EE482 Industrialization: Role of Public and Private Sectors (Section 046401)

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Chapter 6

Introduction to Network Analysis and Economic Complexity Index (ECI)

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Introduction

Production and industrial activities have undergone significant transformations due to the influence of the "second unbundling." This has allowed producers to distribute their production across various regions of the world, leading to increased complexity in international production and trade. As a result, production and trade data have become increasingly extensive.

This change necessitates the development of new analytical methods capable of handling the expansion of large-scale data and the complexity of industrial processes. Consequently, it has led to the analysis of data using alternative approaches. In this chapter, we will present two newly developed methods that provide insights into the structure of the economy and the interconnections between production sectors. We will also discuss the significance and roles of different production sectors.

The first analysis method is Network Analysis, and the second is the Economic Complexity Index. The fundamental theories and application of these methods will be presented in the following sections.

6.1 Network Analysis and its Applications in Economics

Over the past two decades, knowledge in the field of Network Analysis has seen significant development and has gained popularity for various applications in different fields. Figure 6.1 illustrates the number of citations per year in research articles related to Network Analysis, which is the most frequently cited research area. Additionally, Figure 6.2 displays the frequency of important keywords in research searches, with Network Analysis being the most frequently searched term, surpassing keywords like AI (Artificial Intelligence) and Quantum. This highlights its substantial significance in various applications.

Network Analysis has become a crucial tool for analysis not only in the fields of science but also for studying the molecular and structural components of matter in physics and chemistry. It is also applied to analyze the components and networks of cells, which is highly beneficial for medical analysis and cancer treatment development.

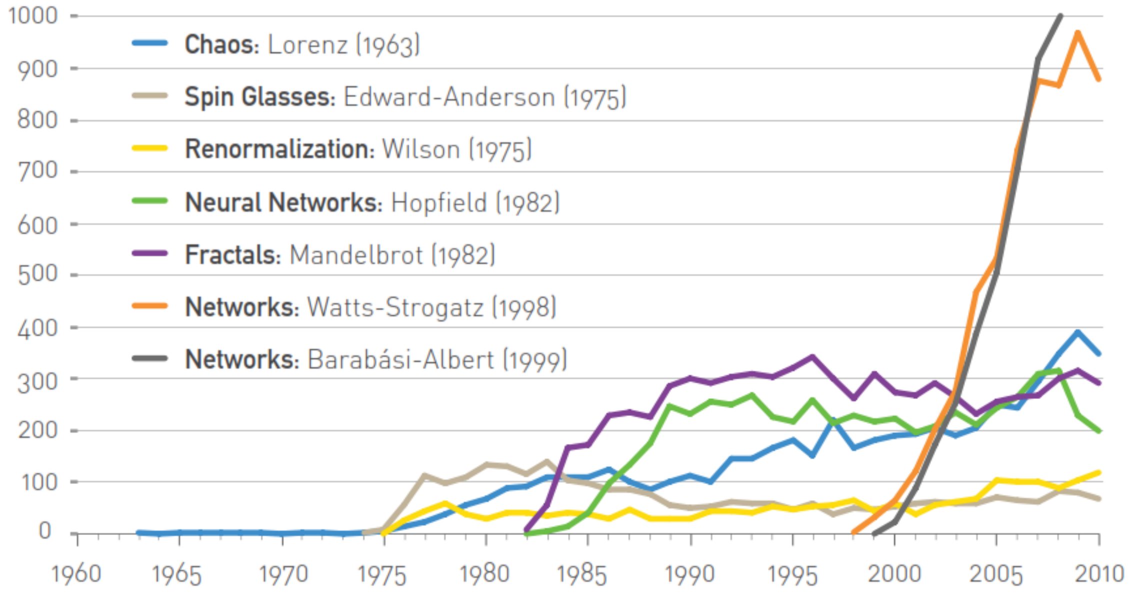

Figure 6.1 Number of Citations per Year

Source: Barabási (2016)

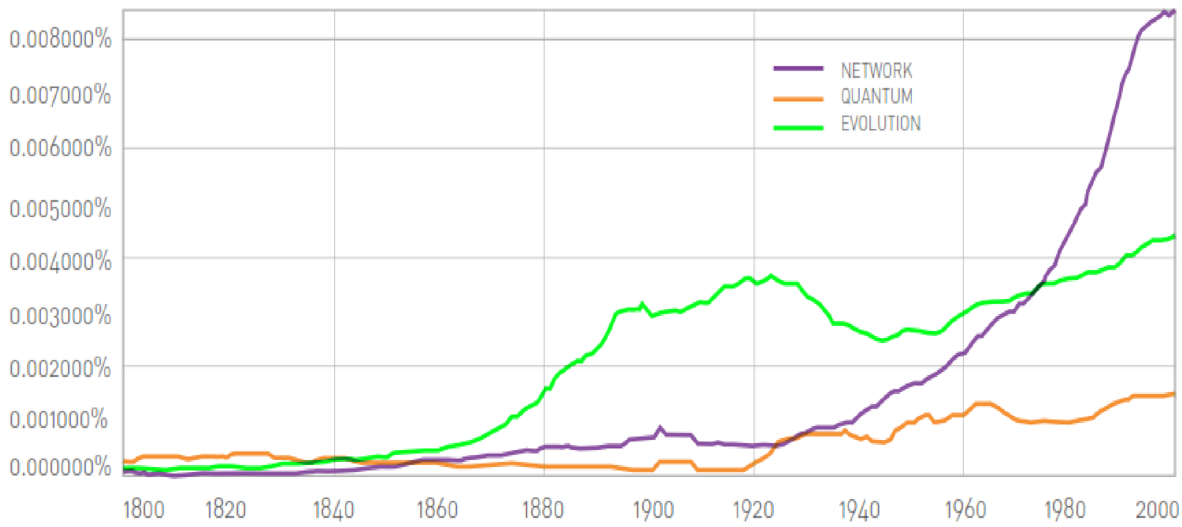

Figure 6.2 The frequency of keyword searches

Source: Barabási (2016)

Additionally, Network Analysis is employed in engineering and data science, aiding in understanding the global internet system's structure and simplifying the comprehension of large-scale Big Data. Moreover, Network Analysis has evolved into a primary research tool in social sciences. This shift is attributed to the vast amount of data generated by social media, which connects people on a massive scale. The extensive communication within these networks results in the fast growing amount of Big Data. Consequently, this enables tracking behavioral patterns and understanding the significant foundation – the interconnected interactions of individuals as they create communities and societies. This marks a novel dimension, fusing social science knowledge with quantitative computation and the utilization of Big Data.

In the field of economics, Network Analysis has emerged as a new tool for understanding issues related to the characteristics of economic systems. It can be divided into two main types of analysis:

1. **Individual-Based Analysis**: In this approach, individual-level data is the foundation for analysis. Each data unit represents an individual, and Network Analysis can be used to demonstrate the relationships between these individuals, creating a network. This kind of analysis has implications for market characteristics or economic system attributes. Furthermore, it can identify which individuals play the most crucial roles within the network.
2. **Sector-Based Analysis**: This approach is primarily based on data related to production sectors. It often involves factors such as production and output data (Input-Output tables) at both the national and international levels. This type of analysis can depict the structure of an economic system, highlighting the linkages between different sectors within the economic system. It can also reveal the connections between international trade and production (Global Value Chain or Global Supply Chain). The analysis can provide indices that indicate the importance of each production sector's impact on the economy or on international trade and production.

To comprehensively understand the basic theories and their application in economics, the following sections will present foundational theories and examples of analysis using both individual-level data and data from Input-Output tables.

6.1.1. Basic Theory of Network Analysis

Network analysis is a method used to analyze relationships using mathematics. It is based on the principles of graph theory, which represents relationships between data using nodes to represent individuals or objects, and linkages (sometimes called edges or arcs) to show connections between nodes. Network relationships, which are network-like in nature, can be visually represented using nodes and linkages together. This makes it possible to illustrate relationships from data that are presented in numeric table or matrix formats. Along with matrix algebra for analyzing relationships and data characteristics, network analysis can be categorized into the following types of analysis:

(1) Creating diagrams to illustrate the connections among components within the dataset.

Given the large size of data in today's context, understanding the structure of data is a fundamental necessity for analyzing the underlying relationships within all the data. Therefore, the primary benefit of using network analysis is to create diagrams illustrating the connections between nodes with linkages indicating the connections between nodes. This facilitates a comprehensive understanding of all relationships and serves as the foundation for analyzing the overall characteristics of the network and the characteristics of each node within the network going forward.

(2) Overall Network Characteristics

This analysis focuses on the size of the network, which is expressed by the number of nodes and linkages. Additionally, it can illustrate properties such as network density, diameter, and clustering coefficient.

(3) Characteristics of Each Node in the Network

This analysis can show the importance of each node in the network, such as the Betweenness index, which indicates the significance of a node as a crucial pass-through point in the network, the standardized average degree, which denotes the number of linkages for that node, and the PageRank index, which reflects the centrality level of the node within the network.

6.1.2. Overall Network Characteristics

Each network possesses unique characteristics that can be represented through various computational methods. The analysis of these characteristics is rooted in the theory of Erdős and Rényi (1959), who created models to demonstrate how nodes initiate connections and establish linkages, resulting in the continuous growth of larger networks. These characteristics are illustrated in Figure 6.3, which shows that each node begins to expand its connections over an extended period. In cases of random linkages, the occurrence of linkages in each node follows statistical patterns, either in a binomial or Poisson distribution, as shown in Figure 6.4. In this scenario, every node has a relatively equal importance within the network.

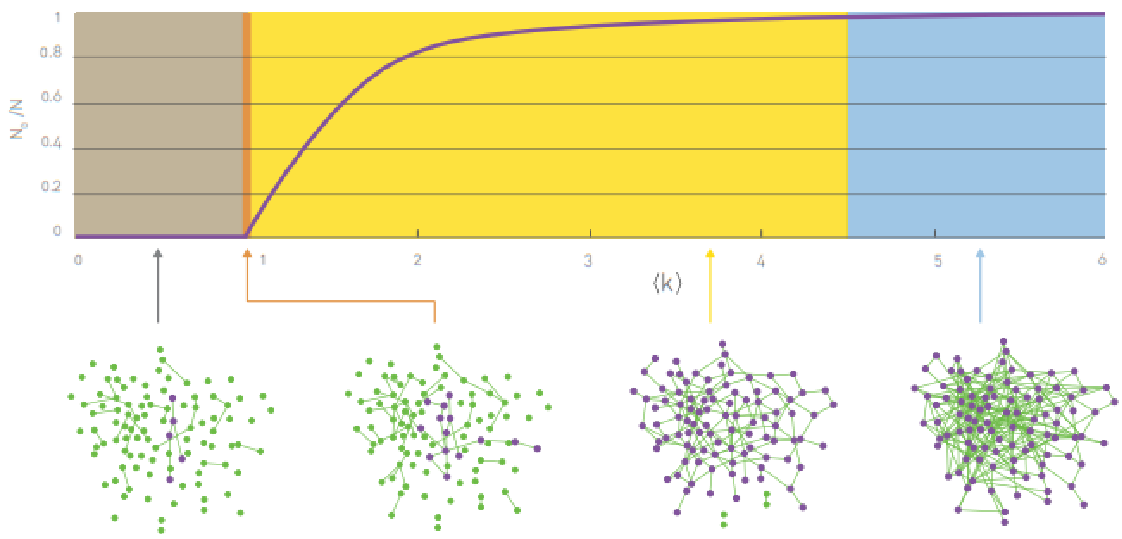

Figure 6.3 Network expansion increasing over time

Source: Barabási (2016)

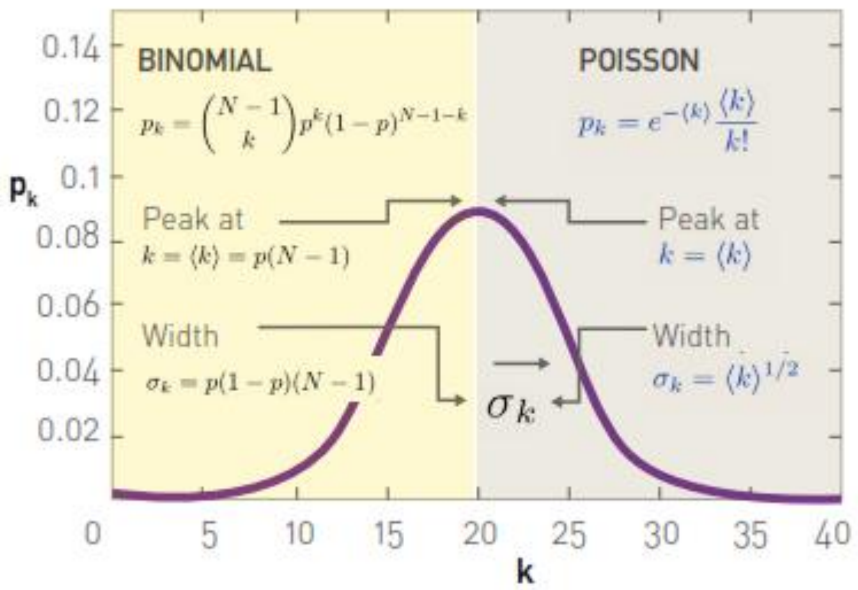

Figure 6.4 Statistical Characteristics of Linkage Occurrence in Each Node
Source: Barabási (2016)

In some cases, certain nodes are more important than others, as shown in Figures 6.5 and 6.6, which compare the characteristics of road networks and air transportation networks in the United States. In the case of road networks, each city (or node) has a similar number of road linkages connecting to other cities. In contrast, in the case of air transportation networks, only a few cities serve as central hubs, resulting in a greater number of linkages. This distribution exhibits a statistical pattern known as a Power law (or long-tailed), indicating that only a few cities (or nodes) have a high number of linkages.

