

INTERCONNECTEDNESS AND RESILIENCE OF THE U.S. ECONOMY

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An economy consists of interconnected sectors which are specialized in producing different products or providing particular services. We study the interconnectedness of the U.S. economy using a network approach, finding that sectors are highly clustered in this “economy network” and play different roles in facilitating the transactions within the economy. When it comes to resilience of the economy as a whole, however, all sectors play different but nontrivial roles by facilitating alternative input–output routes when a crisis occurs in single or multiple sectors. Diversity in sectors’ specialties appears to be the truly important characteristic that keeps the economy functional when facing internal and external challenges.

Keywords: Complex network; economic network; input–output; resilience; economy.

1. Introduction

Since the late 1990s, fundamental research on complex networks [1, 2] has developed real-world case studies in various disciplines including biology, ecology, engineering, and sociology [3, 4]. Today, complex network analysis has become a key method to understand systems with multiple components interacting with each other. However, little research has been done using network theory to understand the interaction of economic sectors and its implications on the functionality of the economy as a whole [5–7]. Given unpredicted and serious perturbations such as the recent economic downturn, there is an urgent need for better understanding of how economic sectors interconnect with each other [8]; network analysis provides an important novel perspective on overall systemic resilience that extends beyond standard economics [9].

Essentially, economies are complex adaptive systems in the sense that constituent components (e.g. sectors, firms, or individual consumers) are self-organized and connected with each other in complex ways [10–12]. Previous studies modeled such interactions primarily at the global scale by examining international trade [13–16] as well as at the levels of organizations [17, 18] and individuals [19], while little attention was paid on a national scale.

Think of a national economy as a set of sectors that are connected with each other by the exchange of products or economic transactions. Thus, an economy can be regarded as a network consisting of heterogeneous nodes represented by sectors and heterogeneous and directional links represented by economic transactions between sectors. This network model can be populated by data from existing economic input–output (EIO) models, the most sophisticated existing method to characterize the interconnectedness between economic sectors [20, 21]. Based on the input–output relationship between each pair of sectors, an EIO model quantifies both direct and indirect impacts on each sector’s economic output caused by changes in another sector or set of sectors, as shown in Table 1. The economy is composed of n sectors. For sector i , Y_i denotes the final demand (or consumption) of its output, V_i represents industrial inputs to it other than commodities or services, or value added, and X_i indicates its total output which is equal to its total input. The element x_{ij} denotes the input of sector i to the production of sector j .

The Appendix provides more details about the EIO model. Using purely mathematical methods, the EIO model can provide insights on impacts of sectors on supply and demand changes, employment, and environmental pollution [21–23], but hardly can reveal the role of the interaction between sectors in keeping the economy as a whole functional when facing a variety of perturbations. However, the national EIO accounts contain valuable information in that regard, provided that those data can be appropriately presented and interpreted.

In the U.S., the Bureau of Economic Analysis (BEA) has been publishing national benchmark EIO accounts at the detailed level (around 500 sectors) according to the Standard Industry Classification (SIC) codes [24] in every five years since 1967 [25]. The emerging industries that are beyond the scope of SIC system are included in BEA’s national EIO accounts after 1999 by adopting the North

Table 1. A stylized representation of the EIO model.

		Output	Intermediate output sector				Final demand	Total output
			1	2	...	n		
Input						Y	X	
Intermediate input	Sector	1	x_{11}	x_{12}	...	x_{1n}	Y_1	X_1
		2	x_{21}	x_{22}	...	x_{2n}	Y_2	X_2
				
		n	x_{n1}	x_{n2}	...	x_{nm}	Y_n	X_n
Value-added		V	V_1	V_2	...	V_n		
Total input		X	X_1	X_2	...	X_n		

