Network-Based Driving Force of National Economic Development: A Social Capital Perspective

Lizhi Xing [1,2,*] **, Xi Ai** [1] **, Jiaqi Ren** [1] **and Dawei Wang** [1]

1   College of Economics & Management, Beijing University of Technology, Beijing 100124, China; aixi@emails.bjut.edu.cn (X.A.); renjq@emails.bjut.edu.cn (J.R.); wangdawei@emails.bjut.edu.cn (D.W.)
2   International Business School, Beijing Foreign Studies University, Beijing 100089, China
*   Correspondence: koken@bjut.edu.cn

Abstract: Network science has been widely applied in theoretical and empirical studies of global value chain (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 paper, we build up global industrial value chain network (GIVCN) models based on World Input–Output Database, introduce the theoretical framework of Social Capital, and define the network-based indicators with economic meanings. Second, 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.

Keywords: global value chain; inter-country input-output table; complex network model; social capital; structural equation model

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 Global Value Chain (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/region'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, focus 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/region 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 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 [1], as shown in Figure 1.
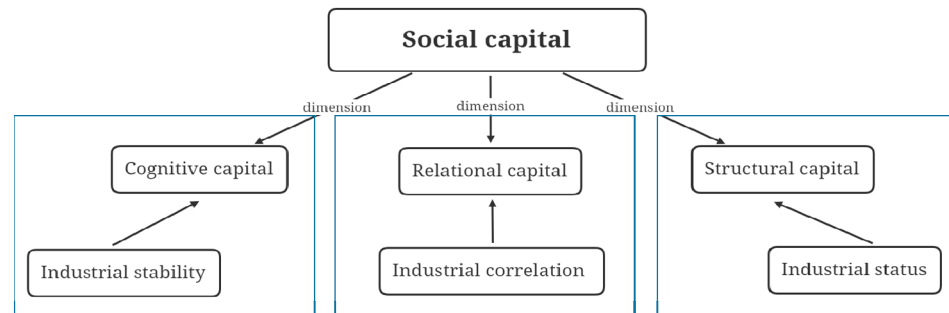
Figure 1. Conceptual map.

The purpose of this paper 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 Section 2. Section 3 presents the data, model, and setups. Section 4 builds up the analytical framework from a network-based social capital perspective. Section 5 carries out the hypothesis testing, which is followed by the discussions of causal relationship among and between dependent and independent variables in Section 6. Finally, conclusion is provided in Section 7.

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 [2]. 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 [3]. 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 [4].

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 [5]. In their in-depth analyses, scholars divided 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 [6]. Putnam divided social capital into two dimensions: bridging social capital and bonding social capital [4]. Nahapiet

and Ghoshal adopted a resource-based organization view to illustrate the relationship between social capital development and organizational performance [7], arguing that social capital has structural, relational, and cognitive dimensions [1]. In this paper, 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.

3. Data

The Inter-Country Input-Output (ICIO) data are utilized in this paper not only for its ability of reshowing flows of intermediate products, final goods, and services but also for possible comparison on the same basis. Given that a world economy with m countries/regions ($u, v = 1, 2, \ldots, m$), n sectors within each country/region, and totally $N = m \times n$ sectors ($i, j = 1, 2, \ldots, N$), as shown in Table 1 (referring to our former study [8]).

Table 1. The layout of ICIO table.

Input	Output Country		Intermediate Use Country A	Country B	ROW	Final Demand Country A	Country B	ROW	Total Output
		Sector	$A_1, \ldots, A_n$	$B_1, \ldots, B_n$	$R_1, \ldots, R_n$	$A_1, \ldots, A_n$	$B_1, \ldots, B_n$	$R_1, \ldots, R_n$	
Intermediate Inputs	Country A	$A_1, \ldots, A_n$	Z^{AA}	Z^{AB}	Z^{AR}	Y^{AA}	Y^{AB}	Y^{AR}	X^A
	Country B	$B_1, \ldots, B_n$	Z^{BA}	Z^{BB}	Z^{BR}	Y^{BA}	Y^{BB}	Y^{BR}	X^B
	ROW	$R_1, \ldots, R_n$	Z^{RA}	Z^{RB}	Z^{RR}	Y^{RA}	Y^{RB}	Y^{RR}	X^R
	Value-Added		VA^A	VA^B	VA^R				
	Total Input		X^A	X^B	X^R				

