Key Economic Sectors and Their Transitions: Analysis of World Input-Output Network

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Abstract In the modern society, all major economic sectors have been connected tightly in an extremely complicated global network. In this type of network, a small shock occurred at certain point can be spread instantly through the whole network and may cause catastrophe. Production systems, traditionally analyzed as almost independent national systems, are increasingly connected on a global scale. The world input-output database, only recently becoming available, is one of the first efforts to construct the global and multi-regional input-output tables. The usual way of identifying key sectors in an economy in Input-output analysis is using Leontief inverse matrix to measure the backward linkages and the forward linkages of each sector. In other words, evaluating the role of sectors is performed by means of their centrality assessment. Network analysis of the input-output tables can give valuable insights into identifying the key industries in a world-wide economy. The world input-output tables are viewed as complex networks where the nodes are the individual industries in different economies and the edges are the monetary goods flows between industries. We characterize a certain aspect of centrality or status that is captured by the network measure. We use an α-centrality modified method to the weighted directed network. It is used to identify both how a sector could be affected by other sectors and how it could infect the others in the whole economy. The data used is the world input-output table, part of the world input-output database (WIOD) funded by European Commission from 1995 to 2011. We capture the transition of key industries over years through the network measures. We argue that the network structure captured from the input-output tables is a key in determining whether and how microeconomic expansion or shocks propagate throughout the whole economy and shape aggregate outcomes. Understanding the network structure of world input-output data can better inform on how the world economy grows as well as how to prepare for and recover from adverse shocks that disrupt the global production chains. Having analyzed these

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results, the trend of these sectors in that range of time will be used to reveal how the world economy changed in the last decade.

Keywords Production network · α Centrality · Amplification Index · Vulnerability Index · Key industrial sector · World input output network

1 Introduction

In the modern society, all major economic sectors have been connected tightly in an extremely complicated global network. In this type of network, a small shock occurred at certain point can be spread instantly through the whole network and may cause catastrophe. The usual way of identifying key sectors in an economy in Input-output analysis is using Leontief inverse matrix to measure the backward linkages and the forward linkages of each sector. The input-output table initially formalized by Leontief [12] has been used extensively by economists, environmentalists, and policy makers. By keeping track of the inter-industrial relationships, the input-output table offers a reasonably accurate measurement of the response of any given economy in the face of external shocks or policy interventions.

The fundamental underlying relationship of input-output analysis proposed by Leontief is that the amount of a product (good or service) produced by a given sector in the economy is determined by the amount of that product that is purchased by all the users of the product. By its nature, input-output analysis encompasses all the formal market place activity that occurs in an economy, including the service sector which is frequently poorly represented. Consequently, input-output analysis frequently plays a fundamental role in the construction of the national accounts. In effect, an input-output model provides a snapshot of the complete economy and all of its industrial interconnections at one time. The power of the model is that it can show the distribution of overall impacts. A column of the total requirements table indicates which sectors in the region will be affected and by what magnitude. This can be used to make important policy decisions when translated into income and employment effects. Policy makers can use the information derived from the model to identify an industrial growth target and others.

Today input-output analysis has become important to all the highly-industrialized countries in economic planning and decision making because of this flow of goods and services that it traces through and between different industries. Input-output analysis is capable of simulating almost any conceivable economic impact. The nature of input-output analysis makes it possible to analyze the economy as an interconnected system of industries that directly and indirectly affect one another, tracing structural changes back through industrial interconnections. This is especially important as production processes become increasingly complex, requiring the interaction of many different businesses at the various stages of a product's processing. Input-output techniques trace these linkages from the raw material stage to the sale of the product as a final, finished good. This allows the decomposition analysis to account for the fact that a decline in domestic demand. In analyzing an economy's reaction to changes in the economic environment, the ability to capture the indirect effects of a change is a unique strength of input-output analysis. One of the interests in the field of input-output economics lies with the fact that it is very concrete in its use of empirical data.

Alternatively, Acemoglu et al. [1] and Carvalho [10] argue that the structure of the production network is a key in determining whether and how microeconomic shocks propagate throughout the economy and shape aggregate outcomes. Therefore, understanding the structure of the production network can better inform on the origins of aggregate fluctuations and policymakers on how to prepare for and recover from adverse shocks that disrupt these production chains. The usual way of identifying key sectors in an economy in Input-output analysis is using Leontief inverse matrix to measure the backward linkages and the forward linkages of each sector. Alternatively, they evaluate the role of sectors by means of network measures such as degree centrality and α-centrality.

All changes in the endogenous sectors are results of changes in the exogenous sectors. The input-output analysis also allows a decomposition of structural change which identifies the sources of change as well as the direction and magnitude of change. Most importantly, an input-output based analysis of structural change allows the introduction of a variable which describes changes in producer's recipes—that is, the way in which industries are linked to one another, in input-output language, called the "technology" of the economy. It enables changes in output to be linked with underlying changes in factors such as exports, imports, domestic final demand as well as technology. This permits a consistent estimation of the relative importance of these factors in generating output and employment growth. In a general sense, the input-output technique allows insight into how macroeconomic phenomena such as shifts in trade or changes in domestic demand correspond to microeconomic changes as industries respond to changing economic conditions.