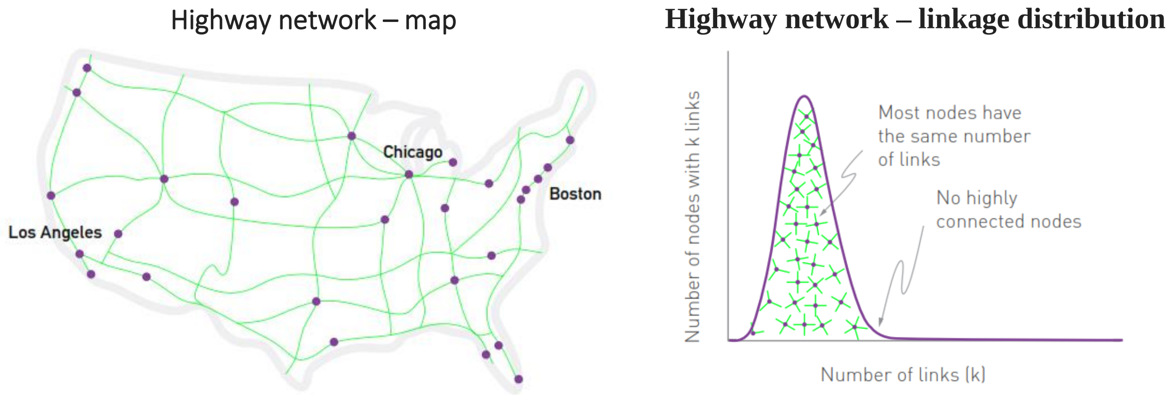

Figure 6.5 Characteristics of the Highway Network
Source: Barabási (2016)

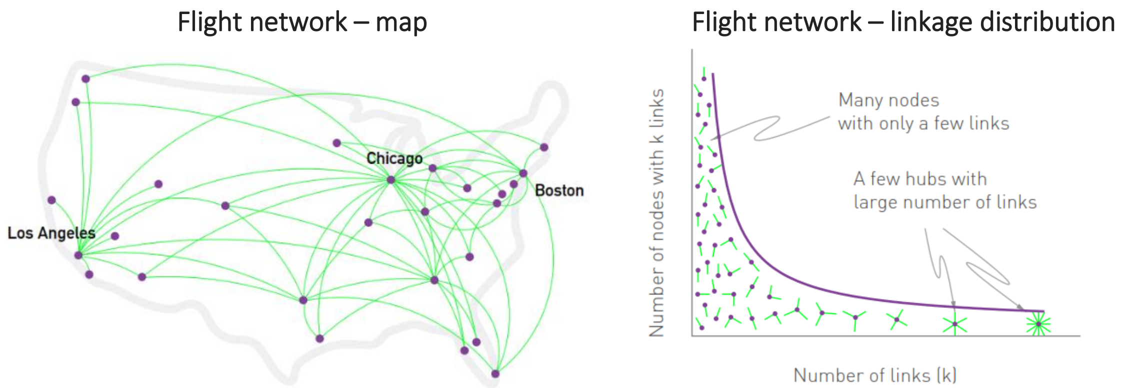

Figure 6.6 Characteristics of the Flight Network
Source: Barabási (2016)

From the examples of these two networks, the patterns can be visualized as in Figure 6.7. It is evident that in the case of the road network, there is a balanced distribution, where each node is of roughly equal importance throughout the network. In contrast, the imbalanced distribution pattern makes some nodes have more influence on the network than others.

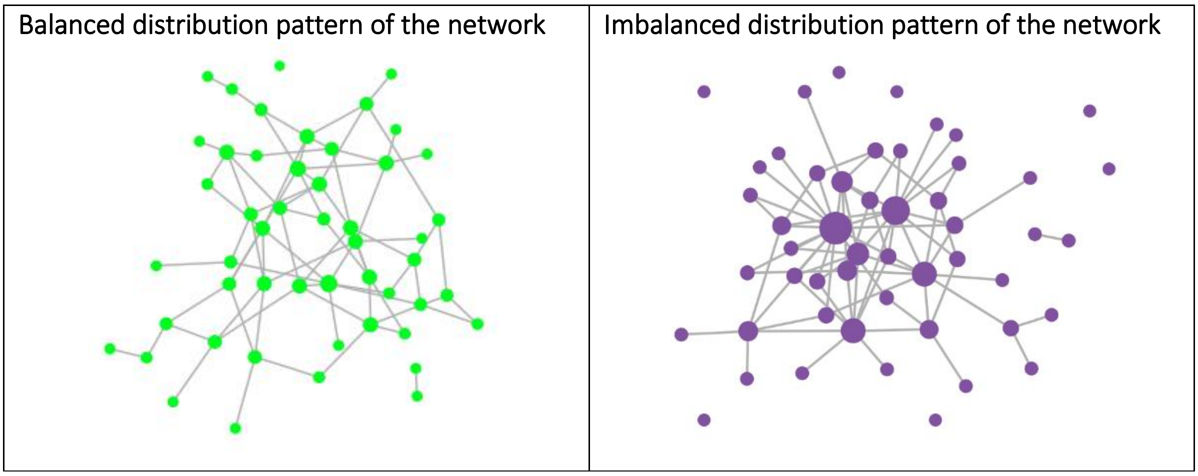

Figure 6.7 Characteristics of the Network
Source: Barabási (2016)

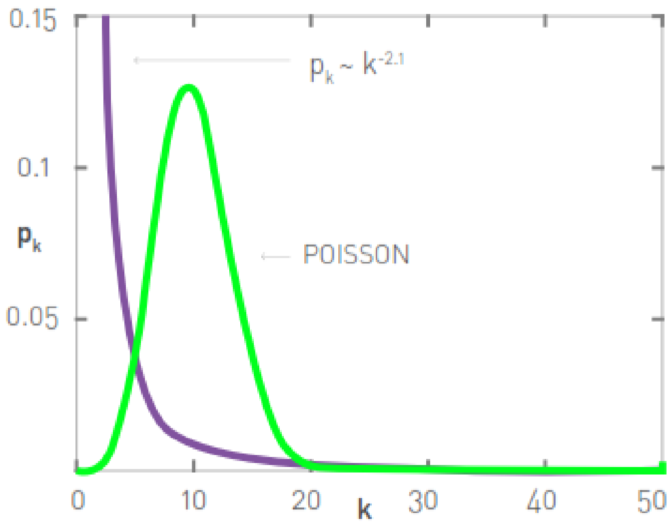

Figure 6.8 Statistical Distribution Pattern
Source: Barabási (2016)

The characteristics of a network can be represented in various index forms. Popular indices used for this purpose include:

Degree (L): This calculates the number of linkages that connect a given node to other nodes. It is computed using the following mathematical formula:

$$L = \frac{1}{2}\sum_{i=1}^{N} k_i$$

where, k_i represents the number of linkages of node i, and N is the total number of nodes. L represents the total number of linkages within the network.

Average Degree <k>: This calculates the average number of linkages by dividing by N, the total number of nodes:

$$<k> = \frac{1}{N}\sum_{i=1}^{N} k_i = \frac{2L}{N}$$

Average Path Length <d>: It calculates the average distance between two nodes, which indicates one form of network density. A lower value implies more connections and shorter distances between nodes, and it is computed as follows:

$$<d> = \frac{1}{N(N-1)} \sum_{i,j=1 \; and \; i \neq j}^{N} d_{i,j}$$

Diameter: This represents the network's centermost point, indicating the longest distance that links any two nodes within the network.

Shortest Path: It represents the shortest distance connecting two nodes within the network.

Density (S): This quantifies the network structure's density by comparing the total number of linkages within the network to the maximum possible linkages based on the number of nodes in the network. It is calculated as follows:

$$S = \frac{2L}{N(N-1)}$$

The value of S falls between 0 and 1, with 0 indicating no connections between nodes in the network and 1 indicating that every node is connected to every other node in the network.

6.1.3. Characteristics of Each Node in the Network

In addition to the overall analysis of the network using the indices presented in the previous section, the details within the network can be further analyzed. Each component (or node) can be examined by calculating centrality indices, which indicate the level of importance of each node within the entire network. Calculating centrality indices can take various forms, as exemplified in Figure 6.9.

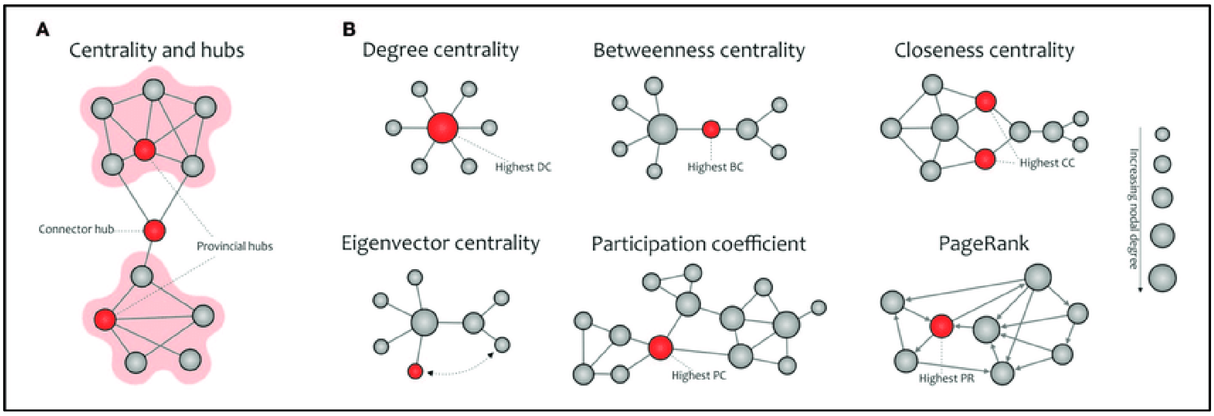

Figure 6.9 Centrality Index Patterns
Source: Barabási (2016)

Since calculating centrality indices involves extensive mathematical details, not all details are presented in this lecture note. However, a summary of the popular centrality indices is provided as follows:

• Degree centrality: Highlights nodes with the highest degree of linkages.

• Betweenness centrality: Identifies nodes that act as connectors (or bridges) between subnetworks.

• Closeness centrality: Reveals nodes with the shortest average distance to other nodes in traveling.

• Eigenvector centrality: Emphasizes nodes highly connected to other influential nodes.

• Participation coefficient: Spotlights nodes serving as central hubs or gateways to connect different subnetworks in the system (similar to Betweenness centrality).

• PageRank coefficient: Reflects the likelihood of reaching the respective node through the shortest distance (originated by Larry Page, co-founder of Google, and remains a significant part of Google's analysis to show websites that best match search keywords).

6.2 Examples of Network Analysis Using Individual-Level Data

For example, in the field of economics, we will analyze the connectivity patterns of individuals serving as board members across multiple companies registered in the stock market. This exhibits a network structure, reminiscent of the characteristics of Zaibatsu in Japan. The following table showcases the research findings that employ network analysis to study the characteristics of corporate board networks.

Table 6.1: Research Survey Utilizing Network Analysis to Investigate Board of Directors' Network Characteristics in Registered Companies.

Counties	**Related literatures**
US	Battiston and Catanzaro (2004)
	Caldarelli and Catanzaro (2004)
	Davis et al. (2003)
	Strogatz (2001)
	Conyon and Muldon (2006)
	Caldarelli (2007)
	Robins and Alexander (2004)
	Kogut (2012)
UK	Conyon and Muldon (2006)
	Kogut (2012)
Australia	Robins and Alexander (2004)
Canada	Kogut (2012)
Italy	Battiston and Catanzaro (2004)
	Caldarelli and Catanzaro (2004)
	Caldarelli (2007)
	Kogut (2012)
Germany	Conyon and Muldon (2006)
	Kogut (2012)
The Netherlands and Switzerland	Kogut (2012)
	Heemskerk and Schnyder (2008)
Denmark, Norway and Sweden	Kogut (2012)
	Sinani et al. (2008)
South Africa	Durbach and Parker (2009)
South Korea	Kogut (2012)
	Nam and An (2017)
Poland	Sankowska and Siudak (2016)
Greek	Dimitrios and Vasileios (2015)
Spain, France, Brazil, Chile, Israel, Mexico and Taiwan	Kogut (2012)

Source: Puttanapong (2018)

The main conclusion of the analysis in Table 6.1 is that the network exhibits the characteristics of a small world network. This is a distinctive feature found in human societies where there is a high clustering coefficient. Such characteristics were observed in every country presented in the table. This clustering indicates that the relationships among companies in the stock market are also interrelated, suggesting that the links among companies in the stock market are based on human social relationships. Therefore, the mechanism of information transmission and impact within the stock market is influenced by the fundamental structure of human social networks, facilitating rapid data transmission and impact.

The results of the analysis of the network of corporate board members in the Thai stock market are depicted in Figure 10. In this figure, we can observe that approximately 6,000 board members are connected in a large-scale social network. This connectivity arises from board members serving in multiple companies and is a fundamental factor contributing to the interconnections between companies registered in the stock market, as illustrated in Figure 6.11.