Notes: $Z^{uv} = \begin{pmatrix} Z_{u_1 v_1} & \cdots & Z_{u_1 v_n} \\ \vdots & \ddots & \vdots \\ Z_{u_n v_1} & \cdots & Z_{u_n v_n} \end{pmatrix}$;
$X^A = VA^A + Z^{AA} + Z^{BA} + \ldots + Z^{RA}$;
$X^A = Z^{AA} + Z^{AB} + \ldots + Z^{AR} + Y^{AA} + Y^{AB} + \ldots + Y^{AR}$.

In the ICIO table, Z^{uv} is an $n \times n$ 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 an $n \times 1$ vector giving gross outputs in country u; and VA^u denotes a $n \times 1$ vector of direct value-added in country u [9,10]. 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.

The data of this paper are derived from the World Input-Output Database (WIOD) released in 2016 (WIOD2016 for short), which is value-type Input-Output (IO) table and covers the trade data of intermediate and final goods of 56 industrial sectors in 43 countries/regions and Rest of World (RoW) from 2000 to 2014 [11]. Data for 56 sectors are classified according to the International Standard Industrial Classification Revision 4. In detail, the names and abbreviations of countries are listed in Table A1, and those of industrial sectors are listed in Table A2 in the part of Appendix A.

The part of intermediate use in WIOD2016 is straightforwardly adopted to build graph $G = (V, E, W)$, containing N nodes, drawn to represent sectors within a country/region and denote a node set V. Pairs of nodes are linked by edges to reflect their interdependencies, thereby forming an asymmetric edge set E. In valued graphs, a set E can be replaced by weight set W, which is just the region of inter-country and inter-industry use and supply in ICIO table. Finally, we name this weighted and directed network the Global Industrial Value Chain Network (GIVCN) model.

4. Methodology

The issue studied in this paper is based on the theoretical framework of social capital, and we use network-based indicators to measure the impact of structural capital, relational capital, and cognitive capital on the country/region's macroeconomic performance.

4.1. Structural Capital: Industrial Status

Structural capital is mainly used to characterize the status of industrial sectors on the GVC, i.e., the macro performance of the industrial sector and its participation in worldwide synergic production. According to our previous study [12], the Random Walk Centrality (denoted as C_{RC}) can measure the national competitiveness on the GVC. The derivation process of GIIC is shown in Figure 2 and the details are attached in the Appendix B.1 Supplementary Description of GIIC.
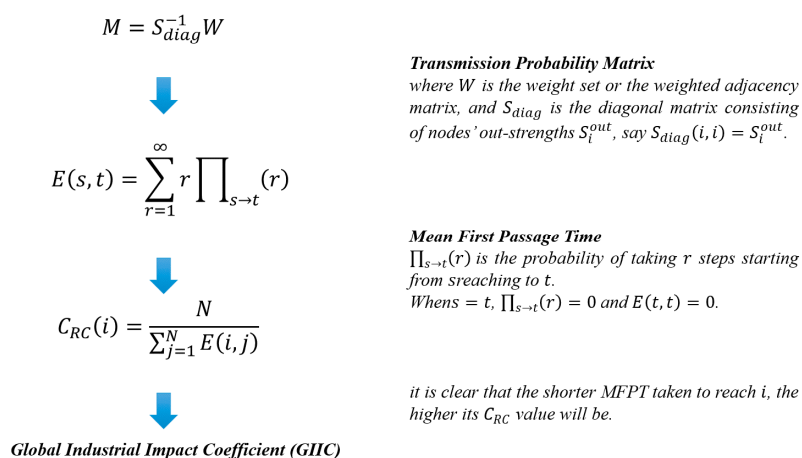
$$M = S_{diag}^{-1} W$$