Production systems, traditionally analyzed as almost independent national systems, are increasingly connected on a global scale. As the global economy becomes increasingly integrated, an isolated view based on the national input-output table is no longer sufficient to assess an individual economy's strength and weakness, not to mention finding solutions to global challenges such as climate change and financial crises. Hence, a global and multi-regional input-output data is needed to draw a high-resolution representation of the global economy. Only recently becoming available, the World Input-Output Database (WIOD) is one of the first efforts to construct the global multi-regional input-output (GMRIO) tables. By viewing the world input-output system as an interdependent network where the nodes are the individual industries in different economies and the edges are the monetary goods flows between industries. Cerina et al. [11] analyzed the network properties of the so-called world input-output network (WION) and investigate its evolution over time. At global level, we find that the industries are highly but asymmetrically connected, which implies that micro shocks can lead to macro fluctuations. We also propose the network-based measures and these can give valuable insights into identifying the key industries.

In the modern economy, industry sectors have specific roles in an extremely complicated linked network despite of their size or range of effect. Since the linkage structure in the economy is considered to be dominated by a small group of sectors (key sectors) that connect to other different sectors in different supply chains, even a small shock originated from any firm could be conducted through the network and cause the significant impacts to the whole economy. Hence, to identify the sectors that belong to the such kind of hub group in the economy, it is not only based on the sector's output production or how much resource is used, but also its influence to all other nodes throughout the whole economy network, as well as its own external impact. These sectors play very important role in the whole economy since knowing them will help the policymakers actively preparing for and recovering from the impact of them to the economy. Traditionally, some network measurements are used to identified the key sectors such as the high forward and backward linkages with the rest of the economy, and most of these methodologies consider only the direct input or output coefficient (weight) of the sectors as the basis to determine sector's importance. There are two examples that use these methods to identify the key sectors of the economy; one is Alatriste-Contreras [2] used forward and backward to identify the major sectors of EU economy; and the other is Botri [8] who identified the key sectors of the Croatian economy.

In regard to key sectors, the first thought is that they are very important to the whole economy. However, some sectors or firms will mostly influence to the other sectors, and in the same way some of them might be the mostly affected from the other sectors. The economy is the very complicated linkages of different supply chains, which involve companies, people, activities, information producing, handling and/or distributing a specific product to the end users (customers). These supply chains are being connected together by means of some very specific industries. That is, if there is any economy shock originated from these key sectors, it will propagate throughout the economy and influences to the production of all other firms [10]. These key industries are also known as the hub sectors that shorten the distance between unrelated sectors in the economy. They provide the bridges for the separated parts which do not have direct trade inputs entire the economy. Therefore, the aggregate performance of the network also could be contributed by these kind of sectors as the shock from anywhere in the network may be conducted via them.

This paper aims to provide the different methods to identify the key economic sectors that most contribute to the economy based on the sector's influence scores to other nodes. These influence scores are calculated regarding the supply and consume from the input-output network. These scores do not depend much on the economic sector's direct transactions, but its relationship with the others throughout the whole network and its own external influence. In general, if there is any shock originating from one of these key economy sectors, it will be propagated through the entire the economy network via its links to the others whether its transaction is high or not. The introduced methods are developed based on the measurement of α-centrality. Two types of measurement are proposed: Amplification Index (AI) and Vulnerability Index (VI). The AI score is a measurement of influence to others, that is, how each economic sector influences the other economic sectors. The VI score measures influences from the other economic sectors, that is, it measures the impact that a sector receives from all other sectors. These scores also vary according to the value of a specific parameter that is the capital coefficient. A dataset of the world input-output network, which conducted by a project of European Commission, were used to demonstrate these methods. This dataset is the collection of intermediate matrixes that contains relationships between the industries in each economy and between the economies in the world in 17 years. For each year data, AI and VI are calculated, and then from those scores, a list of key economic sectors of the world economy is identified and their transitions over years are also traced. These results are compared with the results from other well-known measurement such as eigenvector centrality.

2 A Model of Input-Output Network

Consider an economy where production takes place at N distinct nodes, each specializing in a different good. These goods can be used as an intermediate input to be deployed in the production of other goods. A natural interpretation for these production nodes is to equate them with the different sectors of an economy. They assume that the production process at each of these sectors is well approximated by a Cobb-Douglas technology with constant returns to scale, combining a primary factor—which in this case is labor—and inter-mediate inputs. The output of sector i is then given by: Let's begin with the networks of input flows. In an economy, an industry's production Y is computed based on the investment in capital K and labor L. The Cobb-Douglas production is defined as

$$\mathbf{Y} = \mathbf{F}(\mathbf{L}, \mathbf{K}) = \mathbf{A}\mathbf{K}^{\alpha}\mathbf{L}^{\beta} \tag{1}$$

Where:

Y: total production (the real value of all goods produced in a year)
L: labor input (the total number of person-hours worked in a year)
K: capital input (the real value of all machinery, equipment, and buildings)
A: total factor productivity

α and β are the output elasticity of capital (K) and labor (L), respectively. These values are constants determined by available technology.

The basic input-output analysis assumes constant returns to scale, the change of output subsequent to a proportional change in all inputs. The input-output model assumes that the same relative mix of inputs will be used by an industry to create output regardless of quantity. Therefore in this case, $\alpha + \beta = 1$. The different values of α and A are selected depends on the specific economy and its current status. For example, in 2014, in the top positions of businesses listed in Tokyo Stock Exchange, this formula above was used in regard to about 1000 manufacturing industries, α is estimated as 0.121 and A = 0.081 [3].