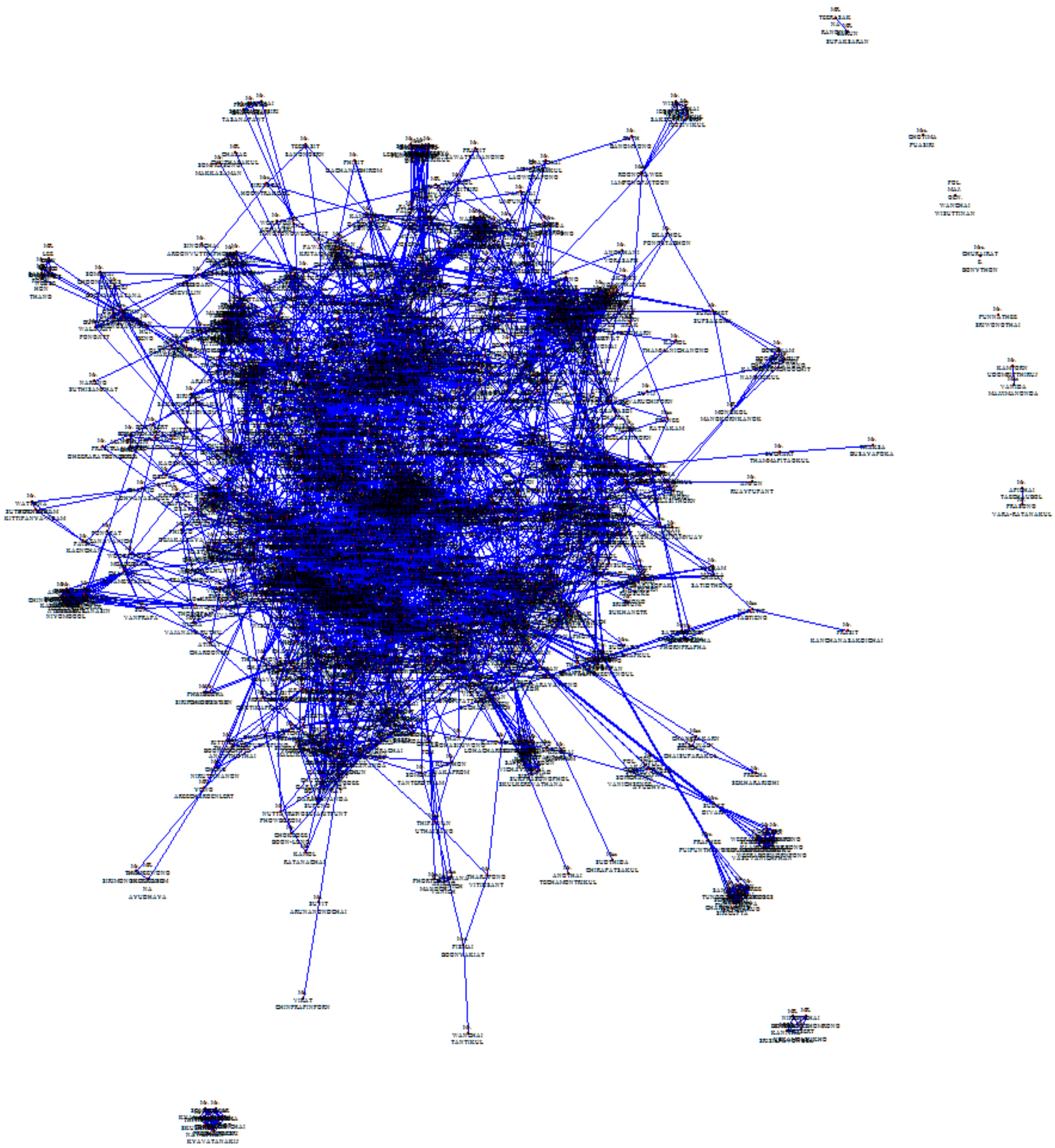

Figure 6.10 Social Network Diagram of Corporate Board Members in the Securities Market of Thailand

Source: Puttanapong (2018)

Table 6.2 Index Values Showing the Characteristics of the Social Network of Corporate Board Members in the Securities Market of Thailand

Year	Density	Diameter	Average shortest path length
2012	0.0082	10	4.105
2013	0.0121	9	3.813
2014	0.0119	9	3.846
2015	0.0101	11	3.928
2016	0.0117	10	4.031

Source: Puttanapong (2018)

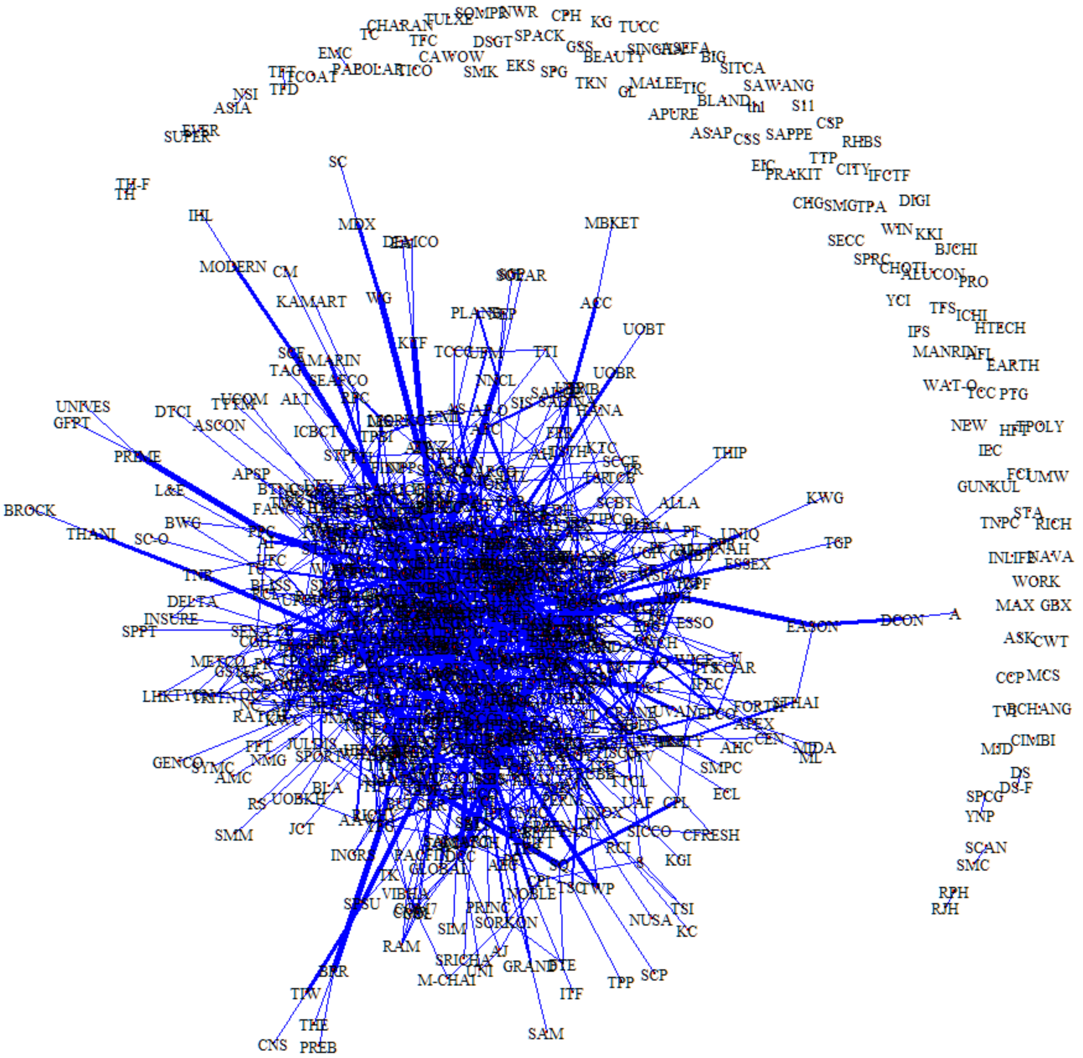

Figure 6.11 Network Diagram of the Relationship between Registered Companies in the Securities Market of Thailand

Source: Puttanapong (2018)

Table 6.3 Indices Showing the Characteristics of the Relationship Network Among Registered Companies in the Securities Market of Thailand.

Year	Density	Diameter	Average shortest path length
2012	0.0081	15	4.234
2013	0.0094	15	3.956
2014	0.0094	12	4.018
2015	0.0093	11	3.947
2016	0.0083	13	4.159

Source: Puttanapong (2018)

Table 6.4 Board Members in the Securities Market of Thailand with the Highest Importance, Ranked by Betweenness Centrality

2012	
Mr. CHACKCHAI PANICHAPAT	0.039
Mr. PRAKIT PRADIPASEN	0.037
Mrs. CHANTRA PURNARIKSHA	0.033
Mr. SUCHIN WANGLEE	0.032
Mr. WEERAWONG CHITTMITTRAPAP	0.031
Mr. MANU LEOPAIROTE	0.03
Mr. WISSANU KREA - NGAM	0.03
MR. PONG SARASIN	0.029
Mr. CHAI SOPHONPANICH	0.025
Mr. CHATCHAVAL JIARAVANON	0.025

2013	
Mr. MANU LEOPAIROTE	0.045
Miss POTJANEE THANAVARANIT	0.036
Mr. SUCHIN WANGLEE	0.036
Mr. CHATCHAVAL JIARAVANON	0.036
Mr. PRASERT BUNSUMPUN	0.033
Mr. WISSANU KREA - NGAM	0.028
Mrs. NUALPHAN LAMSAM	0.028
Mr. PRAKIT PRADIPASEN	0.028
Mr. JOTI BHOKAVANIJ	0.025
Mrs. KULPATRA SIRODOM	0.025

2014	
Mr. CHATCHAVAL JIARAVANON	0.05
Mr. MANU LEOPAIROTE	0.041
Mr. SUCHIN WANGLEE	0.04
Miss POTJANEE THANAVARANIT	0.037
Mr. PRAKIT PRADIPASEN	0.032
Mr. PRASERT BUNSUMPUN	0.031
Mr. SUVARN VALAISATHIEN	0.028
Mr. SIRI GANJARERNDEE	0.026
Mr. SATIT CHANJAVANAKUL	0.024
Mr. CHAI SOPHONPANICH	0.023

2015	
Mr. MANU LEOPAIROTE	0.046
Mr. SUCHIN WANGLEE	0.043
Miss POTJANEE THANAVARANIT	0.037
Mr. CHATCHAVAL JIARAVANON	0.036
Mr. PRAKIT PRADIPASEN	0.034
Mr. WEERAWONG CHITTMITTRAPAP	0.033
Mr. PRASERT BUNSUMPUN	0.032
Mr. SIRIPOL YODMUANGCHAROEN	0.027
Mr. ARSA SARASIN	0.026
Mr. CHAI SOPHONPANICH	0.024

2016	
Mr. MANU LEOPAIROTE	0.064
Mr. PRASERT BUNSUMPUN	0.049
Mr. SUCHIN WANGLEE	0.04
Mr. ARSA SARASIN	0.038
Mr. PRAKIT PRADIPASEN	0.036
Mr. RAWAT CHAMCHALERM	0.032
Mr. VIRACH APHIMETEETAMRONG	0.031
Mr. SUVARN VALAISATHIEN	0.03
Mr. CHAINOI PUANKOSOOM	0.026
Mr. CHATCHAVAL JIARAVANON	0.026

Source: Puttanapong (2018)

The results of calculating the indices that describe the characteristics of the social network of board members in companies registered in the Thai stock market, as shown in Table 6.2, and the aforementioned network relationship indices among registered companies in the Thai stock market, as presented in Table 6.3, when compared, exhibit similar characteristics. These indices have remained relatively stable over the years from 2012 to 2016.

The analysis can be further extended to include listing the names of individuals with the highest importance, as illustrated in Table 6.4. This table provides a ranking of board members by their Betweenness centrality index, which aids in determining the overall role of each individual within the network of board members of all companies registered in the securities market of Thailand.

6.3 An Example of Analysis Using Production Data

In addition to using individual-level data as the basis for analysis, network analysis methods can also be applied to data that provide details at the level of production sectors. Typically, data organized in the form of production factor and output tables are commonly used for analysis. The results of such analysis can describe the overall economic structure, illustrate the network of production (or depict Global Value Chains), and even determine the level of importance of each production sector within the entire economic system.

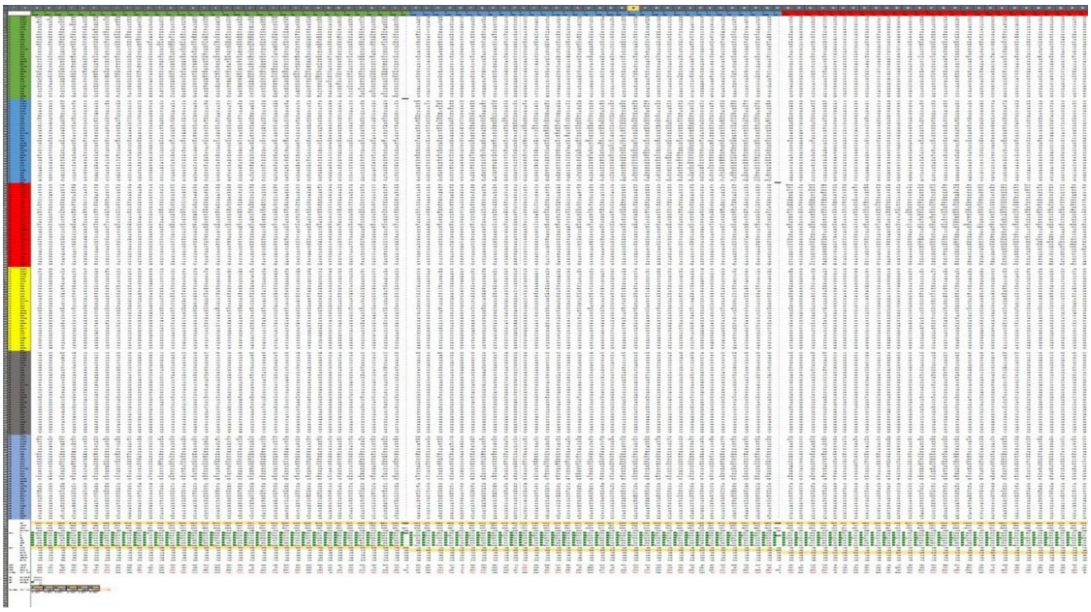

Figure 6.12 An Example of Data Characteristics in a Global Input-Output Table
Source: Compiled by the author from data published by ADB

The figure in 6.12 illustrates the format of a Global Input-Output Table, which provides details about the import and export of goods among various production sectors of different countries. However, this data is highly detailed and doesn't readily reveal the connections and structure of the economic system. Yet, when such data is analyzed using network analysis methods in the initial stages, the information can be transformed into a visual representation, as shown in Figure 6.13. This is an example of the transformation of data from a Global Input-Output Table for the years 1995 and 2011. Through this transformation, it becomes possible to depict the interconnections between production sectors in each country. When aggregating all types of goods, the resulting visualization is displayed in Figure 6.14. This can indicate the centrality of the production and trade network of large economies, including the United States, Germany, China, Japan, the United Kingdom, Italy, and France.