Transmission Probability Matrix
where W is the weight set or the weighted adjacency matrix, and S_{diag} is the diagonal matrix consisting of nodes' out-strengths S_i^{out}, say $S_{diag}(i,i) = S_i^{out}$.

$$E(s,t) = \sum_{r=1}^{\infty} r \prod_{s \to t}(r)$$

Mean First Passage Time
$\prod_{s \to t}(r)$ is the probability of taking r steps starting from s reaching to t.
When $s = t$, $\prod_{s \to t}(r) = 0$ and $E(t,t) = 0$.

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

it is clear that the shorter MFPT taken to reach i, the higher its C_{RC} value will be.

Global Industrial Impact Coefficient (GIIC)

Figure 2. Formula derivation of GIIC.

In order to measure the relative competitive advantage of a country/region and analyze the interrelation between national industrial impact and its global economic status, we define the Global Industrial Impact Coefficient (GIIC).

GIIC is hence derived from the sum of C_{RC} of all the sectors within each country/region to evaluate the national competitiveness on the GVC:

$$GIIC(u) = 10^3 \times \sum_{i \in \tau(u)} C_{RC}(i) \tag{1}$$

where $GIIC(u)$ is the GIIC of country/region u; $\tau(u)$ is a set of numbers standing for the row sequence number of a certain country/region in the adjacent matrix Z^{uv}. For instance, China is the 8th economy in WIOD2016, so $\tau(8) = \{393, 394, \cdots, 448\}$ because each economy owns $n = 56$ sectors. Besides, 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.

In addition, the GVC well depicted by ICIO data is a sort of complex network from the perspective of econophysics, and we can further investigate the relationship between final demand and intermediate goods production. According to our previous study [8], the Counting First Passage Betweenness (denoted by C_{FP}) tracks how often a given node is visited on the first-passage walks between all source-target pairs. The derivation process of GDDI is shown in Figure 3 and details are attached in the Appendix B.2 Supplementary Description of GDDI.

Frequency of Taking e_{ij} as Random Walk Path
the element (s, i) of the matrix $\left((M_{-t})^r\right)_{si}$ gives the probability of a random walk starting at $s(s \neq t)$ and being at i $(i \neq t)$ in r steps; and then the probability of going from i to j is m_{ij}, thus the probability of taking r steps and then choosing e_{ij} as next path is $\left((M_{-t})^r\right)_{si} m_{ij}$.

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

First Passage Frequency
the total number of times 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 t $(i \neq s, t)$, this node will be visited $\sum_{j=1, j \neq t}^{\infty} \left(F_{ij}^{st} + F_{ji}^{st}\right)/2$ times. Due to the existence of self-loops, the random walk may take e_{ii} as path, so i will be visited twice consecutively, which can be divided into two cases.

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

when $i = s$, i.e., one extra visit happens at the end of source node s

when $i = t$, i.e., random walk is just absorbed by sink node t

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

Global Demand Dependence Index (GDDI)

Figure 3. Formula derivation of GDDI.

In order to measure the country/region-sector's participation in worldwide synergic production, we define the Global Demand Dependence Index (GDDI).

In the GIVCN model, therefore, the sum of C_{FP} of all the sectors within each country/region is defined as the GDDI. Compared with previous studies, this method can better capture the instantaneous dynamic characteristics of value flow.

$$GDDI(u) = \sum_{i \in \tau(u)} C_{FP}(i) \tag{2}$$

where $GDDI(u)$ is the GDDI of country/region u. GDDI is here adopted to measure country-sector's participation in worldwide synergic production, i.e., the bigger the sector's GDDI the higher the degree of globalization.