Acemoglu et al. [1] and Carvalho [10] develop a unified framework for the study of how network interactions can function as a mechanism for propagation and amplification of microeconomic shocks. The framework nests various classes of games over networks, models of macroeconomic risk originating from microeconomic shocks, and models of financial interactions. Under the assumption that shocks are small, they provide a fairly complete characterization of the structure of equilibrium, clarifying the role of network interactions in translating microeconomic shocks into macro-economic outcomes. Using Cobb-Douglas production function in Eq. 1, Acemoglu et al. [1] obtained the output of an economic sector i as:

$$x_i = (z_i l_i)^{1-\alpha} \left(\prod_{j=1}^{N} x_{ji}^{\omega_{ji}} \right)^{\alpha} \tag{2}$$

The first term in Eq. 2 shows the contribution from primary factors to production. The amount of labor hired by sector i is given by l_i, z_i is a sector specific productivity disturbance, and $1 - \alpha$ is the share of labor in production and α is the share of capital.

These interconnections between production nodes come into play with the second term of the production function, which reflects the contribution of intermediate inputs from other sectors. Thus, the term x_{ij} denotes the amount of good j used in the production of good i. The exponent ω_{ij} (≥ 0) in the production function gives the share of good j in the total intermediate input used by sector i. For a given sector i, the associated list of ω_{ij}'s thus encodes a sort of production recipe. Each nonzero element of this list singles out a good that needs to be sourced in order to produce good i. Whenever a ω_{ij} is zero, we are simply stating that sector i cannot usefully incorporate j as input in production, no matter what input prices sector i is currently facing. Note further that all production technologies are, deliberately, being kept largely symmetric: all goods are equally valued by final consumers and all production technologies are equally labor-intensive (specifically, they all share the same α). The only difference across sectors then lies in the bundle of intermediate inputs specified by their production recipe—that is, which goods are necessary as inputs in the production process of other goods.

When we stack together all production recipes in the economy, we obtain a collection of N lists, or rows, each row giving the particular list of ω_{ij}'s associated with the production technology in sector i. This list-of-lists is nothing other than an input-output matrix, W, summarizing the structure of intermediate input relations in this economy. The production network, W, which is the central object of this paper, is then defined by three elements: (i) a collection of N vertices or nodes, each vertex corresponding to one of the sectors in the economy; (ii) a collection of directed edges, where an edge between any two vertices denotes an input-supplying relationship between two sectors; and (iii) a collection of weights, each of which is associated with a particular directed edge and given by the exponent ω_{ij} in the production function.

In this paper; we focus on this matrix to find out the list of what it is called the hub-like unit or key economic sector.

3 Centrality Measures

One of the key concepts in network analysis is the notion of node centrality, which defines as the importance of a node due to its structural position in the network as a whole. Several centrality measures have been defined. Identifying the central input-supplying technologies and ranking their roles in an economy requires applying an appropriate measure of "node centrality" to the production network. While network analysis has developed a variety of centrality measures, here we will focus on so-called "influence measures" of centrality, where nodes are considered to be relatively more central in the network if their neighbors are themselves well-connected nodes.

The best known of these recursively defined centrality measures is called "eigenvector centrality." One of the best-known types of centrality is eigenvector centrality [4]. The eigenvector captures a certain aspect of centrality or status that is not captured by other measures. The idea here is that a node that is connected to nodes that are themselves well connected should be considered more central than a node that is connected to an equal number of less connected nodes. For instance, consider two firms, each with ten customers. Suppose industry A's directly connected industries have many direct connection industries of their own, and those industries have many direct connection industries and so on. Economic sector A's actions potentially affect a great number of other industries downstream. In contrast, if industry B's directly connected industries do not have many direct connection industries of their own, B's actions could have much less effect on the economic system as a whole. Thus, the eigenvector concept takes into account both direct and indirect influences. Variants of eigenvector have been deployed in the sociology literature, notably Eigenvector centrality [4] and Katz Centrality [9], in computer science with Google's PageRank algorithm [5]. Thus, as in the example above, an industry's centrality need not be dictated by its out-degree (or in-degree) alone, but will also be determined by its direct connections' out-degree.

Bonacich et al. [6] introduced α-centrality to address a problem of evaluating key nodes using eigenvalue centrality with an asymmetric network. Unlike eigenvector centrality, α centrality is also appropriated for certain classes of directed networks. In this measure, each node is considered having its own exogenous source that does not depend on other individual in the network. α-centrality expresses the centrality of a node as the number of paths linking it to other nodes, exponentially attenuated by their length. It is defined as Eq. (3) and matrix notation is given in Eq. (4).

$$x_i = \alpha A^T x_i + e \tag{3}$$

$$x = (I - \alpha A^T)^{-1} e \tag{4}$$

if node I does not have a tie to node j, node I still influence node j via other intermediate nodes between them. Therefore, we can also rewrite this centrality as an accumulation of its centrality along with time:

$$x = \left(\sum_{i=0}^{\infty} \alpha^i A^{Ti}\right) e = (1 + \alpha A^T + (\alpha A^T)^2 + ... + (\alpha A^T)^t + ...)e \tag{5}$$

In these equations, x_i is node's α centrality or influence of node i. e is a vector of exogenous source of information, A^T is the transpose matrix. For example, $(\alpha A^T)^t$ considers the direct influence vertices expanded through t steps. The parameter α has 2 different roles in this centrality measurement. First, it is an attenuation parameter or a probability to influence others throughout the network. α-centrality measures the relative influence of not only a node within its network but also a node through intermediate paths of network. It also represents a trade-off between the exogenous source and endogenous or the possibility that each node's status may also depend on information that comes from outside the network or that may regard solely the member. Low value of α makes α-centrality probes only the local structure of the network and a range of nodes contributes to the centrality score of a given node is increased with the increase of α. The rank obtained using α-centrality can be considered as the steady state distribution of information spread process on a network, with probability α to transmit a message or influence along a link.