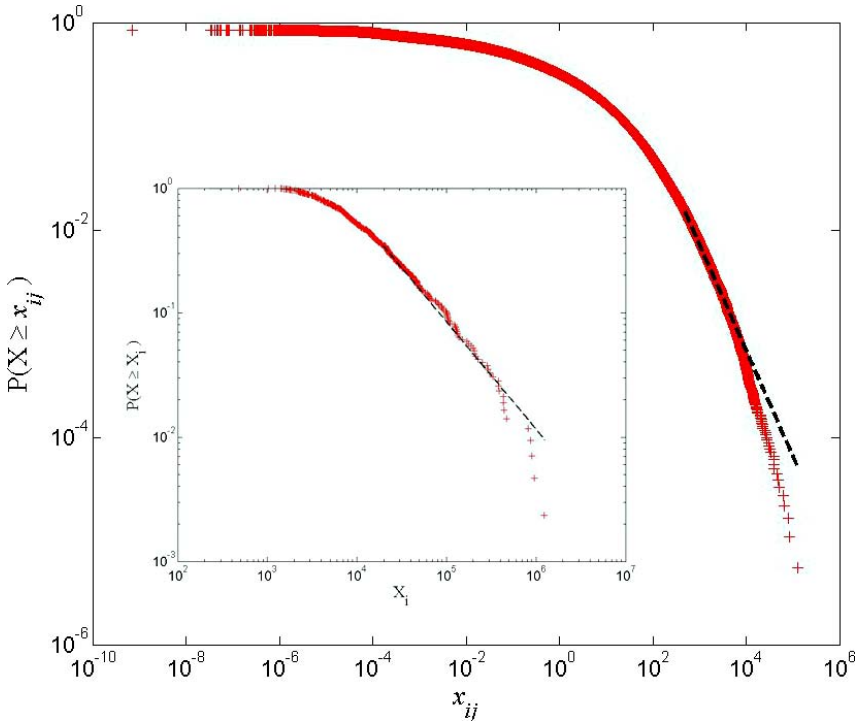


Fig. 1. Cumulative density distribution of the U.S. sectoral economic transactions (x_{ij}). The inset shows the cumulative density distribution of the U.S. sectoral economic outputs (X_i).

American Industry Classification System (NAICS) which is updated every five years to reflect the changes in the composition of the economy [26]. This research utilizes the 2002 U.S. benchmark EIO account [27], which is the most recent data released and contains 426 sectors, to explore the interconnectedness of sectors in the U.S. economy and its implications on economy resilience. The classification of the U.S. sectors can be found in the Appendix. Given that the size of sectors, measured by total output X_i , and the strength of sectoral transactions x_{ij} are far from homogeneous, as shown in Fig. 1, a network representation [4, 28] is useful in understanding the underlying structure of the economy and its implications on resilience. Previous study by Fisher and Vega-Redondo showed the feasibility of presenting an EIO matrix as a directed weighted network [29]. Given that each sector is often connected with all or most of other sectors, the heterogeneity of the links should be the basis of this network representation, rather than treating the links as homogeneous without distinguishing their directions and weights.

2. Skeleton of the U.S. Economy

Figure 2 shows the underlying network structure of the U.S. economy by keeping only the link from which each sector receives its largest input. This abstraction