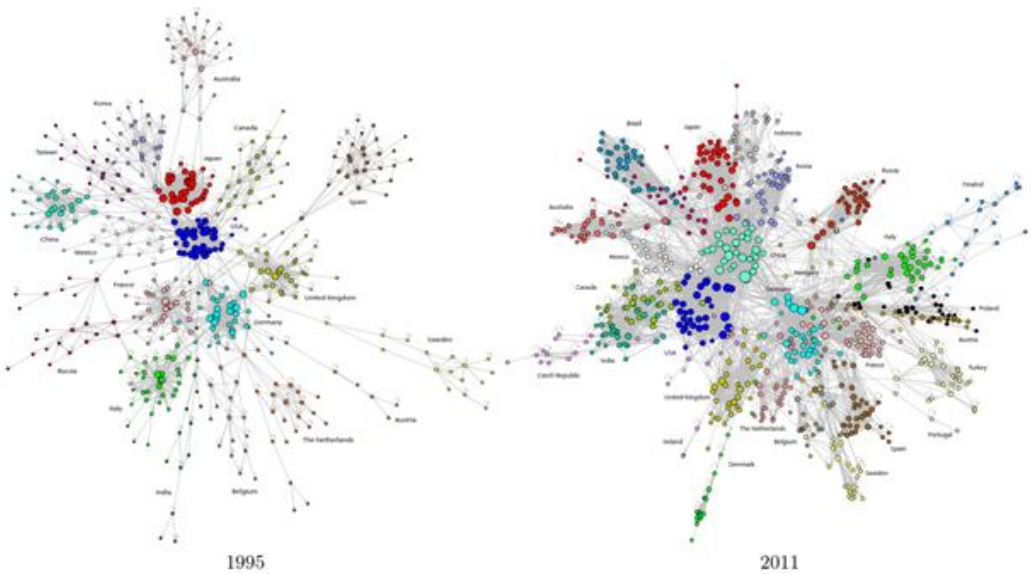

Figure 6.13 Results of Data Transformation into a Network Analysis Visualization
Source: Cerina et al. (2014)

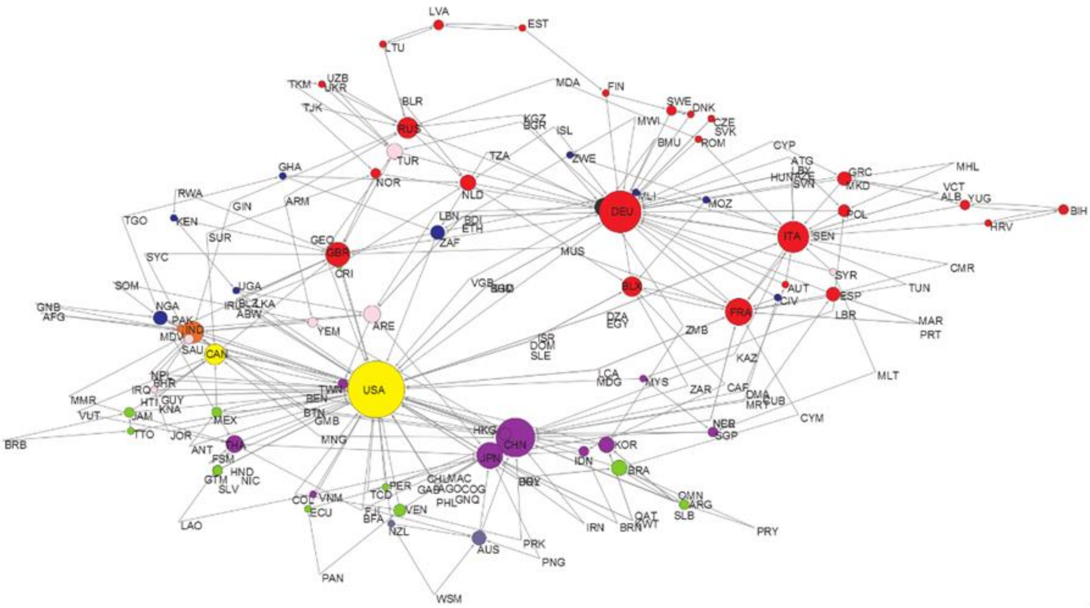

Figure 6.14 Results of Data Transformation using Network Analysis (Including All Types of Goods)
Source: Cerina et al. (2014)

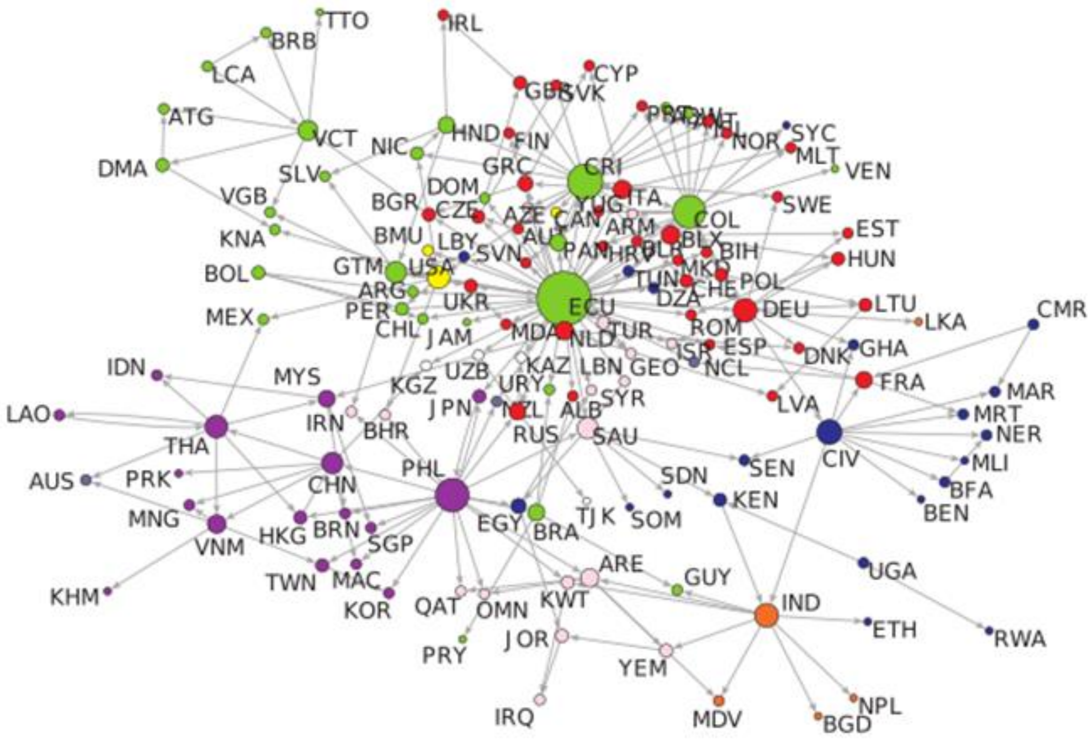

Figure 6.15 Results of Network Analysis of Banana Exporters
Source: Cerina et al. (2014)

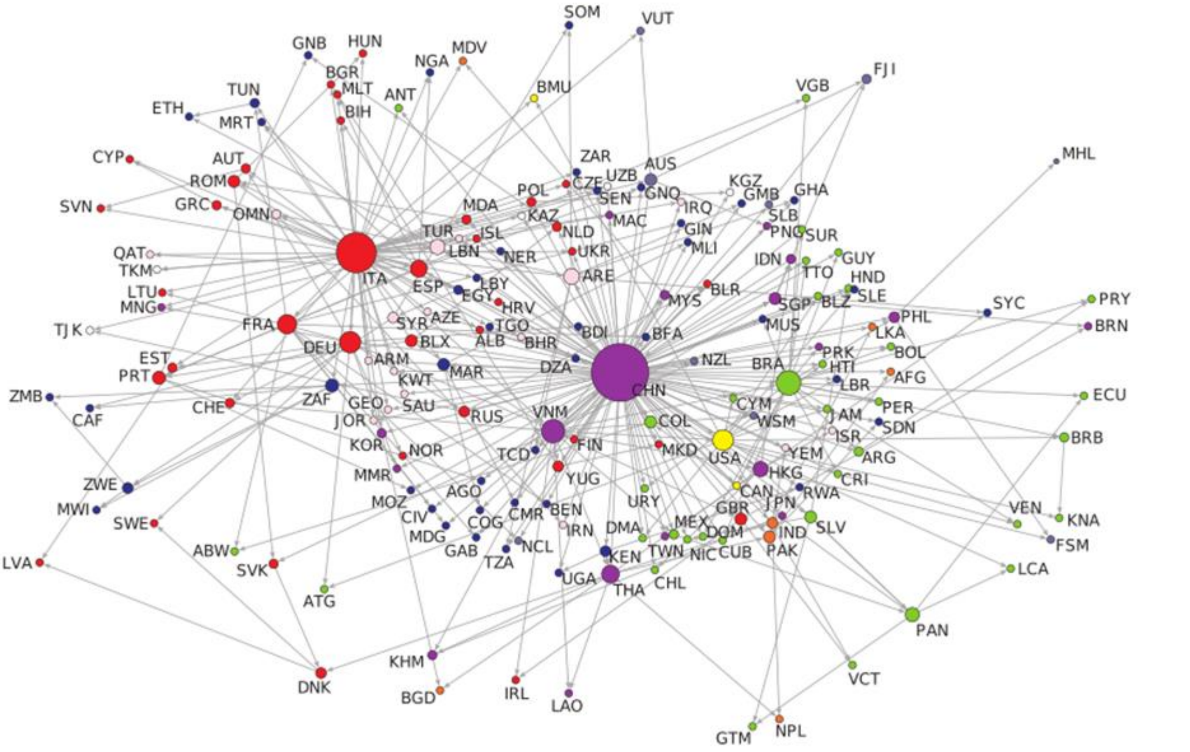

Figure 6.16 Results of Network Analysis of Shoe Manufacturers and Exporters
Source: Cerina et al. (2014)

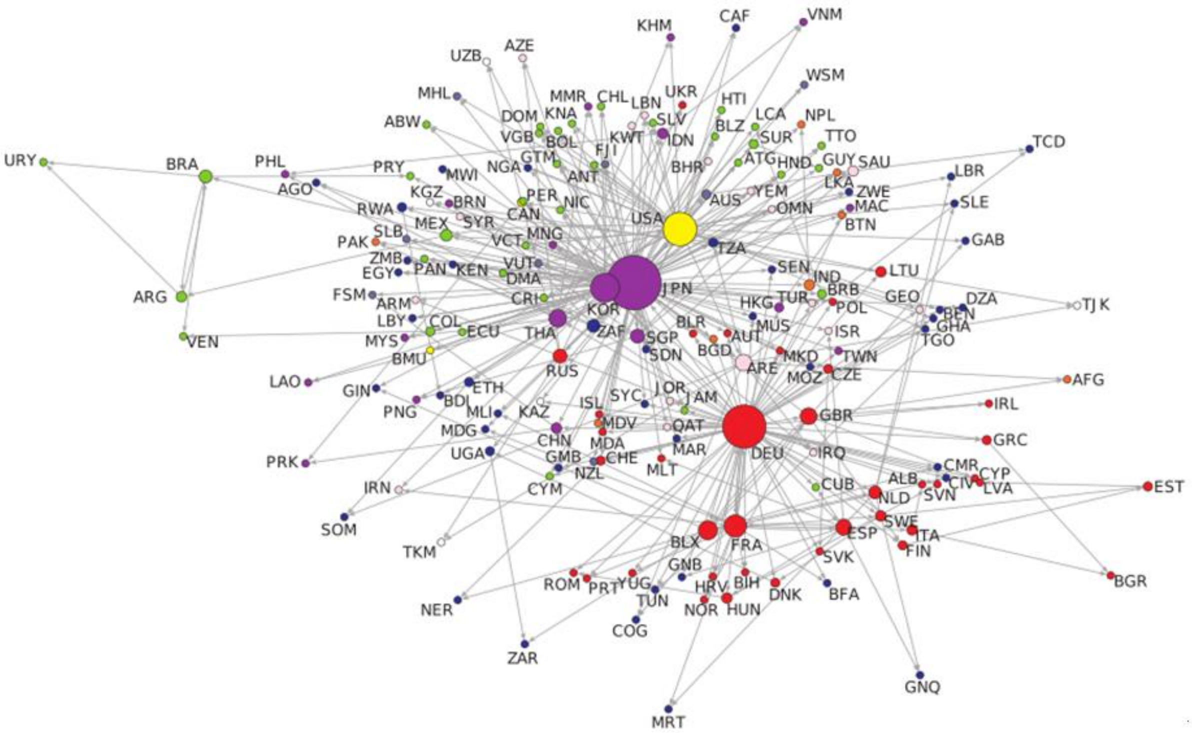

Figure 6.17 Results of Network Analysis of Automotive Manufacturers and Exporters
Source: Cerina et al. (2014)

Figures 6.15 - 6.17 illustrate the application of analyzing data specific to production sectors such as bananas, shoes, and engines. The diagrams clearly indicate that there are a limited number of primary producers for each product in each country. Furthermore, there are interconnections in the form of a production network between countries, with some countries acting as central hubs within the network.

Additionally, apart from analyzing these data with diagrams, it is possible to apply calculations of indices that depict network characteristics using the same dataset. The results of calculating the density index with the input-output table for production and outcomes are shown in Figure 6.18. It reveals a continuous increase in the index, except during the global economic crisis in 2009. Nevertheless, the index showed signs of recovery in 2010. Consequently, it is apparent that economic linkages between countries through the expansion of the Global Value Chain continue to grow steadily, with the impact of the 2009 economic crisis. However, it also demonstrates resilience and recovery following the economic crisis.

