBC* is more applicable to measure relational capital. This is because that the higher the *NIBC*, the closer it is to a relatively downstream position on the GVC; the stronger its ability to create added value, the more intermediate goods it can provide for downstream consumers. In other words, being in a relatively downstream position means that the economies are closer to the market. According to the ***Smile Curve Theory***, the relative competitive advantage would be more prominent if owning more market resources. Thus, we can identify the relative position of an economy based on relational capital and analyze its preferable types of services and industrial status.

On the one hand, relational capital (industrial correlation) positively affects social capital (GDP) with a large beta coefficient and a large effect size ($f^2 = 0.464$). This also reflects that the closer the relationship between the economy and its upstream or downstream counterparts, the richer the market resources it obtains, and the higher the degree of industrial correlation. As for countries, industrial correlation is the basis of sustainable industrial development. The positive correlation between relational capital and social capital indicates that the stronger the degree of industrial correlation, the higher the level of national macroeconomic development.

On the other hand, relational capital (industrial correlation) positively structural capital (industrial status) with a large beta coefficient and a large effect size ($f^2 = 8.545$). In addition, an economy with more market resources will be more closely connected with its upstream and downstream counterparts, which means that the stronger the ability to integrate resources, the more conducive to the formation of complete IVC network. In the meanwhile, this type of country often plays a role in linking pieces of GVC, which bring itself a higher industrial status on the GVC in turn. Specifically, relational capital and structural capital are positively correlated, i.e., the industrial sector with stronger industrial correlation always has a higher industrial status.

The recent trend of economic globalization is the formation of RVC. For instance, the "European Factory" centered on Germany is one of the three cross-border production systems, in which more and more production factors could circulate on the European RVC [26]. Germany imports industrial raw materials and intermediate products from other European Union members, and then exports the reprocessed and manufactured products to them or other countries around the world. From this angle, Germany plays the dual role of the European trade center and the GVC hub between Europe and the world. The case of German manufacturing industry tells us that, strengthening industrial correlation and focusing on the accumulation of relational capital can promote the development of structural capital and social capital.

13.5.3 The Effects of Cognitive Capital

Firstly, cognitive capital (industrial structure) positively affects social capital (GDP) with a small beta coefficient and a small effect size ($f^2 = 0.017$). The cognitive capital incorporating *ETN-NODF* and *ITN-NODF* represents the completeness of industrial structure. If a country's *ETN-NODF* is higher, it will act as a supplier trading intermediate goods with other countries, thus forming a relatively nested export trade network. In the opposite, if the *ITN-NODF* is higher, there will be a relatively nested import trade network. In our opinion, the nested structure stands for the maturity of trade cooperation mechanism. Thus, the process of continuously optimizing the industrial structure is that of the accumulation of cognitive capital, which will be benefit to the economic development at the macro level.

Secondly, cognitive capital (industrial structure) positively affects structural capital (industrial status) with a small beta coefficient and a small effect size ($f^2 = 0.013$). Countries with a nested RVC or GVC network can gain greater participation in global resource allocation and acquire advantageous position in the international division of labor. In sum, cognitive capital needs to be continuously improved in accumulation to achieve the goal of promoting structural capital.

Thirdly, cognitive capital (industrial structure) positively affects relational capital (industrial correlation) with a large beta coefficient and a medium effect size ($f^2 = 0.221$). The rationality and integrity of the industrial layout enable products and values to flow effectively on the IVC, resulting in the close industrial correlation and the highly interdependent trade relationship. To achieve the goal of promoting national economic development, a rational distribution of foreign trade (cognitive capital) is necessary to further consolidate and enhance industrial status and competitive advantage on the GVC.