4.2. Relational Capital: Industrial Correlation

The relational capital in this article is mainly used to characterize the industrial correlation, i.e., to measure the industrial sectors' interdependence with all the upstream and downstream ones. The relative position of the industrial sector on the GVC could be reflected by Backward Closeness and Forward Closeness of Industrial Sectors, and the comparative advantage brought by different locations. Specifically, a single sector on the supply-side is called the upstream sector once 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. Accordingly, we calculate $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$ based on the numerical matrix of Strongest Relevance Path Length (SRPL) [13], which are the counterparts of in-degree and out-degree closeness centrality in complex networks. According to our previous study, the derivation process of $C_c^{RFWA-IN}$ and $C_c^{RFWA-OUT}$ is shown in Figure 4 and details are attached in the Appendix B.3 Supplementary Description of Backward Closeness and Forward Closeness.
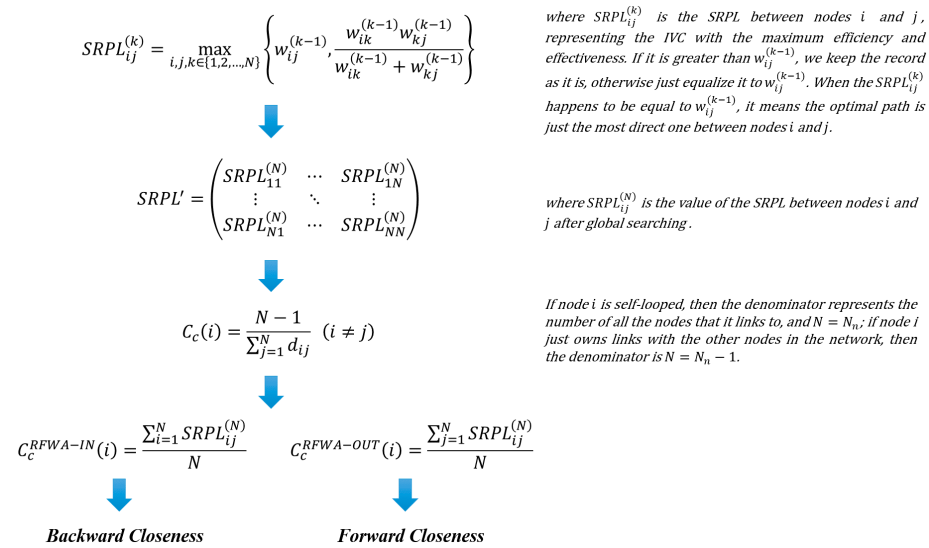
$$SRPL_{ij}^{(k)} = \max_{i,j,k\in\{1,2,\dots,N\}} \left\{ w_{ij}^{(k-1)}, \frac{w_{ik}^{(k-1)} w_{kj}^{(k-1)}}{w_{ik}^{(k-1)} + w_{kj}^{(k-1)}} \right\}$$

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.

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

where $SRPL_{ij}^{(N)}$ is the value of the SRPL between nodes i and j after global searching.

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

If node i is self-looped, then the denominator represents the number of all the nodes that it links to, and $N = N_n$; if node i just owns links with the other nodes in the network, then the denominator is $N = N_n - 1$.

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

Backward Closeness **Forward Closeness**

Figure 4. Formula derivation of backward closeness and forward closeness.

In order to quantify the closeness of relation among countries/regions, 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):

$$NIBC(u) = \sum_{i\in\tau(u)} C_c^{RFWA-IN}(i) \tag{3}$$

$$NIFC(u) = \sum_{i\in\tau(u)} C_c^{RFWA-OUT}(i) \tag{4}$$

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

4.3. Cognitive Capital: Industrial Stability

Different from structural capital and relational capital, the two indicators of cognitive capital are derived from Global Industrial Value Chain Network Bipartite Graph-Filtering Edges (GIVCNBG-FE) model [14]. Our modelling framework is shown in Figure 5.
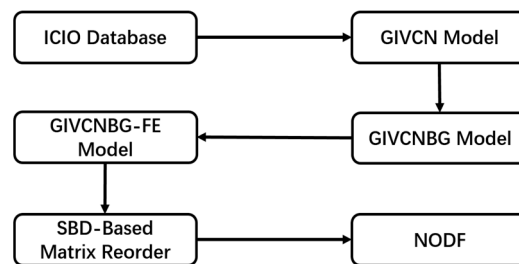

Figure 5. Computational process of NODF.