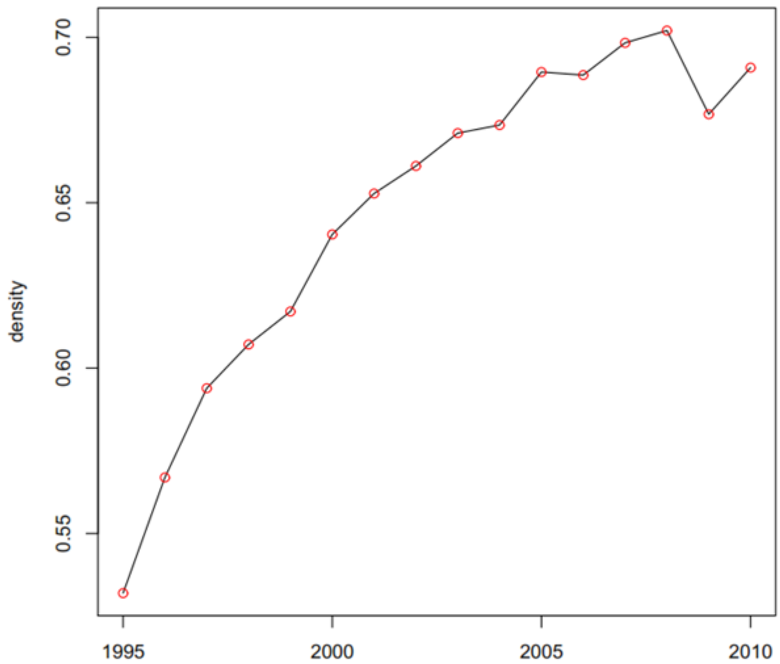

Figure 6.18 The Network Density index calculated from the Global Input-Output Table
Source: Cerina et al. (2014)

Figure 6.19 Centrality Indices calculated from the Global Input-Output

id	i	iso3	country	(1) Out-degree	(2) In-degree	(3) Out-degree percent	(4) In-degree percent	(5) Out-closeness	(6) In-closeness	(7) Out-eigenvector	(8) In-eigenvector
1	533	ABW	Aruba	.35593	.37288	.28634	.29997	.60825	.61458	.0396	.04252
2	4	AFG	Afghanistan	.49718	.48588	.39996	.39087	.66541	.66045	.05651	.05558
3	24	AGO	Angola	.42373	.55367	.34088	.44541	.63441	.69141	.04887	.06264
4	8	ALB	Albania	.62712	.71186	.5045	.57268	.7284	.77632	.06842	.07549
5	530	ANT	Netherlands Antilles	.53107	.46328	.42723	.37269	.68077	.65074	.05777	.05198
6	784	ARE	United Arab Emirates	.9322	.89831	.74993	.72266	.93651	.90769	.09198	.09089
7	32	ARG	Argentina	.93785	.76271	.75448	.61358	.94149	.80822	.09273	.07971
8	51	ARM	Armenia	.57627	.73446	.46359	.59086	.70238	.79018	.06265	.07706
9	28	ATG	Antigua and Barbuda	.51977	.64972	.41814	.52268	.67557	.74059	.05571	.06862
10	36	AUS	Australia	.9887	.9661	.79538	.7772	.98883	.96721	.09499	.09479
...			...	...							...
169	92	VGB	Virgin Islands	.49153	.44633	.39542	.35906	.66292	.64364	.05309	.04982
170	704	VNM	Viet nam	.9209	.77966	.74084	.62722	.9267	.81944	.09161	.08121
171	548	VUT	Vanuatu	.31638	.36158	.25452	.29088	.59396	.61034	.03615	.04019
172	882	WSM	Samoa	.24859	.32203	.19998	.25907	.57097	.59596	.02909	.03725
173	887	YEM	Yemen	.59887	.66102	.48177	.53177	.71371	.74684	.06487	.07087
174	891	YUG	Serbia and Montenegro	.83616	.88701	.67267	.71357	.85922	.89848	.08553	.08965
175	711	ZAF	South Africa	.9887	.98305	.79538	.79084	.98883	.98333	.09528	.096
176	180	ZAR	Congo Dem. Rep.	.40678	.41243	.32724	.33179	.62766	.62989	.04611	.04724
177	894	ZMB	Zambia	.55932	.66667	.44996	.53631	.69412	.75	.06171	.07135
178	716	ZWE	Zimbabwe	.77966	.59887	.62722	.48177	.81944	.71371	.07986	.06467

Source: Cerina et al. (2014)

The analysis can also be applied to calculate centrality indices, which can demonstrate the overall importance to the economy. Figure 6.19 illustrates the results of such calculations, sorted by country name.

In the case of using production and outcome factor tables for an individual country, as shown in Figures 6.20 and 6.21, Network analysis is applied to analyze the relationships between production sectors within the United States' economy. It is clear that in 1947, the structure of the U.S. economy consisted of trade and retail, agriculture, and the federal government sectors, with real estate playing a significant role in production and interconnections between production sectors. However, the economic structure has undergone significant changes, as in 2015, the real estate sector became a major component of the economy, with the technology and information technology service sector as the second largest. Additionally, local government became a significant part of the economic system. These changes have reduced the importance of traditional economic sectors such as agriculture and trade.

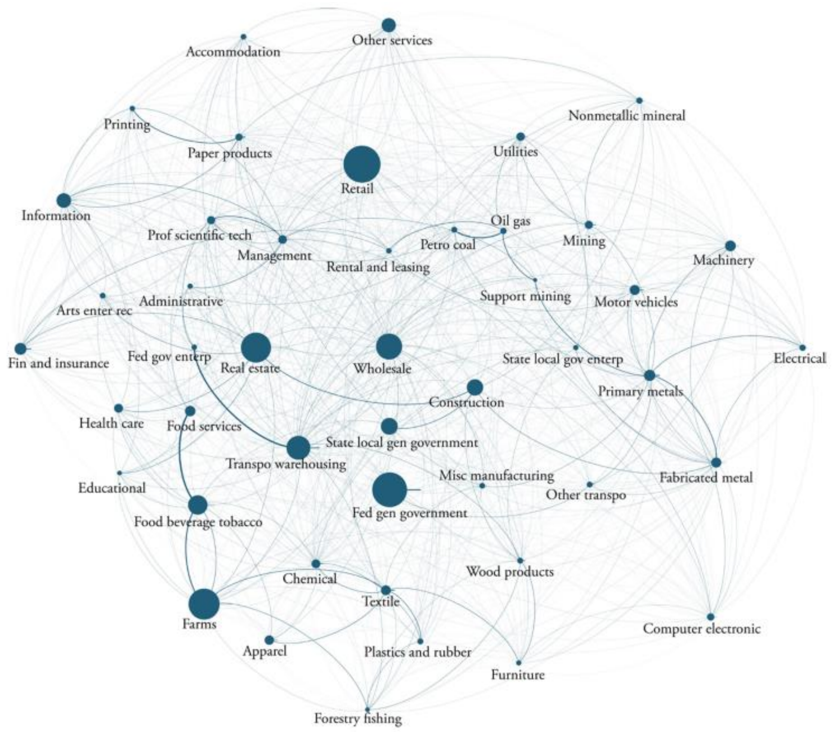

Figure 6.20 Results of the Network analysis applied to the production and outcome factor table of the United States in 1947
Source: Foerster and Choi (2017)

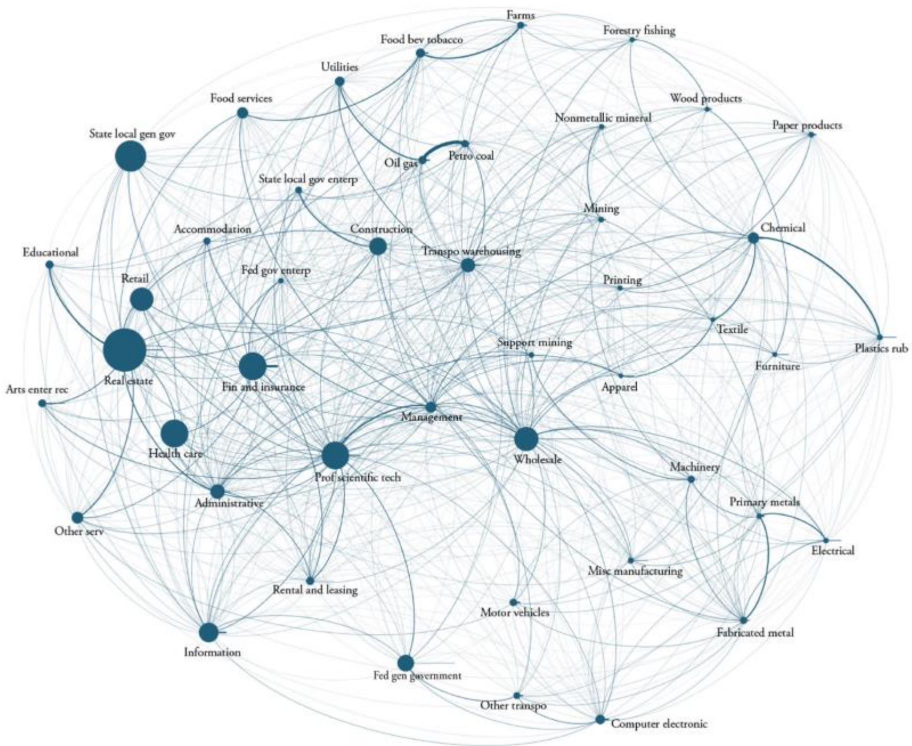

Figure 6.21 Results of the Network analysis applied to the production and outcome factor table of the United States in 2015
Source: Foerster and Choi (2017)

Analyzing the overall characteristics of the United States' economic structure using data from the production and outcome factor table in conjunction with the density index is depicted in Figure 6.22. The results, obtained by using data from the years 1947 to 2015, reveal that the network density of the economic structure remained relatively stable. However, there is a slight decreasing trend after 2000. Continuous monitoring is essential to study the trends and factors influencing this change.

The analysis in the centrality index format, as shown in Figures 6.23 and 6.24, aligns with the results presented as diagrams in Figures 6.20 and 6.21. Sectors such as real estate, finance, information technology services, and government management have continuously increased in centrality index, highlighting the transformation of the U.S. economy towards a more service-oriented economy. The real estate and financial sectors play significant roles in the economy, which could potentially pose vulnerabilities and lead to economic crises in the future.

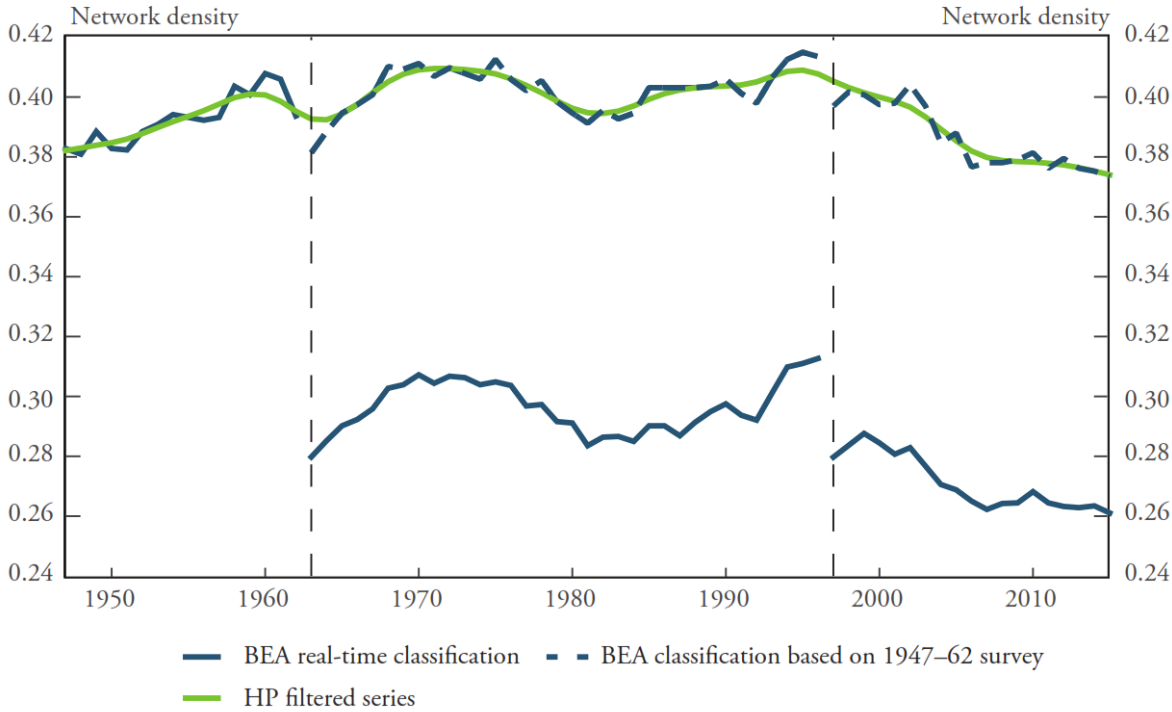

Figure 6.22 Density Index of the United States Economy (Production and Outcome Factors Table)
Source: Foerster and Choi (2017)

Top 5 central industries in 1947	Top 5 central industries in 2015
Transportation and warehousing	Professional, scientific, and technical services
Primary metals	Finance and insurance
Wholesale trade	Administrative and waste management services
Food and beverage and tobacco products	Wholesale trade
Farms	Transportation and warehousing
Bottom 5 central industries in 1947	**Bottom 5 central industries in 2015**
State and local government enterprises	Educational services
Furniture and related products	Furniture and related products
State and local general government	Apparel and leather and allied products
Health care and social assistance	Support activities for mining
Educational services	Health care and social assistance
Top 5 rank improvements from 1947–2015	**Top 5 rank decline from 1947–2015**
Administrative and waste management services	Textile mills and textile product mills
Computer and electronic products	Farms
Rental and leasing services and lessors of intangible assets	Paper products
Plastics and rubber products	Food and beverage and tobacco products
Professional, scientific, and technical services	Miscellaneous manufacturing