With its accession to the WTO, China has been actively participating in the international division of labor at different levels, maintaining a good momentum of development. China boasts the world's most complete industrial system and steady industrial support ability, both ensures its strong resilience of economy. After the subprime mortgage crisis, China adjusted its industrial layout through industrial transformation and upgrading, to better participate in resource allocation and market competition on a global scale. As a result, its competitiveness of new technology-intensive industries has been greatly enhanced. In addition, China's huge domestic consumer market and potentials have also accelerated the accumulation of cognitive capital, leading to the continuously optimized and upgraded industrial structure. However, the COVID-19 pandemic has exposed the shortcomings of China in the fields of high-end equipments and products, primary agricultural product, and important mineral resources. This will inevitably push China to form a more comprehensive industrial layout that takes into account both domestic and foreign markets. In addition, China's implementation of **Supply-Side Structural Reforms and Dual-Circulation Strategy** urges itself to coupling with the new dynamics of deglobalization of the world economy.

13.6 Summary

Network science has been widely applied in theoretical and empirical studies of GVC, and many related articles have emerged, forming many more mature and complete analytical frameworks. Among them, the GVC accounting method based on complex network theory is different from the mainstream economics in both research angle and content. In this chapter, we introduce the theoretical framework of Social Capital, and define the network-based indicators with economic meanings. Secondly, we follow the econometric framework to analyze the hypothesis and test whether it is true. Finally, we study how the three types of capital constituted by these indicators interact with each other, and discuss their impact on the social capital (economic development level, i.e., GDP). The results prove that the structural capital (industrial status) has a positive impact on the social capital; the relational capital (industrial correlation) has a positive impact on both social capital and structural capital; the cognitive capital (industrial structure) has a small impact on the social capital, structural capital, and relational capital.

In sum, we provide an analytical framework to summarize the driving factors of national economic development in the context of globalization, and taking the main economies in the world as examples. By doing so, we have laid the foundation for further theoretical development and empirical research.

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Postscript

This book researches the complex network-based global value chain accounting system through the methods of positive study and normative study. But there are still many shortcomings and deficiencies due to the limited time and ability of authors.

Firstly, from the perspective of micro-structure, the industrial relations in the IO data have more economic meanings than that in industrial sectors, for government agencies and economists divided the industrial sectors with the original intention to effectively supervise and regulate them. The quantitative IO relations existing between countries or within countries, however, accurately reflect value stream, information flow and material flow formed by self-organization during the evolution of the global economic system, which finally constitute the complex topological structure of GVC. In the follow-up empirical research, we will pay more attention to how to simulate the trend of industrial linkages between economies and the cascade effects that spread along different conduction paths, thus evaluating countries' status as well as optimizing relevant trade policies in the multiple international political backgrounds.

Secondly, from the perspective of macro-structure, GVC has the characteristics of the multi-layer network, both on the sectoral level and the national level. We can assume that the value-added process of products or services is the result of the cooperation of relevant countries on the IVCs. Or otherwise, it is also true that the political and economic game among countries is based on their economy and trade cooperation throughout GVC. Anyway, no country in the era of global economic integration can isolate itself from the supply and demand on the GVC, or achieve its sustainable socio-economic development. It is noteworthy that even though the international trade policies of some important economies have shown the so-called anti-globalization trend in recent years (such as the Brexit and the US-led Sino-US trade war), the relevant functional departments of each country should weigh on domestic industrial layout and international trade policies from the perspective of system science, so as to maximize the interests of the community of a shared future for all mankind (such as China's BRI). It is both vital and feasible to combine the

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multi-layer network modeling method and ***Synergy Theory*** to form a network-based GVC research framework, no matter in theory or practice.

Thirdly, from the perspective of the evolutionary mechanism, further deepening the understanding of the topological structure of GVC is a necessary condition for predicting the law and trend of the global industrial layout. At present, the Internet and advanced manufacturing technologies continue to subvert the cognitive boundaries of economic theory on the law of industrial development. Existing analytical tools can hardly explain the rise of emerging industries and the ongoing industrial changes. In consequence, econophysics starts to show its scientificity, reliability and practicality in terms of theories and models. It is used to analyze various political and economic phenomena from a new perspective and has become a hot spot in the field of GVC research. More importantly, its interdisciplinary compatibility enables itself to continuously absorb cutting-edge theories from various fields, integrate data mining tools including ***Networking Embedding***, ***Deep Learning***, and ***Casual Inference*** and finally become able to analyze massive high-dimensional data. Of course, in order to make full use of the theoretical advantages of econophysics in studying the world economy, our research team still need to update ourselves with the latest relevant knowledge.