Based on the structure of the input-output network that we are considering (weighted and directed network), when applying α-centrality measurement, we can divide it into 2 different cases, Amplification Index (AI) and Vulnerability Index (VI). The idea of AI is to calculate the infection of a sector (or industry), or how the sector infects other nodes in the network. In the economy, the impact of an industry can be measured by a transaction between it and other industries. We measure the total influence (both directly and indirectly) that a sector gives to all other sectors.

$$x_i = \alpha \sum_j \omega_{ij} x_j + e_i \tag{6}$$

w_{ij} represents the flow from the sector i to sector j, e_i is the exogenous factor of sector i. In the framework of the Cobb-Douglas production in Eq. (1) or (2), α is the output elasticity of the capital or the share of capital. The vector of these measurements of all sectors defined as the Amplification Index (AI), which is obtained

$$AI = (I - \alpha W)^{-1} e \tag{7}$$

In some cases a sector may not have any direct connection to other sectors in the economy, it still indirectly impact them via other intermediate sectors. This could be done if we measure its influence in a period of time. Hence, the formula (7) could be rewritten as an accumulative one

$$AI = \left(\sum_{i=0}^{\infty} \alpha^i W^i\right) e = (I + \alpha W + (\alpha W)^2 + \cdots + (\alpha W)^t + \cdots) e \tag{8}$$

Another measurement is the total influence (both directly and indirectly) that a sector receives from all other sectors, which is obtained as

$$x_i = \alpha \sum_j \omega_{ji} x_j + e_i \tag{9}$$

The vector of these measurements of all sectors defined as the Vulnerability Index (VI), which is obtained as

$$VI = (I - \alpha W^T)^{-1} e \tag{10}$$

Similarly to the accumulative AI, we represent the formula (10) as

$$VI = \left(\sum_{i=0}^{\infty} \alpha^i W^{Ti}\right) e = (I + \alpha W^T + (\alpha W^T)^2 + \ldots + (\alpha W^T)^t + \ldots) e \tag{11}$$

In the next section, we will obtain AI and VI values using the input-output database of the world economy and identify some key industries in the world economy.

4 Applying to the World Economy Data

Ever since Leontief formalized its structure, the input-output table has been used extensively. By keeping track of the inter-industrial relationships, the input-output table offers a reasonably accurate measurement of the response of any given economy in the face of external shocks or policy interventions. However, as the global economy becomes increasingly integrated, an isolated view based on the national input-output table is no longer sufficient to assess an individual economy's strength and weakness, not to mention finding solutions to global challenges such as climate change and financial crises. Hence, a global multi-regional input-output (GMRIO) framework is needed to draw a high-resolution representation of the global economy.

Cerina et al. [11] constructed the WION based on the World Input-Output Database (WIOD). The empirical counterpart to a network of production technologies consisting of nodes that represent different sectors and directed flows these capture input transactions between sectors is given by input-output data. To investigate the network structure of sector-to-sector input flows, we use WIOD. At the time of writing, the WIOD input-output tables cover 35 industries for each of the 40 economies

(27 EU countries and 13 major economies in other regions) plus the rest of the world (RoW) and the years from 1995 to 2011. For each year, there is a harmonized global level input-output table recording the input-output relationships between any pair of industries in any pair of economies. The relationship can also be an industry to itself and within the same economy. The numbers in the WIOD are in current basic (producers') prices and are expressed in millions of US dollars.

We will take as nodes in the sector input-network. Each nonzero (i, j) entry is a directed edge of this network—that is, a flow of inputs from supplying sector j to customer i. For some of the empirical analysis below, we will be focusing only on properties of the extensive margin of input trade across sectors. To do this, we use only the binary information contained in this input-output data—that is, who sources inputs from whom—and disregard the weights associated with such input linkages.

Recognizing a network structure or the complexity of a network can help us understanding more the world economic behaviors. The data we are trying to work around is the world input-output table (WIOT). This dataset is a part of the world input-output database (WIOD), which was funded by the European Commission. Although WIOD main data tables contains 4 different tables, namely, world input-output Tables, National input-output tables, Socio Economic Accounts and Environmental Accounts, we only take an advantage on WION since this table contains 40 countries' economy transaction value to find out which country's industries are the most important to the world economy. WIOT is provided in current prices, denoted in millions of dollars, and covers 27 EU countries and 13 other major countries in the world, which contains 35 main industries each. While the data is available from 1995 to 2011, we will mainly focus on the latest year's dataset (2011) and make use of the others as an addition trend analysis. This table includes the flows between the industries of 40 countries and 1 group (Rest of the World). We considered only the transactions of those 40 major countries' industries; hence we have 40*35 = 1,400 sectors as nodes in the sectorial input-output network. Let's have a glance at some network's characterization at the regional level first. This world input-output network consists of 1,400 nodes with about 908,587 nonzero edges out of possible 1400^2 edges; therefore, this network is dense with the network density

$$\rho = \frac{m}{n * (n-1)} = \frac{908587}{1400 * 1399} = 0.46 \quad (12)$$

Regarding the transaction volume, there were 52 sectors that had the total transactions (both input and output transactions) larger than 500 billion dollars. In the top 10 highest total transaction sectors illustrated in Fig. 1, all of them were from China and the USA.

All 27 EU countries plus 13 other major countries are divided into 4 main groups, European Union, North America, Latin America and Asia and Pacific group, as shown in Table 1.