The cognitive capital is mainly used to characterize the degree of perfection of the industrial structure by measuring the degree of nested structure of the network. Higher degree of nestedness of GVC network indicates the stable industrial structure, the mature industrial trade mechanism, the regular and orderly industrial trade network, and the deeper integration between industries [15]. The Nested Overlap and Decreasing Fill (NODF) metric proposed by Almeida-Neto et al. is generally applied to calculate the nestedness of the network, which is based on two basic properties: Decreasing Fill (DF) and Paired Overlap (PO) [16] (see the Appendix B.4 Supplementary Description of NODF for details.)

Considering that a country/region's macroeconomic performance is affected by both domestic and international trade cycles, we define two indicators, i.e., Export Trade Network-Nested Overlap and Decreasing Fill (ETN-NODF) and Import Trade Network-Nested Overlap and Decreasing Fill (ITN-NODF), to measure the nestedness of the local network in terms of economies.

$$ETN - NODF(u) = NODF(Export\ Trade\ Network\ of\ Country/Region\ u) \tag{5}$$

$$ITN - NODF(u) = NODF(Import\ Trade\ Network\ of\ Country/Region\ u) \tag{6}$$

where, $ETN - NODF(u)$ measures the nestedness of export trade network of country/region u, which is formed while industrial sectors within country/region u, as upstream sectors (in the supply side), export intermediate goods to the others; in the opposite, $ITN - NODF(u)$ measures the nestedness of the import trade network, which is formed while industrial sectors within country/region u, as downstream sectors (in the demand side), import intermediate goods from the others.

4.4. Econometric Model

After Structural Equation Model (SEM) had been used to analyze the causality between latent variables [17], Wold created Partial Least Squares (PLS) as a complementary approach to factor-based SEM [18]. As a popular research tool, PLS can test hypotheses in an exploratory way, especially in complex path models with relaxed expectations on data [19]. In recent years, PLS-SEM has become popular in management, social sciences, and psychology [20]. 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 [21], and in identifying relationships between constructs [22]. 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 [20]. Hair et al. used the Finite Mixture PLS (FIMIX-PLS) module of SmartPLS 3 software [23] based on a popular corporate reputation model, identified and processed the unobserved heterogeneity in PLS-SEM [24,25]. 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 [26].

Since it offers the flexibility needed for the interplay between theory and data [27], PLS-SEM is becoming more and more popular in modelling the causality [28]. 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 [29]. Khan et al. applied Social Network Analysis (SNA) to investigate the knowledge network structure of PLS-SEM and identified the key journals for network knowledge dissemination [30]. 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.

5. Hypotheses

5.1. 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/region'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/region's GDDI, the higher its degree of globalization. Accordingly, we propose the hypothesis:

Hypothesis 1. *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 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/region and its upstream or downstream counterparts. It urges economies to reinforce the ability to integrate upstream or downstream industrial resources. A country/region 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:

Hypothesis 2. *Relational capital should positively affect social capital.*

Hypothesis 3. *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/region 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/region'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/region 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:

Hypothesis 4. *Cognitive capital should positively affect social capital.*

Hypothesis 5. *Cognitive capital should positively affect structural capital.*

Hypothesis 6. *Cognitive capital should positively affect relational capital.*
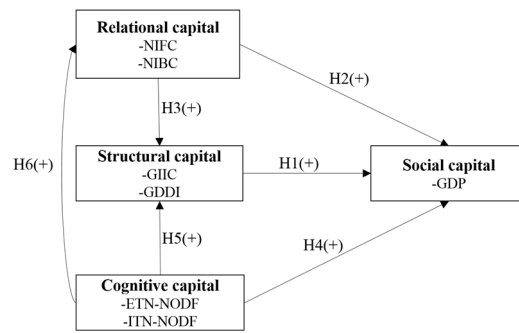
Figure 6 shows the hypothesis conceptual framework.