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Lizhi Xing.
Beijing.
October 14th, 2021.

Appendix A

See Tables A.1, A.2, A.3, A.4, A.5, A.6, A.7, A.8, A.9, A.10 and A.11.

Table A.1 Countries/regions' names and their abbreviations in WIOD2016

No.	Abbr.	Country	No.	Abbr.	Country
1	AUS	Australia	23	IRL	Ireland
2	AUT	Austria	24	ITA	Italy
3	BEL	Belgium	25	JPN	Japan
4	BGR	Bulgaria	26	KOR	Korea
5	BRA	Brazil	27	LTU	Lithuania
6	CAN	Canada	28	LUX	Luxembourg
7	CHE	Switzerland	29	LVA	Latvia
8	CHN	China	30	MEX	Mexico
9	CYP	Cyprus	31	MLT	Malta
10	CZE	Czech	32	NLD	Netherlands
11	DEU	Germany	33	NOR	Norway
12	DNK	Denmark	34	POL	Poland
13	ESP	Spain	35	PRT	Portugal
14	EST	Estonia	36	ROU	Romania
15	FIN	Finland	37	RUS	Russia
16	FRA	France	38	SVK	Slovak
17	GBR	United Kingdom	39	SVN	Slovenia
18	GRC	Hellenic	40	SWE	Sweden
19	HRV	Croatia	41	TUR	Turkey
20	HUN	Hungary	42	TWN	Chinese Taipai
21	IDN	Indonesia	43	USA	United States
22	IND	India	44	ROW	Rest of the world

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Table A.2 Industrial sectors' names and their abbreviations in WIOD2016

No.	Abbr.	Industrial sector
1	S1	Crop and animal production, hunting and related service activities
2	S2	Forestry and logging
3	S3	Fishing and aquaculture
4	S4	Mining and quarrying
5	S5	Manufacture of food products, beverages and tobacco products
6	S6	Manufacture of textiles, wearing apparel and leather products
7	S7	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
8	S8	Manufacture of paper and paper products
9	S9	Printing and reproduction of recorded media
10	S10	Manufacture of coke and refined petroleum products
11	S11	Manufacture of chemicals and chemical products
12	S12	Manufacture of basic pharmaceutical products and pharmaceutical preparations
13	S13	Manufacture of rubber and plastic products
14	S14	Manufacture of other non-metallic mineral products
15	S15	Manufacture of basic metals
16	S16	Manufacture of fabricated metal products, except machinery and equipment
17	S17	Manufacture of computer, electronic and optical products
18	S18	Manufacture of electrical equipment
19	S19	Manufacture of machinery and equipment n.e.c
20	S20	Manufacture of motor vehicles, trailers and semi-trailers
21	S21	Manufacture of other transport equipment
22	S22	Manufacture of furniture; other manufacturing
23	S23	Repair and installation of machinery and equipment
24	S24	Electricity, gas, steam and air conditioning supply
25	S25	Water collection, treatment and supply
26	S26	Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services
27	S27	Construction
28	S28	Wholesale and retail trade and repair of motor vehicles and motorcycles
29	S29	Wholesale trade, except of motor vehicles and motorcycles
30	S30	Retail trade, except of motor vehicles and motorcycles
31	S31	Land transport and transport via pipelines
32	S32	Water transport
33	S33	Air transport
34	S34	Warehousing and support activities for transportation
35	S35	Postal and courier activities

(continued)

Table A.2 (continued)