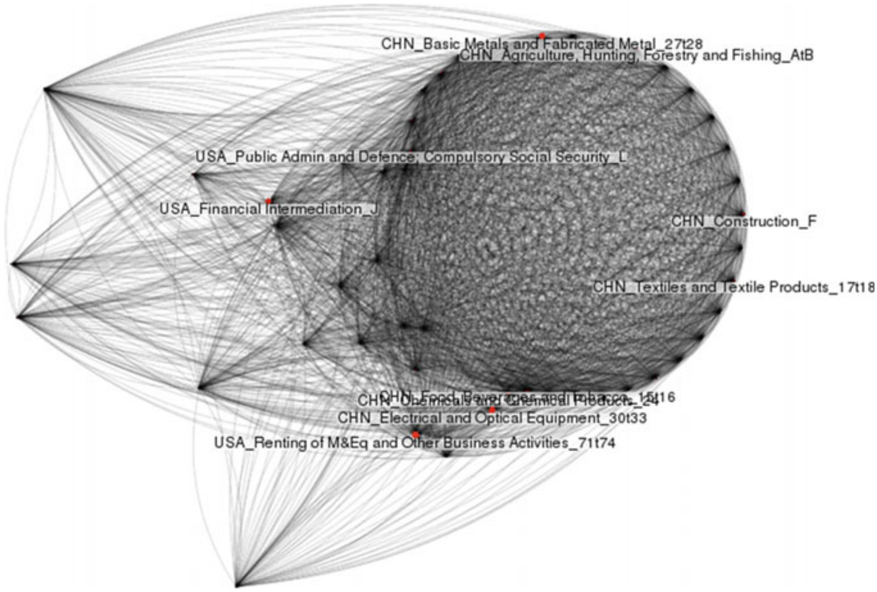

Fig. 1 The world input-output network (year 2011). 52 sectors had total transaction greater than 500 billion dollars

Table 1 Major countries and their groups in WIOT

European Union
Austria Germany Netherlands Belgium Greece Poland Bulgaria Hungary
Portugal Cyprus Ireland Romania Czech Republic Italy Slovak Republic Denmark
Lavia Slovenia Estonia Lithuania Spain Finland Luxembourg Sweden France
Malta United Kingdom
North America
Canada United States
Latin America
Brazil Mexico
Asia and Pacific
China India Japan South Korea Australia Taiwan Turkey Indonesia Russia

We consider these groups as the sub-networks of the whole world economy network. We calculate the network density of each sub-network (group), and compare their economic connectivity. Each sub-networks (or groups), European Union (EU), North America (NA), Latin America (LA), and Asia and Pacific (AP), has a very high network density, 0.9, 0.95, 0.91, and 0.7 respectively. This fact indicates high linkage among the countries within the same sub-network (group). It is also unsurprising that the group North America, consists of the two strong economy countries, namely USA

Table 2 Network parameters of 4 groups

Group	Nodes	Non-zero edges	Density	Average inner transaction
European Union	945	808722	0.91	15685.28
North America	70	4635	0.96	169905.61
Latin America	70	4415	0.91	30522.54
Asia and Pacific	315	71056	0.72	84787.40

and Canada, has very high intra transactions, and leads this comparison list with the total inner-transaction is about 170 billion dollars. The following position belongs to Asia and Pacific group in the presence of China and Russia (about 87,787 million dollars). These values are summarized in Table 2.

We now identify the key economic sectors (industries) among 40 best economies of the world by obtaining their AI and VI from the world input-output table. Through the lenses of our model, sectors such as real estate, management of companies and enterprises, advertising, wholesale trade, telecommunications, iron and steel mills, truck transportation, and depository credit intermediation alongside a variety of energy-related sectors—petroleum refineries, oil and gas extraction, and electric power generation and distribution—are seemingly key to U.S. aggregate volatility as they sit at the center of the production network. When applying these equations in the real economic input-output network (ION), we see that the intermediate table of this network is a directed and weighted network. Each element of this intermediate matrix (W) represents the trade volume either between 2 commodities or a node itself, measured by a unit of million dollars. Using two measurements from Eqs. (8) and (11), assuming time is infinite, the measurements' results will be diverge if the values of each element in the matrix W is larger than 1. Hence, to overcome this problem, each element of W is divided by the maximum value of the matrix element. We denote the normalized input-output matrix as M = W/max(W), and we define VI as

$$VI = (I + (\alpha M^T) + (\alpha M^T)^2 + ... + (\alpha M^T)^t + ...)e \tag{13}$$

Similarly, AI matrix is defined as

$$AI = (I + (\alpha M) + (\alpha M)^2 + ... + (\alpha M)^t + ...)e \tag{14}$$

Table 3 shows the top five economic sectors with the highest AI from the input-output data in 2011 with the different α values. In most cases, the top economic sectors were from China, which leading by the "Basic metals and fabricated metals" sector, and "Electrical and optical equipment" with the high value of α. These sectors from China were the greatest impact to the world economy in that period of time. However, if lower the range of sectors affected by a given sector, or reduce the value of α, the U.S' sector "Renting of M&Eq and Other Business Activities" replaced the