Figure 6. The hypothesis conceptual framework.

5.2. Hypothesis Testing

The model calculation data as Supplementary Materials named "PLS-SEM data.xlsx". 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 2.

Table 2. 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

According to the research of Hair, Ringle, and Sarstedt [31], PLS approach is applicable to evaluate the influence of social capital theory on macroeconomic development [32]. Strictly speaking, the desired level of the ratio is between 15 and 20 observations for each independent variable [33]. 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 Figure 7.
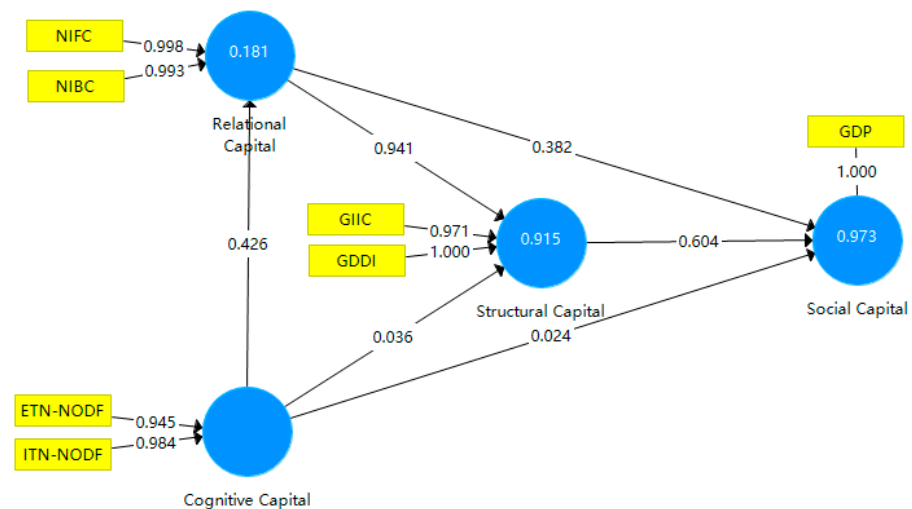

Figure 7. Tests for the hypothesized associations.

Overall, structural capital positively affects social capital (H1: β = 0.604, $p < 0.001$), so H1 is supported. Relational capital positively affects social capital and structural capital (H2: β = 0.382, $p < 0.001$; H3: β = 0.941, $p < 0.001$), so H2 and H3 are supported. Cognitive capital positively affects social capital, structural capital, and relational capital (H4: β = 0.024, $p < 0.001$; H5: β = 0.036, $p < 0.01$; H6: β = 0.426, $p < 0.001$), so H4, H5, H6 are supported.

Through the bootstrapping operation in the SmartPLS3 software, the data shown in Table 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.

In order to assess the effect size of a particular independent variable on a dependent variable [31], the squared multiple (or multiple partial) correlation (R^2) is used to calculate Cohen's f^2 [34]. The formula of effect size is as follows.

$$\text{Cohen's } f^2 = \frac{R^2_{full} - R^2_{reduced}}{1 - R^2_{full}} \tag{7}$$

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 [32,34].

As Cohen proposed in his research [33], 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 3 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.

Table 3. 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

[a] Type II error in hypothesis testing in statistics. Compare the absolute effect or contribution of each coefficient. [b] The overall effect sizes $f^2 < 0.02$, 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).

6. 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.

6.1. 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/region'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/region 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/regions 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/region with high global industrial influence and high industrial status, the global economic system will be severely affected.

6.2. The Effects of Relational Capital

Relational capital composed of NIBC and NIFC well explains the internal mechanism forming the competitiveness of country/region. 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/regions, 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) is positively correlated with 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 Industrial Value Chain (IVC) network. In the meanwhile, this type of country/region 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 Regional Value Chain (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 [35]. 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/regions 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.