No.	Abbr.	Industrial sector
36	S36	Accommodation and food service activities
37	S37	Publishing activities
38	S38	Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities
39	S39	Telecommunications
40	S40	Computer programming, consultancy and related activities; information service activities
41	S41	Financial service activities, except insurance and pension funding
42	S42	Insurance, reinsurance and pension funding, except compulsory social security
43	S43	Activities auxiliary to financial services and insurance activities
44	S44	Real estate activities
45	S45	Legal and accounting activities; activities of head offices; management consultancy activities
46	S46	Architectural and engineering activities; technical testing and analysis
47	S47	Scientific research and development
48	S48	Advertising and market research
49	S49	Other professional, scientific and technical activities; veterinary activities
50	S50	Administrative and support service activities
51	S51	Public administration and defence; compulsory social security
52	S52	Education
53	S53	Human health and social work activities
54	S54	Other service activities
55	S55	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
56	S56	Activities of extraterritorial organizations and bodies

Table A.3 Countries/regions' names and their abbreviations in WIOD2013

No.	Abbr.	Country	No.	Abbr.	Country
1	AUS	Australia	22	ITA	Italy
2	AUT	Austria	23	JPN	Japan
3	BEL	Belgium	24	KOR	Korea
4	BGR	Bulgaria	25	LTU	Lithuania
5	BRA	Brazil	26	LUX	Luxembourg
6	CAN	Canada	27	LVA	Latvia
7	CHN	China	28	MEX	Mexico
8	CYP	Cyprus	29	MLT	Malta

(continued)

Table A.3 (continued)

No.	Abbr.	Country	No.	Abbr.	Country
9	CZE	Czech	30	NLD	Netherlands
10	DEU	Germany	31	POL	Poland
11	DNK	Denmark	32	PRT	Portugal
12	ESP	Spain	33	ROU	Romania
13	EST	Estonia	34	RUS	Russia
14	FIN	Finland	35	SVK	Slovak
15	FRA	France	36	SVN	Slovenia
16	GBR	United Kingdom	37	SWE	Sweden
17	GRC	Hellenic	38	TUR	Turkey
18	HUN	Hungary	39	TWN	Chinese Taipai
19	IDN	Indonesia	40	USA	United States
20	IND	India	41	ROW	Rest of the world
21	IRL	Ireland			

Table A.4 Industrial sectors' names and their abbreviations in WIOD2013 and ADB2019

No.	Abbr.	Industrial sector
1	S1	Agriculture, hunting, forestry and fishing
2	S2	Mining and quarrying
3	S3	Food, beverages and tobacco
4	S4	Textiles and textile products
5	S5	Leather, leather and footwear
6	S6	Wood and products of wood and cork
7	S7	Pulp, paper, paper, printing and publishing
8	S8	Coke, refined petroleum and nuclear fuel
9	S9	Chemicals and chemical products
10	S10	Rubber and plastics
11	S11	Other non-metallic mineral
12	S12	Basic metals and fabricated metal
13	S13	Machinery, Nec
14	S14	Electrical and optical equipment
15	S15	Transport equipment
16	S16	Manufacturing, Nec; recycling
17	S17	Electricity, gas and water supply
18	S18	Construction

(continued)

Table A.4 (continued)

No.	Abbr.	Industrial sector
19	S19	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel
20	S20	Wholesale trade and commission trade, except of motor vehicles and motorcycles
21	S21	Retail trade, except of motor vehicles and motorcycles; repair of household goods
22	S22	Hotels and restaurants
23	S23	Inland transport
24	S24	Water transport
25	S25	Air transport
26	S26	Other supporting and auxiliary transport activities; activities of travel agencies
27	S27	Post and telecommunications
28	S28	Financial intermediation
29	S29	Real estate activities
30	S30	Renting of M&Eq and other business activities
31	S31	Public admin and defence; compulsory social security
32	S32	Education
33	S33	Health and social work
34	S34	Other community, social and personal services
35	S35	Private households with employed persons