Table 3 The top 5 economic sectors with high amplification index (AI) in 2011

α	Rank	Sector	AI
1	1	(CHN) Basic metals and fabricated metal	0.233
1	2	(CHN) Electrical and optical equipment	0.090
1	3	(CHN) Mining and quarrying	0.068
1	4	(CHN) Electricity, gas and water supply	0.053
1	5	(CHN) Chemicals and chemical products	0.043
0.85	1	(CHN) Basic metals and fabricated metal	0.233
0.85	2	(CHN) Electrical and optical equipment	0.090
0.85	3	(CHN) Mining and quarrying	0.068
0.85	4	(CHN) Electricity, gas and water supply	0.053
0.85	5	(CHN) Chemicals and chemical products	0.043
0.5	1	(CHN) Basic metals and fabricated metal	0.004
0.5	2	(USA) Renting of M&Eq and other business activities	0.004
0.5	3	(USA) Financial intermediation	0.003
0.5	4	(CHN) Electrical and optical equipment	0.0026
0.5	5	(CHN) Chemicals and chemical products	0.0019
0.25	1	(USA) Renting of M&Eq and other business activities	0.0016
0.25	2	(CHN) Basic metals and fabricated metal	0.0015
0.25	3	(USA) Financial intermediation	0.0014
0.25	4	(CHN) Electrical and optical equipment	0.0013
0.25	5	(CHN) Chemicals and chemical products	0.0011

sector “Basic metals and Fabricated metals” of China to become the most influenced industry. These results also indicate the evidence that USA and China enjoyed the largest economy in the world in 2011.

Similarly, in the Table 4 below, the top five economic sectors with the highest vulnerability index in the different cases of the value of α in 2011 are pointed out. The top most be influenced economic sectors were still belong to China, which leading by the “Electrical and Optical Equipment” and “Basic metals and fabricated metals” sector, despite of the change of the value of α. Even a small change of any other industries may also lead to a fluctuation of this sector’s transaction.

Comparing to the result of World Input-Output network analysis by Federica Cerina et al. [11] in 2011, the authors used 4 different parameters to evaluate the industries. The first calculation was produced by the Laumas method of backward linkages (w), next was the eigenvector method of backward linkages e, the third and the

Table 4 The top 5 economic sectors with high vulnerability index (VI) in 2011

α	Rank	Sector	AI
1	1	(CHN) Electrical and optical equipment	0.200
1	2	(CHN) Basic metals and fabricated metal	0.076
1	3	(CHN) Construction	0.075
1	4	(USA) Financial intermediation	0.055
1	5	(CHN) Machinery, nec	0.053
0.85	1	(CHN) Electrical and optical equipment	0.200
0.85	2	(CHN) Basic metals and fabricated metal	0.076
0.85	3	(CHN) Construction	0.075
0.85	4	(USA) Financial intermediation	0.055
0.85	5	(CHN) Machinery, nec	0.054
0.5	1	(CHN) Electrical and optical equipment	0.004
0.5	2	(CHN) Basic metals and fabricated metal	0.003
0.5	3	(CHN) Construction	0.003
0.5	4	(USA) Financial intermediation	0.002
0.5	5	(USA) Public admin and defence; compulsory social security	0.002
0.25	1	(CHN) Electrical and optical equipment	0.0014
0.25	2	(CHN) Construction	0.0013
0.25	3	(CHN) Basic metals and fabricated metal	0.0013
0.25	4	(USA) Financial intermediation	0.0011
0.25	5	(USA) Public admin and defence; compulsory social security	0.0011

fourth were PageRank centrality PR and the community coreness measure—dQ—respectively. In the Table 5, we compare the results (top 5 sectors) implemented by Cerina et al. (2011) and our measurements with the different values of α. According to this table, the results got from backward linkages method (w) and Vulnerability Index (with the different α values) are almost identical. That is, there is an existence of the same sectors from China and the USA in both methods such as China's Construction (CHN_Cst), "Public Admin and Defence; Compulsory Social Security" from the USA (USA_Pub), etc. However, the results generated by Amplification Index measurement are different to the other methods since an approach of this implement is based on the outward link while the others use the inward link as main factor to measure the centrality.

Table 5 The comparison of results implemented by AI, VI and other methods conducted by Cerina et al. [11]

Rank	w	e	PR	—dQ—	AI(α:1)	AI(α:0.5)	AI(α:0.25)	VI(α:1)	VI(α:0.5)	VI(α:0.25)
1	CHN-Cst	CHN-Tpt	GRB-Hth	CHN-Cst	CHN-Met	CHN-Met	USA-Obs	CHN-Elc	CHN-Elc	CHN-Elc
2	USA-Pub	CHN-Tex	DEU-Tpt	USA-Obs	CHN-Elc	USA-Obs	CHN-Met	CHN-Met	CHN-Met	CHN-Cst
3	USA-Hth	CHN-Elc	USA-Pub	CHN-Met	CHN-Min	USA-Fin	USA-Fin	CHN-Cst	CHN-Cst	CHN-Met
4	USA-Est	CHN-Rub	CHN-Elc	USA-Pub	CHN-Ele	CHN-Elc	CHN-Elc	USA-Fin	USA-Fin	USA-Fin
5	CHN-Elc	CHN-Lth	USA-Hth	USA-Est	CHN-Chm	CHN-Chm	CHN-Chm	CHN-Mch	USA-Pub	USA-Pub

Abbreviation	
CHN: China	USA: the USA
GRB: Great Britain	DEU: Germany
Cst: Construction	Tpt: Transport Equipment
Hth: Health and Social Work	Met: Basic Metals and Fabricated Metal
Obs: Renting of M&Eq and Other Business Activities	Elc: Electrical and Optical Equipment
Mch: Machinery, NEC	Tex: Textiles and Textile Products
Min: Mining and Quarrying	Fin: Financial Intermediation
Est: Real Estate Activities	Rub: Rubber and Plastics
Chm: Chemicals and Chemical Products	Pub: Public Admin and Defence; Compulsory Social Security
Ele: Electricity, Gas and Water Supply	Lth: Leather, Leather and Footwear

5 Transitions of Important Industries

By mixing the top 20 sectors of the highest AI and the top 20 sectors of the highest VI, we get a list of 27 sectors sorted by AI value and VI. We will try to examine whether or not the relationship between an AI and VI value of a sector and its input and output strength in 2011, then take a deeper look at these differences throughout the period of 17 years.