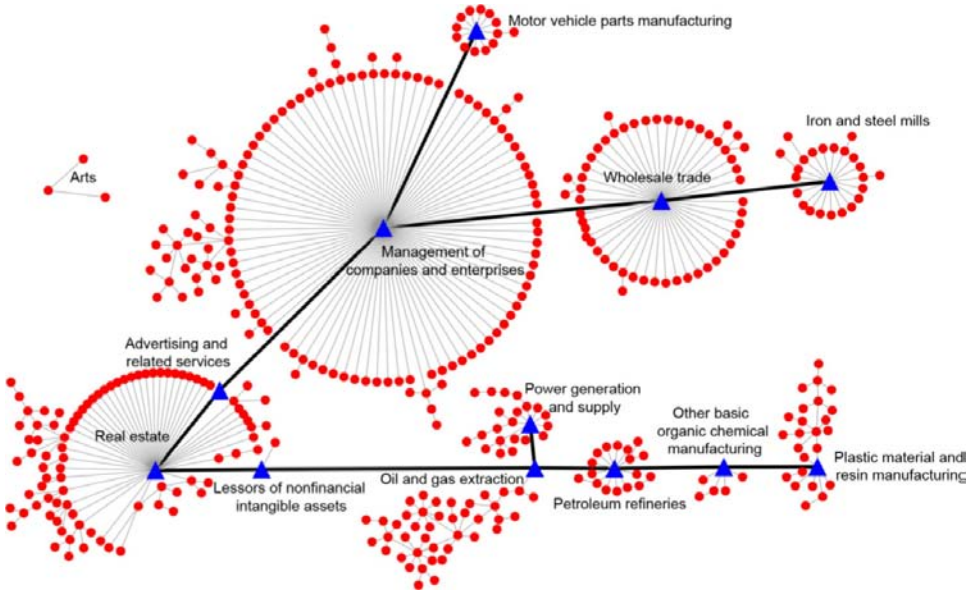


Fig. 2. (Color online) The “skeleton” and “backbone” of the U.S. economy.

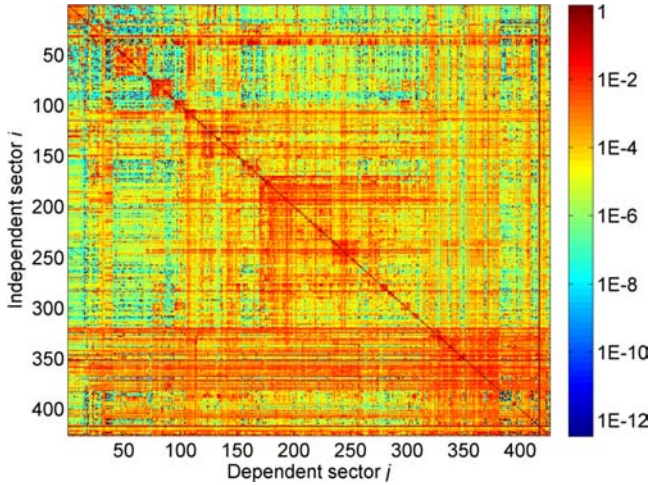
identifies the strongest inter-sectoral connections within the economy. Clearly this network, as the “skeleton” of the U.S. economy, is highly clustered. Most of the sectors are connected through these clusters, except three isolated art-related sectors. The center or root of each cluster is drawn as a blue triangle. Two other sectors, *advertising and related services* and *lessors of nonfinancial intangible assets*, are neither center nor root of any cluster but also drawn as blue triangles because they are critical in connecting those clusters. These sectors illustrated as blue triangles and the links connecting them constitute the “backbone” of the U.S. economy.

In addition to the largest upstream sector, other sectors in the economy may also make non-trivial contribution to a particular sector. Based on this network skeleton, the whole “body” of the economy can be recovered by adding all existing links. Yet it will make the network too complex to distinguish trivial and non-trivial links. Instead, we introduce a dependency coefficient as the concept to identify those non-trivial links for each sector.