Table A.5 Countries/regions' names and their abbreviations in TiVA2018

No.	Abbr.	Country	No.	Abbr.	Country
1	AUS	Australia	34	TUR	Turkey
2	AUT	Austria	35	GBR	United Kingdom
3	BEL	Belgium	36	USA	United States
4	CAN	Canada	37	ARG	Argentina
5	CHL	Chile	38	BRA	Brazil
6	CZE	Czech Republic	39	BRN	Brunei Darussalam
7	DNK	Denmark	40	BGR	Bulgaria
8	EST	Estonia	41	KHM	Cambodia
9	FIN	Finland	42	CHN	China (People's Republic of)
10	FRA	France	43	COL	Colombia
11	DEU	Germany	44	CRI	Costa Rica
12	GRC	Greece	45	HRV	Croatia
13	HUN	Hungary	46	CYP	Cyprus

(continued)

Table A.5 (continued)

No.	Abbr.	Country	No.	Abbr.	Country
14	ISL	Iceland	47	IND	India
15	IRL	Ireland	48	IDN	Indonesia
16	ISR	Israel	49	HKG	Hong Kong, China
17	ITA	Italy	50	KAZ	Kazakhstan
18	JPN	Japan	51	MYS	Malaysia
19	KOR	Korea	52	MLT	Malta
20	LVA	Latvia	53	MAR	Morocco
21	LTU	Lithuania	54	PER	Peru
22	LUX	Luxembourg	55	PHL	Philippines
23	MEX	Mexico	56	ROU	Romania
24	NLD	Netherlands	57	RUS	Russian Federation
25	NZL	New Zealand	58	SAU	Saudi Arabia
26	NOR	Norway	59	SGP	Singapore
27	POL	Poland	60	ZAF	South Africa
28	PRT	Portugal	61	TWN	Chinese Taipei
29	SVK	Slovak Republic	62	THA	Thailand
30	SVN	Slovenia	63	TUN	Tunisia
31	ESP	Spain	64	VNM	Viet Nam
32	SWE	Sweden	65	ROW	Rest of the World
33	CHE	Switzerland			

Table A.6 Industrial sectors' names and their abbreviations in TiVA2018

No.	Abbr.	Industrial sector
1	S1	Agriculture, forestry and fishing
2	S2	Mining and extraction of energy producing products
3	S3	Mining and quarrying of non-energy producing products
4	S4	Mining support service activities
5	S5	Food products, beverages and tobacco
6	S6	Textiles, wearing apparel, leather and related products
7	S7	Wood and products of wood and cork
8	S8	Paper products and printing
9	S9	Coke and refined petroleum products
10	S10	Chemicals and pharmaceutical products
11	S11	Rubber and plastic products
12	S12	Other non-metallic mineral products
13	S13	Basic metals

(continued)

Table A.6 (continued)

No.	Abbr.	Industrial sector
14	S14	Fabricated metal products
15	S15	Computer, electronic and optical products
16	S16	Electrical equipment
17	S17	Machinery and equipment, nec
18	S18	Motor vehicles, trailers and semi-trailers
19	S19	Other transport equipment
20	S20	Other manufacturing; repair and installation of machinery and equipment
21	S21	Electricity, gas, water supply, sewerage, waste and remediation services
22	S22	Construction
23	S23	Wholesale and retail trade; repair of motor vehicles
24	S24	Transportation and storage
25	S25	Accommodation and food services
26	S26	Publishing, audiovisual and broadcasting activities
27	S27	Telecommunications
28	S28	IT and other information services
29	S29	Financial and insurance activities
30	S30	Real estate activities
31	S31	Other business sector services
32	S32	Public admin. and defence; compulsory social security
33	S33	Education
34	S34	Human health and social work
35	S35	Arts, entertainment, recreation and other service activities