6.3. The Effects of Cognitive Capital

First, 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/region'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 benefit to the economic development at the macro level.

Second, 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/regions 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.

Third, 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 World Trade Organization (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 ensure 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.

7. Conclusions

In this paper, an industrial complex network is built up according to the basic framework of econophysics and an econometric analysis framework is adopted to test the relevant hypotheses. It explains why social capital can be used to analyze the causality between microstructure and macro performance in the GVC network. In details, we construct the GIVCN-WIOD2016 model, define six types of indicators with economic meanings based

on the three dimensions of social capital, and explain how they interact and affect the development of the national economy. More importantly, 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.

Appendix A. Basic Information about WIOD2016

Table A1. Countries and their abbreviations in WIOD2016.

No.	Abbreviation	Country	No.	Abbreviation	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

Table A2. Industrial sectors and their abbreviations in WIOD2016.

Abbreviation	Industrial Sector
S1	Crop and animal production, hunting, and related service activities
S2	Forestry and logging
S3	Fishing and aquaculture
S4	Mining and quarrying
S5	Manufacture of food products, beverages, and tobacco products
S6	Manufacture of textiles, wearing apparel, and leather products

Table A2. *Cont.*

Abbreviation	Industrial Sector
S7	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
S8	Manufacture of paper and paper products
S9	Printing and reproduction of recorded media
S10	Manufacture of coke and refined petroleum products
S11	Manufacture of chemicals and chemical products
S12	Manufacture of basic pharmaceutical products and pharmaceutical preparations
S13	Manufacture of rubber and plastic products
S14	Manufacture of other non-metallic mineral products
S15	Manufacture of basic metals
S16	Manufacture of fabricated metal products, except machinery and equipment
S17	Manufacture of computer, electronic, and optical products
S18	Manufacture of electrical equipment
S19	Manufacture of machinery and equipment n.e.c.
S20	Manufacture of motor vehicles, trailers and semi-trailers
S21	Manufacture of other transport equipment
S22	Manufacture of furniture; other manufacturing
S23	Repair and installation of machinery and equipment
S24	Electricity, gas, steam, and air conditioning supply
S25	Water collection, treatment, and supply
S26	Sewerage; waste collection, treatment, and disposal activities; materials recovery; remediation activities and other waste management services
S27	Construction
S28	Wholesale and retail trade and repair of motor vehicles and motorcycles
S29	Wholesale trade, except of motor vehicles and motorcycles
S30	Retail trade, except of motor vehicles and motorcycles
S31	Land transport and transport via pipelines
S32	Water transport
S33	Air transport
S34	Warehousing and support activities for transportation
S35	Postal and courier activities
S36	Accommodation and food service activities
S37	Publishing activities
S38	Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities
S39	Telecommunications
S40	Computer programming, consultancy and related activities; information service activities
S41	Financial service activities, except insurance and pension funding
S42	Insurance, reinsurance and pension funding, except compulsory social security
S43	Activities auxiliary to financial services and insurance activities
S44	Real estate activities
S45	Legal and accounting activities; activities of head offices; management consultancy activities
S46	Architectural and engineering activities; technical testing and analysis
S47	Scientific research and development
S48	Advertising and market research
S49	Other professional, scientific and technical activities; veterinary activities
S50	Administrative and support service activities
S51	Public administration and defence; compulsory social security
S52	Education
S53	Human health and social work activities
S54	Other service activities
S55	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
S56	Activities of extraterritorial organizations and bodies