With $\alpha = 1$, we pick out some sectors to analysis that have both high AI and VI value such as “Basic metals and Fabricated Metal” (CHN_Met), “Electrical and Optical Equipment” (CHN_Elc), “Mining and Quarrying” (CHN_Min) from China, the two sectors “Financial Intermediation” (USA_Fin) and “Renting of M&Eq and Other Business Activities” (USA_Obs) from the US.

Firstly, we will examine the change of AI value of these sectors in the period from 1995 to 2011 (Fig. 2). It can be easily seen that the only two sectors from USA were leading the remain with the fluctuation of their AI values in the first 16 years before dropping down and being replaced by sectors from China in the year 2011. In the first 16-year period, the USA’s sectors had very high values of AI compared to the ones of China. The very important milestone, the financial crisis of 2007–2008 or global financial crisis, caused by the collapse of Lehman Brothers, also affected to the AI value of these two USA’s sectors. After 2008, their reactions to this event were quite different. In this year, while the AI of the sector “Financial Intermediation” felt below

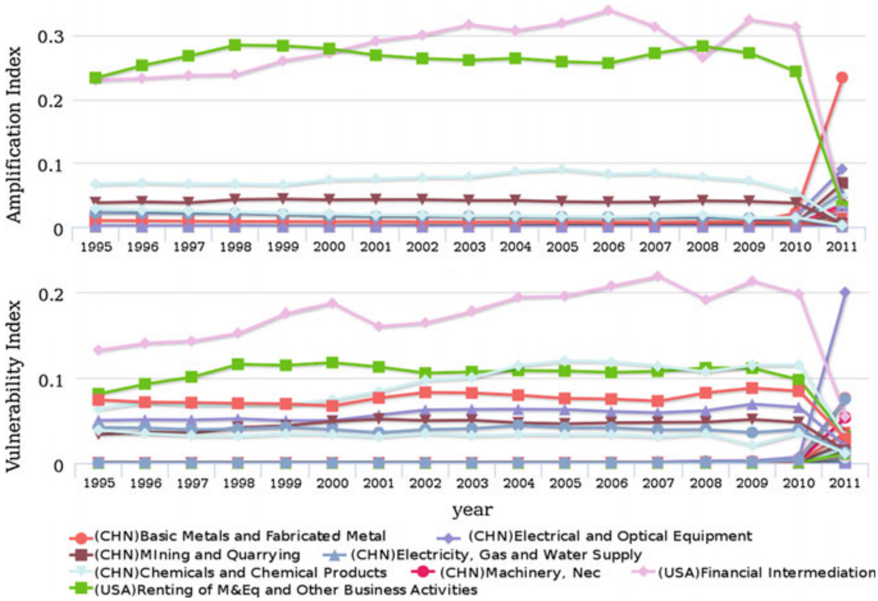

Fig. 2 The transitions of the important sectors in terms of AI and VI ($\alpha = 1$) in the periods 1995–2011

the value of the other the U.S.' sector before bouncing back to the higher value in 2009, the AI value of the sector "Financial Intermediation" of the United States had increased gradually to reach a peak of 0.28 first time since 2000. As we are considering the influence of sector through the entire network of world economy (α is 1), it seems that there was a prediction of this crisis from the reducing value of the sector "Financial Intermediation" since 2006. A year later, both of these sectors had the sharp declines and bottom out around the AI value 0.03 in 2011, and were replaced by the sectors from China. One thing to note is that, while in the previous 16 years, the AI value of these top China's sector were very small compared to other sectors, in the last year of this period (2011), their AI value dramatically rose up to nearly 0.24 and 0.1 corresponding to the sector CHN_Met and CHN_Elec respectively. Similar to the change of AI, the change of VI of these VI had the same trend. While almost the high VI value are of the sectors from the U.S. in the first 16 years, in the year 2011, the sector CHN_Elec from China had a sudden leap to the VI value of 0.2 after having a slight change from 0.002 in 2008 to 0.007 in 2010. However, these changes can be seen considering the total degree of these sectors in the year 2011.

In the other hand, considering the sectors with the highest VI value in 2011, the leading is the sector Electrical and Optical Equipment(CHN_Elc) of China, followed by the sector CHN_Met and the sector Construction (CHN_Cst). Based on the WION, we see that the sector CHN_Elc, itself consumed its products valued about 660 billion dollars, had imported approximately 198 billion dollars mostly from the same industry type of the foreign countries (mostly from Taiwan, Japan and Korea). In China's