Table A.7 Countries/regions' names and their abbreviations in TiVA2015

No.	Abbr.	Country	No.	Abbr.	Country
1	AUS	Australia	32	TUR	Turkey
2	AUT	Austria	33	GBR	United Kingdom
3	BEL	Belgium	34	USA	United States
4	CAN	Canada	35	ARG	Argentina
5	CHL	Chile	36	BGR	Bulgaria
6	CZE	Czech Republic	37	BRA	Brazil
7	DNK	Denmark	38	BRN	Brunei Darussalam
8	EST	Estonia	39	COL	Colombia
9	FIN	Finland	40	CRI	Costa Rica
10	FRA	France	41	CYP	Cyprus
11	DEU	Germany	42	HKG	Hong Kong SAR
12	GRC	Greece	43	HRV	Croatia
13	HUN	Hungary	44	IDN	Indonesia
14	ISL	Iceland	45	IND	India
15	IRL	Ireland	46	KHM	Cambodia
16	ISR	Israel	47	LTU	Lithuania
17	ITA	Italy	48	LVA	Latvia
18	JPN	Japan	49	MLT	Malta
19	KOR	Korea	50	MYS	Malaysia
20	LUX	Luxembourg	51	PHL	Philippines
21	MEX	Mexico	52	ROU	Romania
22	NLD	Netherlands	53	RUS	Russian Federation
23	NZL	New Zealand	54	SAU	Saudi Arabia
24	NOR	Norway	55	SGP	Singapore
25	POL	Poland	56	THA	Thailand
26	PRT	Portugal	57	TUN	Tunisia
27	SVK	Slovak Republic	58	TWN	Chinese Taipei
28	SVN	Slovenia	59	VNM	Viet Nam
29	ESP	Spain	60	ZAF	South Africa
30	SWE	Sweden	61	ROW	Rest of the world
31	CHE	Switzerland	62	COL	Colombia

Table A.8 Industrial sectors' names and their abbreviations in TiVA2015

No.	Abbr.	Industrial sector
1	S1	Agriculture, hunting, forestry and fishing
2	S2	Mining and quarrying
3	S3	Food products, beverages and tobacco
4	S4	Textiles, textile products, leather and footwear
5	S5	Wood and products of wood and cork
6	S6	Pulp, paper, paper products, printing and publishing
7	S7	Coke, refined petroleum products and nuclear fuel
8	S8	Chemicals and chemical products
9	S9	Rubber and plastics products
10	S10	Other non-metallic mineral products
11	S11	Basic metals
12	S12	Fabricated metal products
13	S13	Machinery and equipment, nec
14	S14	Computer, Electronic and optical equipment
15	S15	Electrical machinery and apparatus, nec
16	S16	Motor vehicles, trailers and semi-trailers
17	S17	Other transport equipment
18	S18	Manufacturing nec; recycling
19	S19	Electricity, gas and water supply
20	S20	Construction
21	S21	Wholesale and retail trade; repairs
22	S22	Hotels and restaurants
23	S23	Transport and storage
24	S24	Post and telecommunications
25	S25	Financial intermediation
26	S26	Real estate activities
27	S27	Renting of machinery and equipment
28	S28	Computer and related activities
29	S29	R&D and other business activities
30	S30	Public admin, and defence; compulsory social security
31	S31	Education
32	S32	Health and social work
33	S33	Other community, social and personal services
34	S34	Private households with employed persons