Figure 6.23 Centrality Index Calculated from the United States' Production and Outcome Factors Table
Source: Foerster and Choi (2017)

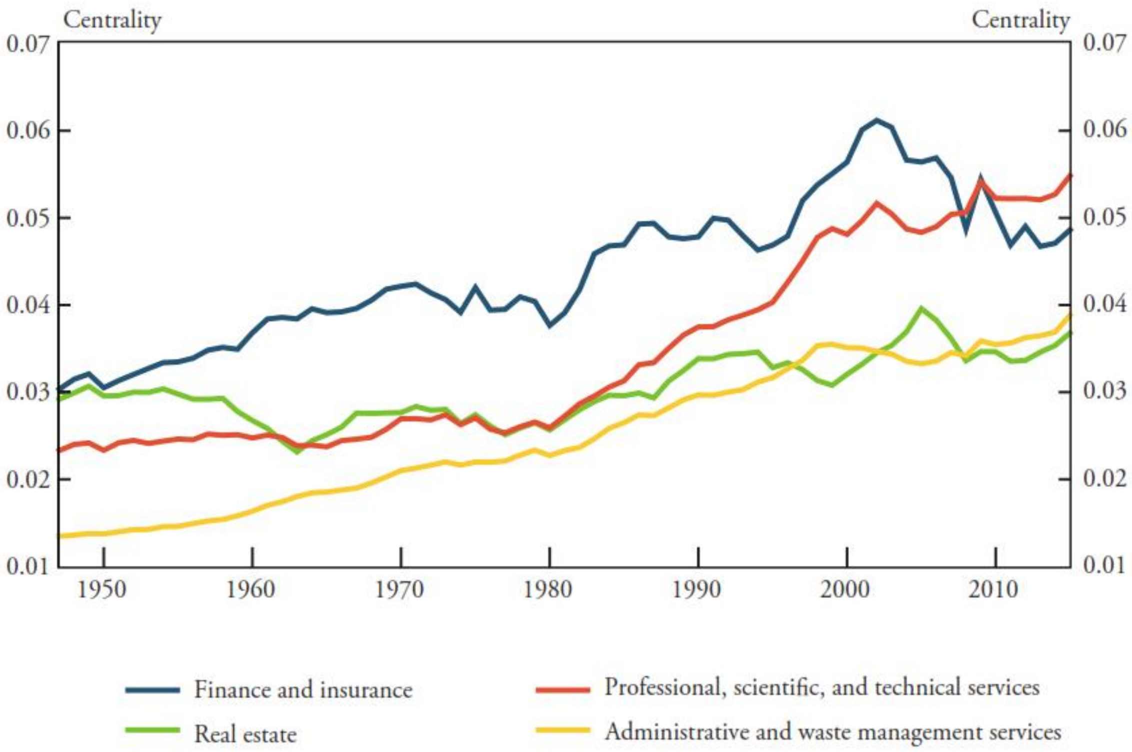

Figure 6.24 Centrality Index Calculated from the United States' Production and Outcome Factors Table
Source: Foerster and Choi (2017)

6.2 Economic Complexity Index: ECI

The relationship between different economic structures and their impact on economic development has been continuously studied, especially with the expansion of development economics research since 1950. However, it remains challenging to demonstrate the connections and impacts between the development of the macroeconomy and the subcomponents of the economic system, particularly the potential of productive branches and their implications for development. Hidalgo et al. (2007) and Hidalgo & Hausmann (2009) have developed a method for the analytical interpretation of economic development processes. They created an index to indicate the complexity level of the production structure of each country, known as the Economic Complexity Index (ECI). This index is computed using network theory, which calculates eigenvectors that represent the linkages of a particular branch of production with others, shown as a diffusion distance.

The concept was further analyzed by integrating it with the Revealed Comparative Advantage (RCA) method, which indicates the competitiveness of sub-sector specialization. The results show that this new index reflects the linkage level of production (linkages), with higher linkages indicating a more complex production system. The ECI has a strong correlation with GDP per capita and emphasizes the importance of technological development and the application of technology in product production for export. This is because exporting only natural resources or basic products (both of which have low ECI values) generates low value-added and keeps national income at a low level. In contrast, shifting from resource-based exports to more advanced and complex products generates higher value-added and leads to increased national income (Hausmann et al., 2007; McMillan & Rodrik, 2011).

While this method can show the relationship between the ECI and GDP per capita at a high level (or, in other words, it yields a high r-squared value when analyzed through regression), there have been criticisms regarding the study and creation of the ECI, which has focused on exports and international trade. The study lacks detailed insights into other dimensions within the economic system, particularly the characteristics of the economic structure and domestic markets within a country, as well as the ability to connect with the characteristics of Global Value Chains (GVC). This demonstrates the importance of trade liberalization and the capacity to create value through the importation, processing, and export of products within a country.

Despite these criticisms, this calculation method can still be effectively used for a comprehensive analysis of economic development processes within each country. It can demonstrate the ability to develop the economy and increase income by engaging in more complex and advanced production processes, which, in turn, generate higher value-added. Hidalgo & Hausmann (2009) and Felipe et al. (2012) have used the ECI to show that growth is higher in countries that diversify their product types and produce products with more production stages. This is a result of development that leads to continued diversification. Felipe et al. (2012) also found that economies and products with greater complexity have a positive relationship with the development and accumulation of technology in exporting countries, aligning with Schumpeterian theory. This is also consistent with the research of Archibugi & Coco (2005), which shows that diversifying the types of exported products and elevating the production process complexity has a positive correlation with per capita income levels.

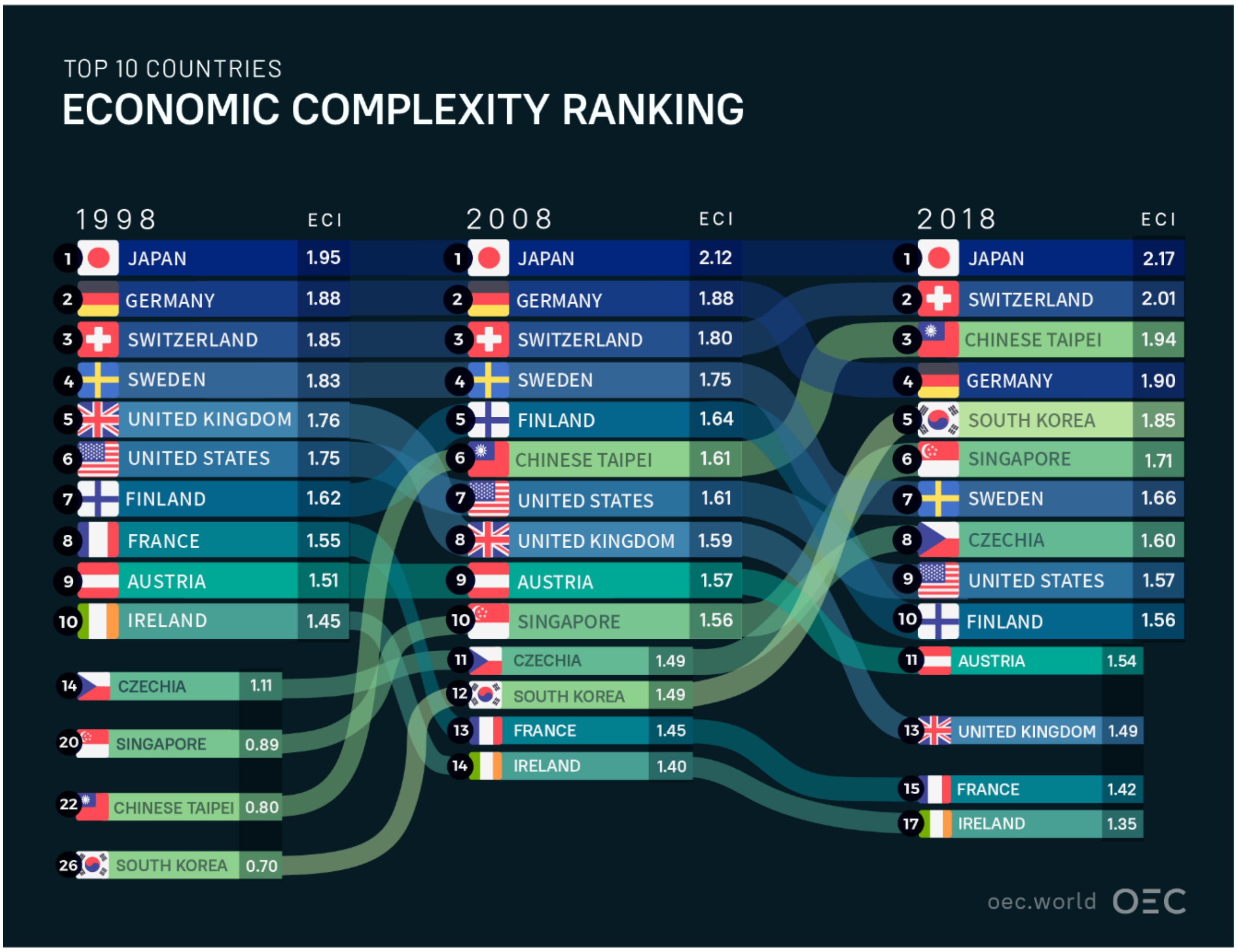

Figure 6.25: Group of countries with the highest ECI for exported products

Source: https://oec.world/

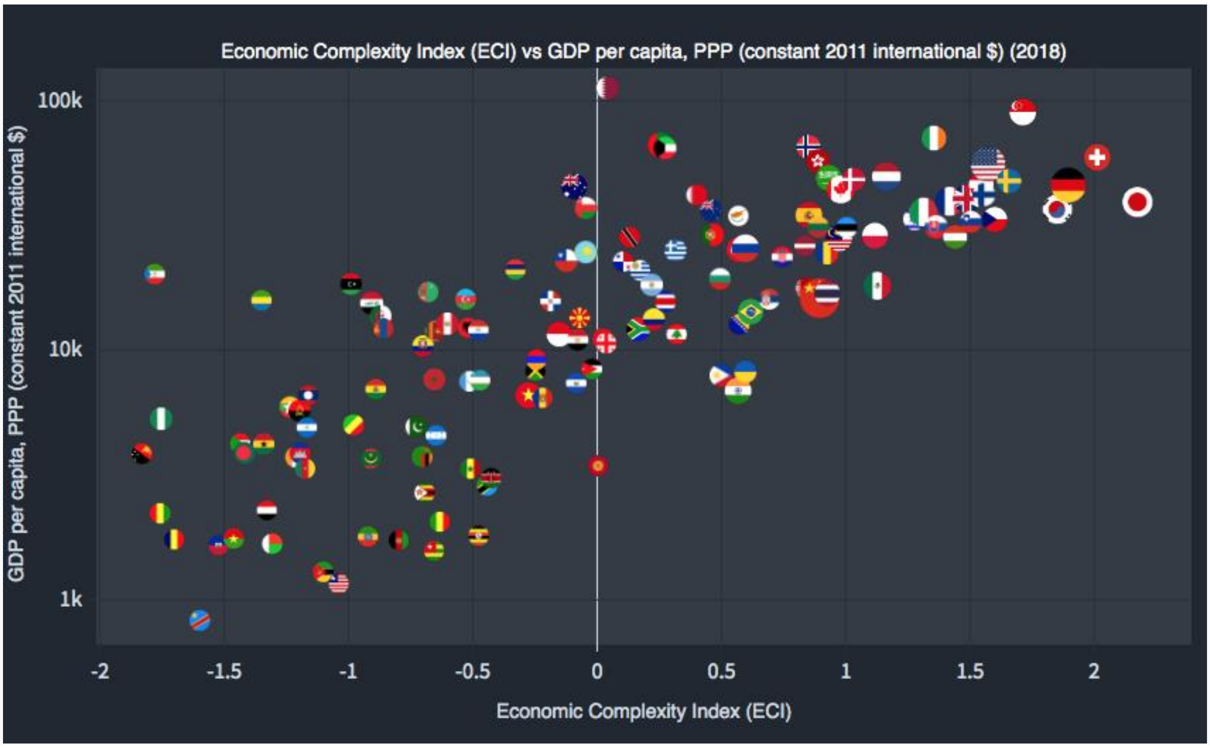

Figure 6.26: The relationship between average income per capita (Thousands of constant 2010 US dollars) and the ECI for exported products
Source: https://oec.world/

The ECI is utilized to analyze a country's level of development by demonstrating the relationship between production linkages (or economic complexity) and economic growth. Many research studies use the ECI in various forms, from case studies to multidimensional economic analysis. In the research of Felipe, McCombie, and Naqvi (2010), it was shown that Pakistan's inability to produce more complex products has led to trade balance issues, impacting its payment balance and subsequently affecting economic growth at a lower level. In contrast, China has experienced rapid growth due to maintaining production growth and transitioning towards more complex production processes, resulting in an increased ECI. This has made China a major producer and exporter of high-complexity products like machinery and electronics (Felipe et al., 2013).

The analysis example illustrates the differences in the development process between Brazil and South Korea, using the ECI as the primary dataset for analysis. During the period from 1960 to 1989, Brazil had a higher average income per capita compared to South Korea. However, after that period, South Korea surpassed Brazil in terms of income per capita, as depicted in Figure 6.26.