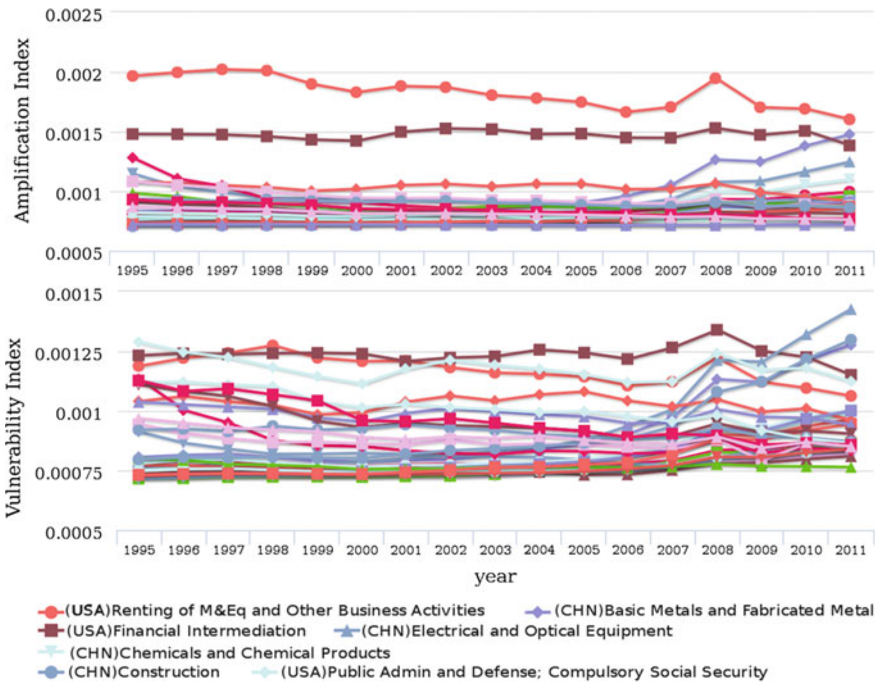

Fig. 3 The transitions of the important sectors in terms of AI and VI (α = 0.25) in the periods 1995–2011

local market, products from the sector CHN_Met were mostly used (about 278 billion dollars), the sectors "Rubber and Plastics", "Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles" and "Chemicals and Chemical Products" were the three following sectors that provided much products to the sector CHN_Elc with 87, 70 and 61 billion dollars respectively. Moreover, these directly supported sectors had a very high ranking of AI value in the top sectors with the highest AI value. This may be one possible explanation of this sector's high VI value.

If we reduce the range of effect to the other sectors by reducing α value, it is clearly seen that any sector had the more direct investment, the higher AI value it got. Similarly, high volume transaction of direct supported sectors had more influence to the VI value of the target sector. For example, with α is 0.25 (Fig. 3), the sector "Renting of M&Eq and Other Business Activities" (or USA Obs) from the United State of America became the top most AI value sector followed by the other sectors from China and the U.S, namely "Basic metals and Fabricated Metal" and "Financial Intermediation" respectively. In 2011, this sector had the highest total-strength and the highest Out-strength (with nearly 2,429 billion dollars), According to the National Accounts Main Aggregates Database of United Nations Statistics Division, the United States was the largest consumer market of the world. Hence, despite of the fact that this sector's output mostly to the USA's local market, it still had the very high AI value comparing to the other industries.

In terms of VI value, the sector CHN_Elc from China was still the most be influenced sectors since it has the very high imported products from other industries of both regional and foreign countries. However, the sector "Construction" of China (CHN_Cst) consumed more products that the sector CHN_Elc from the other China's industries. From the sector "Other Non-Metallic Mineral" of China, about 375 billion dollars was consumed by the sector CHN_Cst. The others were from the sector CHN_Met with 367 billion dollars and CHN_Elc with only 96 billion dollars. Although the sector "Other Non-Metallic Mineral" did not have high AI, in this case of small range of affect ($\alpha = 0.25$), it still had enough influence to make the sector CHN_Cst become more vulnerability than the other sectors.

To conclude this complicated relationship, it is very hard to decide which sectors have high influence or most being affected if based only on their transaction. The use of AI and VI with the varied value of α might make the keys sector evaluation more precisely.

6 Conclusion

In the modern society, all major economic sectors have been connected tightly in an extremely complicated global network. In this type of network, a small shock occurred at certain point can be spread instantly through the whole network and may cause catastrophe. Production systems, traditionally analyzed as almost independent national systems, are increasingly connected on a global scale. Only recently becoming available, the world input-output database is one of the first efforts to construct the global and multi-regional input-output tables. The network measures can give valuable insights into identifying the key industries. By viewing the world input-output tables as complex networks where the nodes are the individual industries in different economies and the edges are the monetary goods flows between industries, we characterize a certain aspect of centrality or status that is captured by the α-centrality measure of the world input-output network. We also capture their evolution of over years. We also argue that the network structure captured from the input-output data is key in determining whether and how microeconomic impacts or shocks propagate throughout the economy and shape aggregate outcomes. Understanding the network structure of world input-output data can better inform on how the world economy grows as well as how to prepare for and recover from adverse shocks that disrupt the global production chains.

The discussion in this paper has attempted to introduce another way to look for the key sectors in the world economy. Applying the method based on the AI and VI, we identified the sectors that could be considered as key, or the major, industries in the world economy in the period from 1995 to 2011. In short, these measurements are defined as:

- Amplification Index, AI, is used to measure the total influence that a sector could affect to other sectors in a long time.
- Vulnerability Index, VI, is, on the other hand, a cumulative impact that a sector could receive from other sectors in a period of time.

Using of the two methods heavily depends on the value of the trade-off parameter α. The value of α determines how far influence could be spread through the network. The higher value of α, the further nodes that impact could reach to. If α is chosen correctly according to the considering economy and the research scale of the economists, AI and VI might be the useful measurements for the economist to evaluate the influence of the key sectors in that economy.

Since there are some traditional ways to analyze key sectors in the economy such as finding Forward links and Backward links, these introduced methods may be contributed to the policy makers' toolkit to help them in analyzing the economy easily, and also preparing and recovering from adverse shocks that disrupt the production chains.

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