Table A.9 Countries/regions' names and their abbreviations in Eora26

No.	Abbr.	Country	No.	Abbr.	Country
1	AFG	Afghanistan	96	LSO	Lesotho
2	ALB	Albania	97	LBR	Liberia
3	DZA	Algeria	98	LBY	Libya
4	AND	Andorra	99	LIE	Liechtenstein
5	AGO	Angola	100	LTU	Lithuania
6	ATG	Antigua	101	LUX	Luxembourg
7	ARG	Argentina	102	MAC	Macao SAR
8	ARM	Armenia	103	MDG	Madagascar
9	ABW	Aruba	104	MWI	Malawi
10	AUS	Australia	105	MYS	Malaysia
11	AUT	Austria	106	MDV	Maldives
12	AZE	Azerbaijan	107	MLI	Mali
13	BHS	Bahamas	108	MLT	Malta
14	BHR	Bahrain	109	MRT	Mauritania
15	BGD	Bangladesh	110	MUS	Mauritius
16	BRB	Barbados	111	MEX	Mexico
17	BLR	Belarus	112	MCO	Monaco
18	BEL	Belgium	113	MNG	Mongolia
19	BLZ	Belize	114	MNE	Montenegro
20	BEN	Benin	115	MAR	Morocco
21	BMU	Bermuda	116	MOZ	Mozambique
22	BTN	Bhutan	117	MMR	Myanmar
23	BOL	Bolivia	118	NAM	Namibia
24	BIH	Bosnia and Herzegovina	119	NPL	Nepal
25	BWA	Botswana	120	NLD	Netherlands
26	BRA	Brazil	121	ANT	Netherlands Antilles
27	VGB	British Virgin Islands	122	NCL	New Caledonia
28	BRN	Brunei	123	NZL	New Zealand
29	BGR	Bulgaria	124	NIC	Nicaragua
30	BFA	Burkina Faso	125	NER	Niger
31	BDI	Burundi	126	NGA	Nigeria
32	KHM	Cambodia	127	NOR	Norway
33	CMR	Cameroon	128	PSE	Gaza Strip
34	CAN	Canada	129	OMN	Oman
35	CPV	Cape Verde	130	PAK	Pakistan
36	CYM	Cayman Islands	131	PAN	Panama

(continued)

Table A.9 (continued)

No.	Abbr.	Country	No.	Abbr.	Country
37	CAF	Central African Republic	132	PNG	Papua New Guinea
38	TCD	Chad	133	PRY	Paraguay
39	CHL	Chile	134	PER	Peru
40	CHN	China	135	PHL	Philippines
41	COL	Colombia	136	POL	Poland
42	COG	Congo	137	PRT	Portugal
43	CRI	Costa Rica	138	QAT	Qatar
44	HRV	Croatia	139	KOR	South Korea
45	CUB	Cuba	140	MDA	Moldova
46	CYP	Cyprus	141	ROU	Romania
47	CZE	Czech Republic	142	RUS	Russia
48	CIV	Cote dIvoire	143	RWA	Rwanda
49	PRK	North Korea	144	WSM	Samoa
50	COD	DR Congo	145	SMR	San Marino
51	DNK	Denmark	146	STP	Sao Tome and Principe
52	DJI	Djibouti	147	SAU	Saudi Arabia
53	DOM	Dominican Republic	148	SEN	Senegal
54	ECU	Ecuador	149	SRB	Serbia
55	EGY	Egypt	150	SYC	Seychelles
56	SLV	El Salvador	151	SLE	Sierra Leone
57	ERI	Eritrea	152	SGP	Singapore
58	EST	Estonia	153	SVK	Slovakia
59	ETH	Ethiopia	154	SVN	Slovenia
60	FJI	Fiji	155	SOM	Somalia
61	FIN	Finland	156	ZAF	South Africa
62	FRA	France	157	SDS	South Sudan
63	PYF	French Polynesia	158	ESP	Spain
64	GAB	Gabon	159	LKA	Sri Lanka
65	GMB	Gambia	160	SUD	Sudan
66	GEO	Georgia	161	SUR	Suriname
67	DEU	Germany	162	SWZ	Swaziland
68	GHA	Ghana	163	SWE	Sweden
69	GRC	Greece	164	CHE	Switzerland
70	GRL	Greenland	165	SYR	Syria
71	GTM	Guatemala	166	TWN	Taiwan
72	GIN	Guinea	167	TJK	Tajikistan

(continued)

Table A.9 (continued)