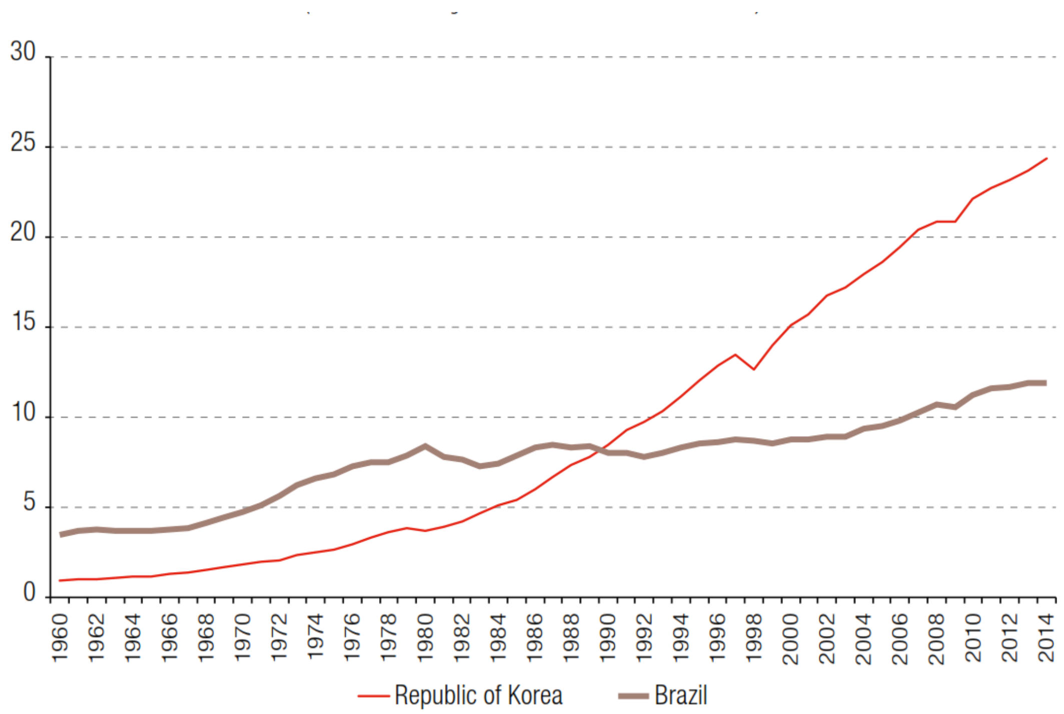

Figure 6.26: Average income per capita of Brazil and South Korea in the period 1960-2014 (Thousands of constant 2010 US dollars)
Source: World Bank, World Development Indicators

The analysis can be applied by utilizing network theory in conjunction with the types of exported products and can be visualized as a Product Space, revealing the interconnections among exported products. Figure 6.27 shows the characteristics of all globally traded products. Meanwhile, Figures 6.28 and 6.29 present maps depicting the linkage of exported products from Brazil and South Korea, respectively. It becomes evident that South Korea consistently developed and was able to produce products with medium and high technology content. The proportion of such products is significantly higher than the case of Brazil, as demonstrated in Figure 6.30, reflecting key fundamental differences in their levels of development after 1989.

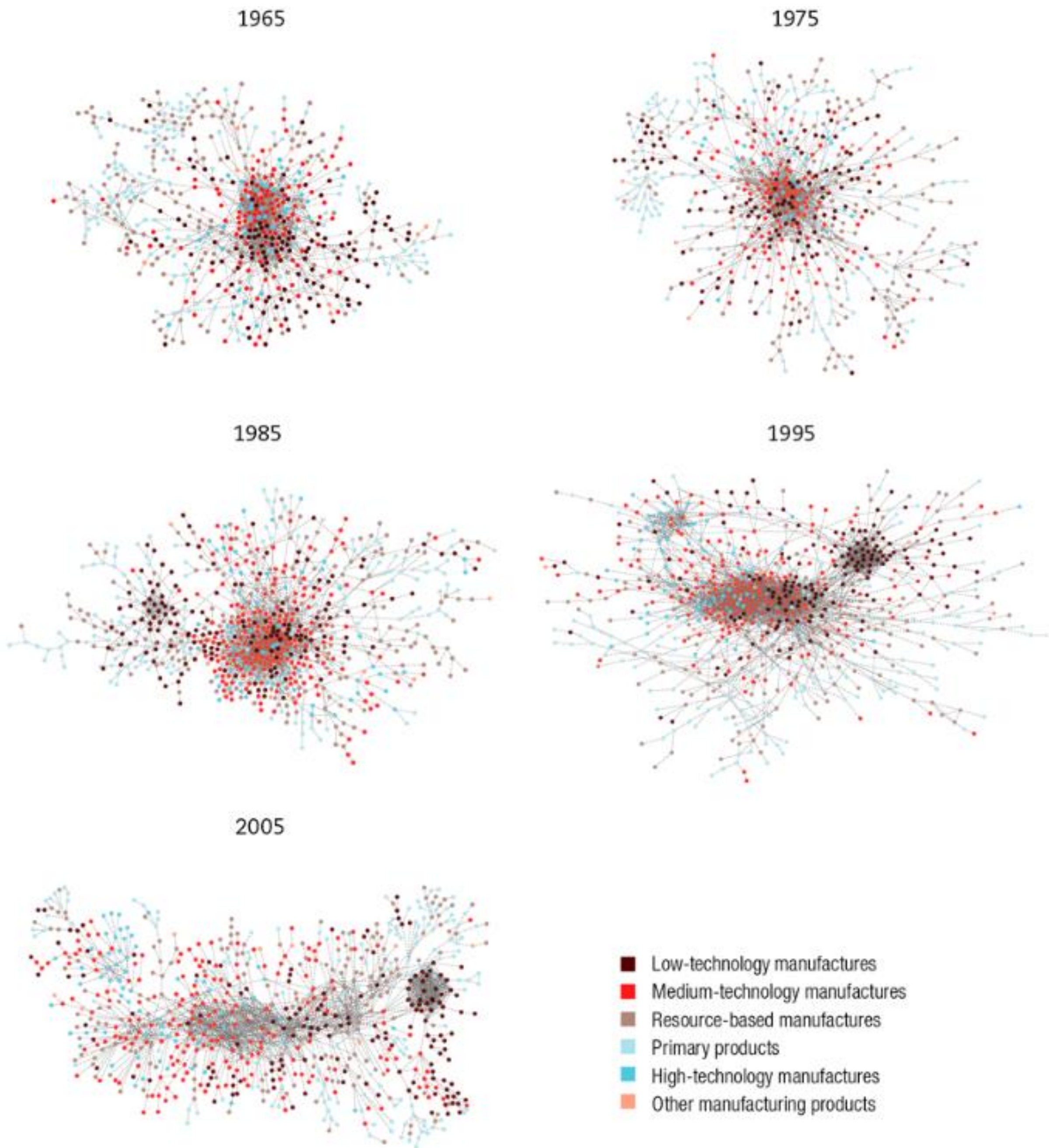

Figure 6.27: The linkage of globally traded products presented in the format of Product Space

Source: Britto et al. (2019)

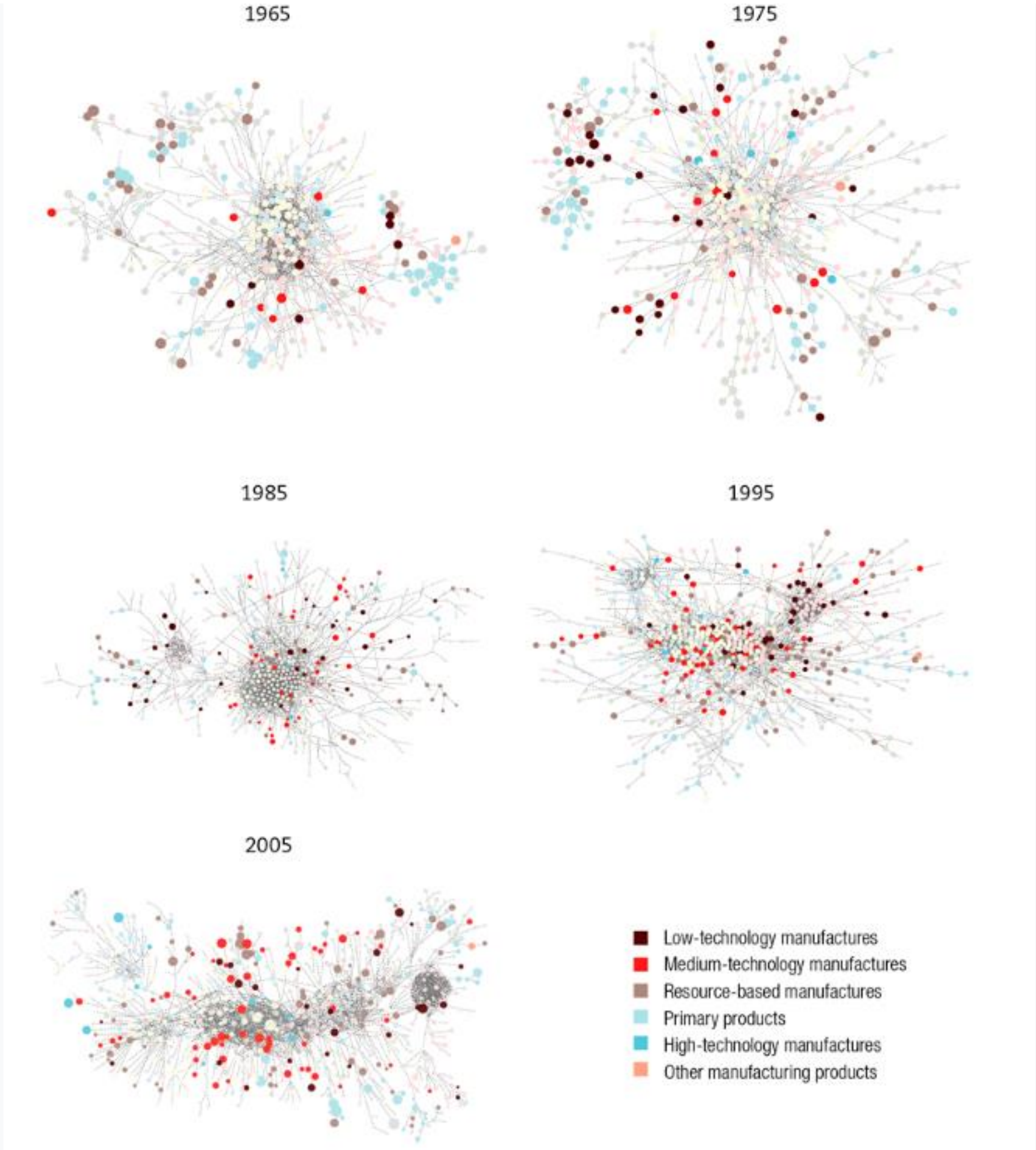

Figure 6.28: The linkage of exported products from Brazil presented in the format of Product Space
Source: Britto et al. (2019)

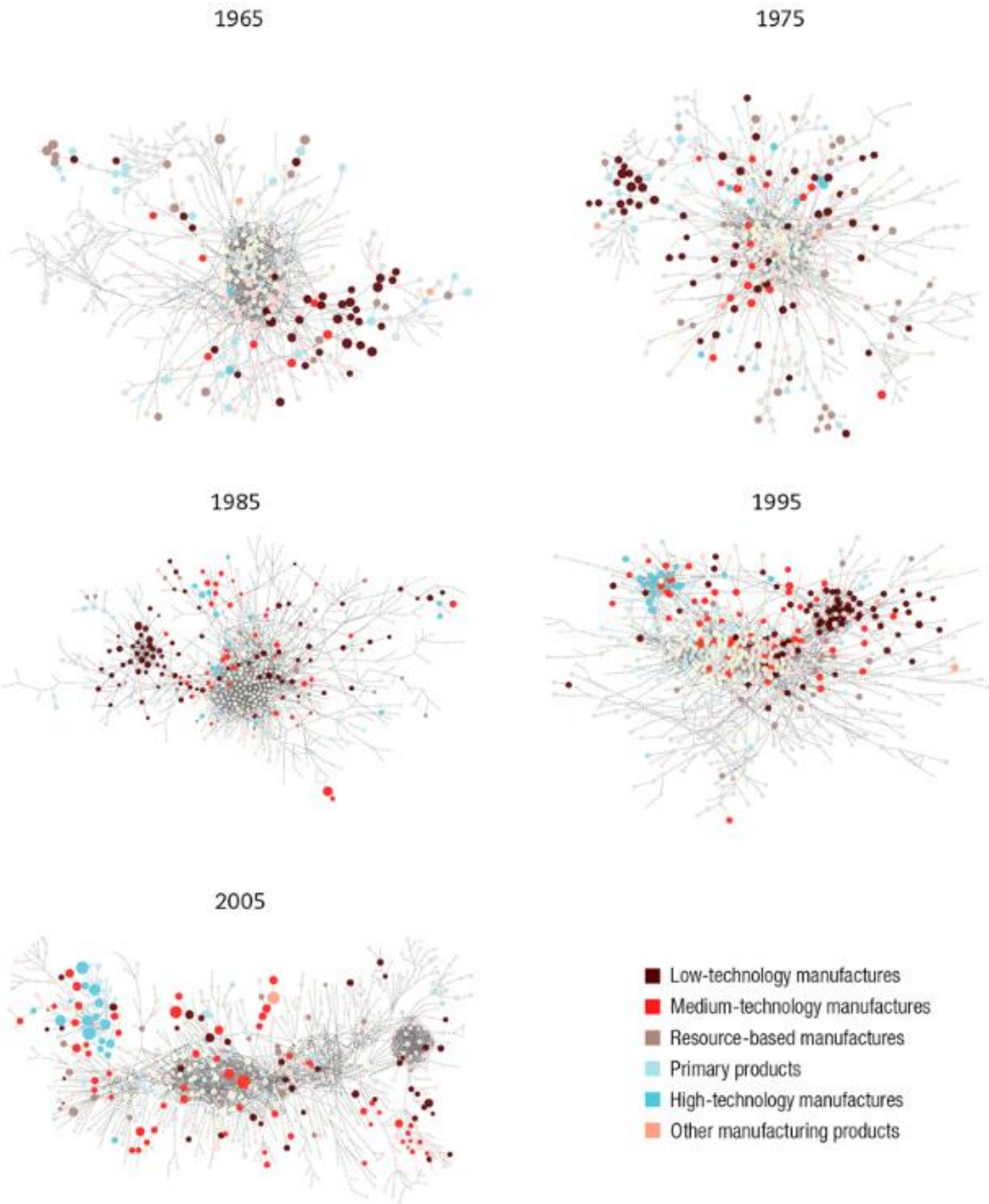

Figure 6.29: The linkage of exported products from South Korea presented in the format of Product Space
Source: Britto et al. (2019)