Appendix B. Supplementary Description of Methodology

Appendix B.1. Supplementary Description of GIIC

As one of the basic dynamic processes, random walk is closely related to the nature of the network topological structure. Three indices are generally involved in studying random walk on networks. The first one is First Passage Time (FPT). After a source node released a walk signal, it will move to other adjacent nodes with equal probability or following certain transmission probability, thus the expected time to reach a pre-set sink node for the first time is FPT. According to FPT, the other two indices can be calculated. One is Mean First Passage Time (MFPT), which is equal to the arithmetic mean of FPT of all nodes in the network, and the other is Mean Absorption Time (MAT), which is obtained by the average of FPT from each other nodes to a certain sink node [36]. In view of progress of social network in recent years, Freeman's Closeness Centrality has been widely applied, generally denoted as C_c. As known, the basic form of IO table is of material-type, but the widely used is of value-type. WIOT adopted as the modeling data source belongs to the latter, so inter-industry relationships are depicted by flows of value stream. In GIVCN models, the transmission probability matrix of random walk, denoted as $M(i, j)$, is subject to the impact of the importance of node j.

Transition probability matrix M describes possibilities when value stream transmits among product 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. 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 for 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 C_{RC} in Figure 2 clearly shows that the shorter MFPT taken to reach i, the higher its C_{RC} value will be. Industrial sectors with bigger C_{RC} will create 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.

Appendix B.2. Supplementary Description of GDDI

As described in Figure 3, when 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}. Next, 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. In the case, a random walk starts from s to t, the First Passage Frequency of node i is $F^{st}(i) = \sum_{j=1, j \neq t}^{\infty} \left(F_{ij}^{st} + F_{ji}^{st} \right)/2$. 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 $F^{st}(s) = \sum_{j=1, j \neq t}^{\infty} \left(F_{sj}^{st} + F_{ji}^{st} \right)/2 + 1$.

Another is that when $i = t$, the random walk is just absorbed by sink node t, $F^{st}(t) = 1$. 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. Thus, $C_{FP}(i) = \frac{\sum_{s \in V} \sum_{t \in (V - \{s\})} F^{st}(i)}{N(N-1)}$. 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.

Appendix B.3. Supplementary Description of Backward Closeness and Forward Closeness

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. We, therefore, divided $w_{ik}w_{kj}$ into $w_{ik} + w_{kj}$ and named the result the Relevance Path Length (RPL). As described in Figure 4, SRPL is regarded as the optimal path in IO networks, which is the synthetic gauge of spreading effectiveness and efficiency of a given path. For this purpose, we put forward the Revised Floyd–Warshall Algorithm (RFWA) as an iterative and convergence algorithm based on operations research. $SRPL_{ij}^{(k)}$ 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. Next, 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.

In non-weighted networks, the Average Path Length (APL) of the whole network can be calculated via classical Floyd–Warshall algorithm, depicting the degree of separation of nodes. 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 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.

The calculation formula of $C_c(i) = \frac{N-1}{\sum_{j=1}^{N} d_{ij}}$ $(i \neq j)$ is inapplicable to either weighted or directed network. 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. First, 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. Second, 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:

$$C_c^{RFWA-IN}(i) = \frac{\sum_{i=1}^{N} SRPL_{ij}^{(N)}}{N} \text{ and } C_c^{RFWA-OUT}(i) = \frac{\sum_{j=1}^{N} SRPL_{ij}^{(N)}}{N}.$$

Appendix B.4. Supplementary Description of NODF

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 $(k, l)(k < l)$, if $MT_k > MT_l$, then $DF_{kl} = 100$, otherwise $DF_{kl} = 0$.

For any pair of rows $(i, j)(i < j)$, PO_{ij} refers to the percentage of 1s in a given row j that are located at identical column positions to the 1s observed in a row i; similarly, for any pair of columns $(k, l)(k < l)$, PO_{kl} refers to the percentage of 1s in a given column l that are located at identical row positions to those in a column k. 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 $N_{paired} = \begin{cases} 0, & if\ DF_{paired} = 0 \\ PO, & if\ DF_{paired} = 100 \end{cases}$. 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": $NODF = \frac{\sum N_{paired}}{\left[\frac{m(m-1)}{2}\right] + \left[\frac{n(n-1)}{2}\right]}$. The NODF values range from 0 to 100, with $NODF = 0$ indicating non-nested network structure and $NODF = 100$ indicating a fully nested network structure.

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