No.	Abbr.	Country	No.	Abbr.	Country
73	GUY	Guyana	168	THA	Thailand
74	HTI	Haiti	169	MKD	TFYR Macedonia
75	HND	Honduras	170	TGO	Togo
76	HKG	Hong Kong	171	TTO	Trinidad and Tobago
77	HUN	Hungary	172	TUN	Tunisia
78	ISL	Iceland	173	TUR	Turkey
79	IND	India	174	TKM	Turkmenistan
80	IDN	Indonesia	175	USR	Former USSR
81	IRN	Iran	176	UGA	Uganda
82	IRQ	Iraq	177	UKR	Ukraine
83	IRL	Ireland	178	ARE	United Arab Emirates
84	ISR	Israel	179	GBR	United Kingdom
85	ITA	Italy	180	TZA	Tanzania
86	JAM	Jamaica	181	USA	United States
87	JPN	Japan	182	URY	Uruguay
88	JOR	Jordan	183	UZB	Uzbekistan
89	KAZ	Kazakhstan	184	VUT	Vanuatu
90	KEN	Kenya	185	VEN	Venezuela
91	KWT	Kuwait	186	VNM	Viet Nam
92	KGZ	Kyrgyzstan	187	YEM	Yemen
93	LAO	Laos	188	ZMB	Zambia
94	LVA	Latvia	189	ZWE	Zimbabwe
95	LBN	Lebanon			

Table A.10 Industrial sectors' names and their abbreviations in Eora26

No.	Abbr.	Industrial sector
1	S1	Agriculture
2	S2	Fishing
3	S3	Mining and quarrying
4	S4	Food and beverages
5	S5	Textiles and wearing apparel
6	S6	Wood and paper
7	S7	Petroleum, chemical and non-metallic mineral products
8	S8	Metal products

(continued)

Table A.10 (continued)

No.	Abbr.	Industrial sector
9	S9	Electrical and machinery
10	S10	Transport equipment
11	S11	Other manufacturing
12	S12	Recycling
13	S13	Electricity, gas and water
14	S14	Construction
15	S15	Maintenance and repair
16	S16	Wholesale trade
17	S17	Retail trade
18	S18	Hotels and restaurants
19	S19	Transport
20	S20	Post and telecommunications
21	S21	Financial intermediation and business activities
22	S22	Public administration
23	S23	Education, health and other services
24	S24	Private households
25	S25	Others
26	S26	Re-export and re-import

Table A.11 Countries/regions' names and their abbreviations in ADB-MRIO

No.	Abbr.	Country	No.	Abbr.	Country
1	AUS	Australia	33	NOR	Norway
2	AUT	Austria	34	POL	Poland
3	BEL	Belgium	35	POR	Portugal
4	BGR	Bulgaria	36	ROM	Romania
5	BRA	Brazil	37	RUS	Russia
6	CAN	Canada	38	SVK	Slovak Republic
7	SWI	Switzerland	39	SVN	Slovenia
8	PRC	People's Republic of China	40	SWE	Sweden
9	CYP	Cyprus	41	TUR	Turkey
10	CZE	Czech Republic	42	TAP	Taipei, China
11	GER	Germany	43	USA	United States

(continued)

Table A.11 (continued)

No.	Abbr.	Country	No.	Abbr.	Country
12	DEN	Denmark	44	BAN	Bangladesh
13	SPA	Spain	45	MAL	Malaysia
14	EST	Estonia	46	PHI	Philippines
15	FIN	Finland	47	THA	Thailand
16	FRA	France	48	VIE	Viet Nam
17	UKG	United Kingdom	49	KAZ	Kazakhstan
18	GRC	Greece	50	MON	Mongolia
19	HRV	Croatia	51	SRI	Sri Lanka
20	HUN	Hungary	52	PAK	Pakistan
21	INO	Indonesia	53	FIJ	Fiji
22	IND	India	54	LAO	Lao People's Democratic Republic
23	IRE	Ireland	55	BRU	Brunei Darussalam
24	ITA	Italy	56	BHU	Bhutan
25	JPN	Japan	57	KGZ	Kyrgyz Republic
26	KOR	Republic of Korea	58	CAM	Cambodia
27	LTU	Lithuania	59	MLD	Maldives
28	LUX	Luxembourg	60	NEP	Nepal
29	LVA	Latvia	61	SIN	Singapore
30	MEX	Mexico	62	HKG	Hong Kong, China
31	MLT	Malta	63	ROW	Rest of the World
32	NET	Netherlands			