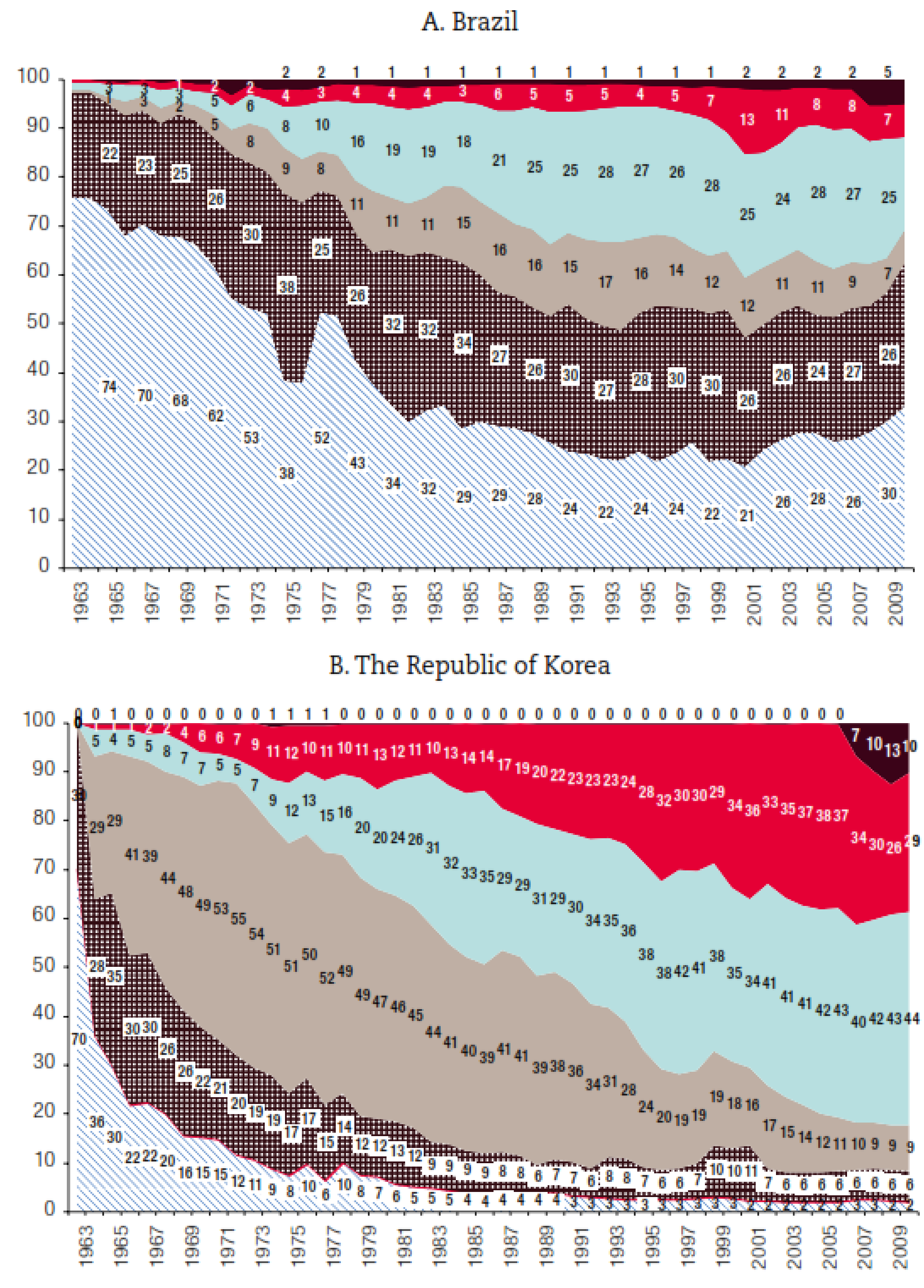

Figure 6.30: The intensity of using technology in producing exported products
Source: Britto et al. (2019)

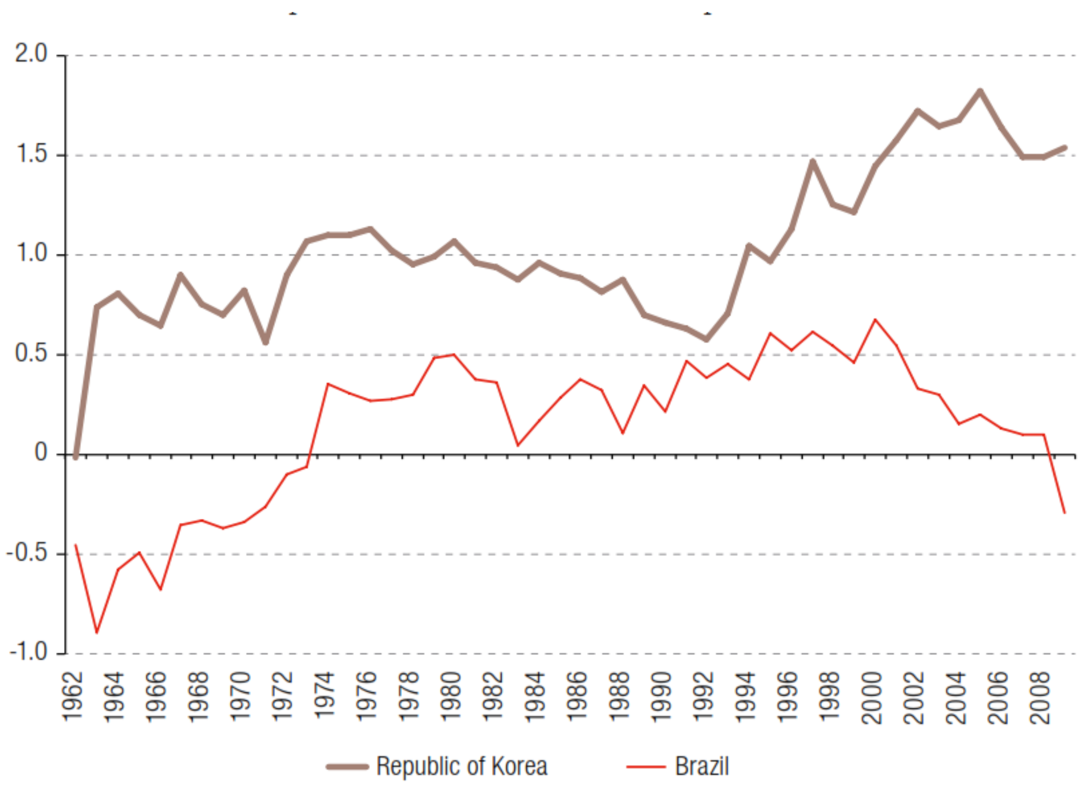

Figure 6.31: The values of ECI for Brazil and South Korea in the period 1962-2011

Source: Britto et al. (2019)

The analysis using the ECI index clearly demonstrates the ongoing economic development planning of South Korea, which transformed its industries continuously over more than 60 years. This planning allowed them to enhance their production capabilities and consistently export complex, highly sophisticated products. This transformation is evident through the ECI index, which reflects increasing linkage intensity, calculated and analyzed using network theory.

In contrast, Brazil did not plan its economic development systematically as South Korea did. Instead, Brazil focused on producing and exporting natural resources and basic processed products. This led to limited expansion in export capabilities, economic growth, and average income per capita.

Therefore, the analysis of industrial potential and competitiveness between countries can effectively utilize a combination of network theory and the ECI index to illustrate the clear differences in the nature of production and industrial structure in each country. Figure 6.32 presents a comparison of the ECI values for various countries worldwide, showing that Thailand is ranked 22nd globally.

Furthermore, Thailand's ranking has improved significantly during the period 2008-2018.

Rank	Country	Economic complexity index (2018)	Change in 5 years (2013-18)	Change in 10 years (2008-18)
1	Japan	2.43	–	–
2	Switzerland	2.17	▲ 1	▲ 1
3	South Korea	2.11	▲ 4	▲ 8
4	Germany	2.09	▼ 2	▼ 2
5	Singapore	1.85	–	▼ 1
6	Austria	1.81	▼ 2	▲ 1
7	Czech Republic	1.80	▼ 1	▲ 2
8	Sweden	1.70	–	▼ 3
9	Hungary	1.66	–	▲ 5
10	Slovenia	1.62	▲ 3	▲ 3
11	United States	1.55	▲ 1	▲ 1
12	Finland	1.55	▲ 2	▼ 1
13	United Kingdom	1.51	▼ 2	▼ 5
14	Italy	1.44	▼ 2	▲ 3
15	Slovakia	1.41	–	▲ 1
16	France	1.37	▼ 2	▼ 1
17	Ireland	1.36	–	▼ 7
18	China	1.34	–	▲ 6
19	Mexico	1.29	–	–
20	Israel	1.20	▲ 6	▲ 3
21	Belgium	1.18	▼ 1	▼ 1
22	Thailand	1.17	▲ 2	▲ 9
23	Poland	1.10	–	▼ 2
24	Denmark	1.09	▼ 3	▼ 6

Figure 6.32: Comparison of ECI values for various countries globally

Source: https://atlas.cid.harvard.edu/rankings

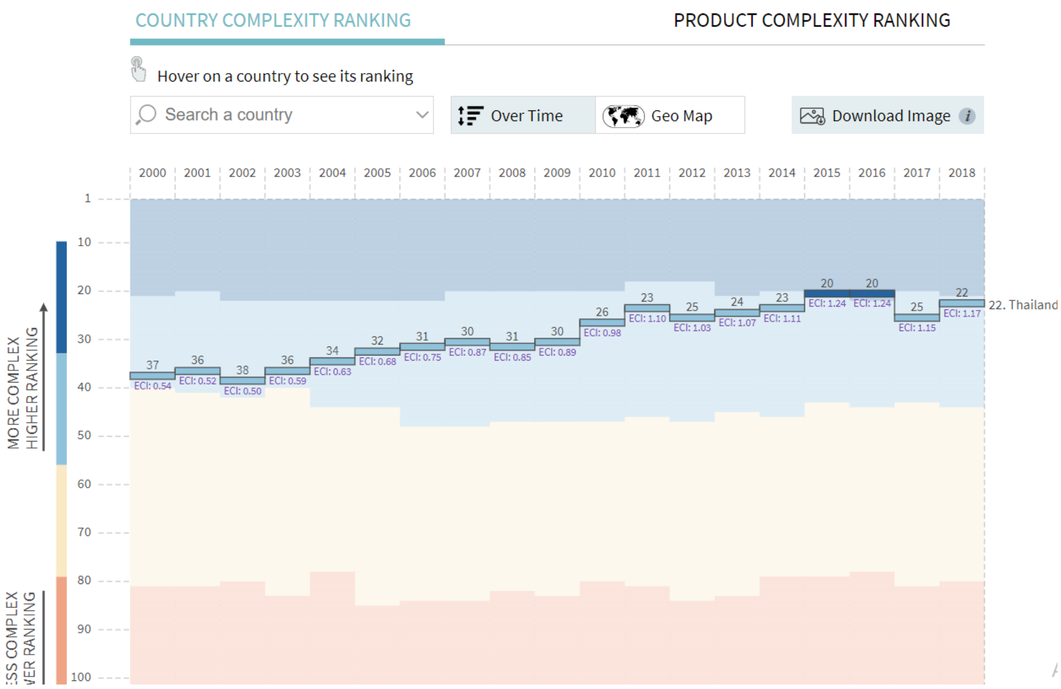

Figure 6.33: Thailand's ranking in the ECI Index

Source: https://atlas.cid.harvard.edu/rankings

Summary

From the content presented in this chapter, two main analytical methods have been discussed. The first method involves Network Analysis, which is a mathematical approach widely used in various scientific fields, including physics, chemistry, biology, medicine, and economics. This method, when applied to production and trade data, allows for the visualization of the interconnectedness between all industries in the form of a network. It provides a convenient way for both the general public and economic policymakers to comprehend the economic structure under production and trade data. Additionally, Network Analysis highlights the network structure in an economic system through various index calculations and can identify the importance and centrality of different industries in the economic system. This method supports the assessment of the relationship between different sectors within the economic system, along with the assessment of the importance of each sector.

The second method is the Economic Complexity Index (ECI), which utilizes the foundation of Network Analysis and applies it to international trade data. ECI facilitates the creation of a product space, showcasing the relationships between products and revealing the diversification patterns in different countries. By calculating various indexes and economic values, the ECI helps demonstrate the complexity and sophistication of a country's export capabilities. It is statistically highly correlated with GDP per capita, reflecting a country's international competitiveness. When a country possesses technological capabilities, it can produce technologically advanced and complex products, resulting in a high average ECI for its exports. This leads to increased value addition in the export of products and a high GDP.

Both Network Analysis and the Economic Complexity Index provide valuable additional insights to analyze the economic structure and industrial capabilities of different countries. Furthermore, the use of multipliers, such as the Backward and Forward Multipliers, can extend the analysis. Combining these methods, policymakers can comprehensively assess the impact and select target industries in economic policy planning.

In conclusion, besides the utilization of multiplier effects and the assessment of the impact and target industries, Network Analysis and the Economic Complexity Index offer supplementary methods that provide a broader perspective on the economic structure and help policymakers develop comprehensive policies.

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