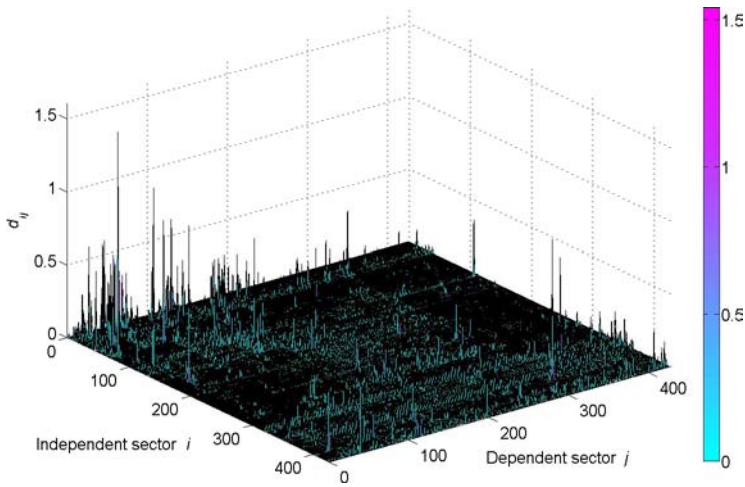
The dependency coefficient of sector j (dependent sector) on sector i (independent sector), expressed as d_{ij} , measures how much the economic performance of sector j depends on its interaction with sector i . Formally, d_{ij} is defined as the ratio of economic transactions between the two sectors to the total economic output of sector j ,

$$d_{ij} = (x_{ij} + x_{ji})/X_j, \quad (i \neq j), \quad (1)$$

where x_{ij} represents the economic transaction from sector i to sector j , and X_j stands for the total economic output of sector j .



(a)



(b)

Fig. 3. (Color online) The matrix of dependency coefficients for the U.S. economy. (a) Each pixel on the 426 by 426 grid represents the dependency coefficient of the corresponding column sector (j) on the corresponding row sector (i). (b) A 3D visualization for the matrix of dependency coefficients.

Figures 3(a) and 3(b) illustrate the matrix of dependency coefficients for the U.S. economy by painting with different colors according to the dependency coefficient value. While detailed classification can be found in the Appendix, sectors are ordered from agriculture, mining, construction, manufacturing, to service with increasing numerical values in coding. Higher dependency coefficients, red spots in Fig. 3(a) or spikes in Fig. 3(b), represent relatively stronger connection between two sectors. Although this network model of the economy is almost fully connected

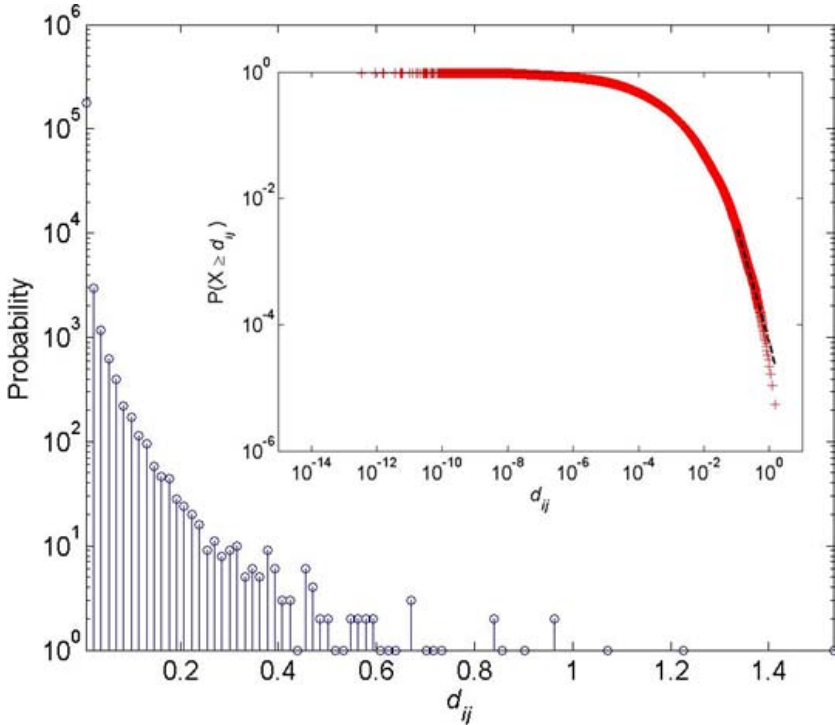


Fig. 4. Density distribution of dependency coefficients (d_{ij}). The inset shows the cumulative density distribution of d_{ij} .

in the sense that links exist between most pairs of sectors, Fig. 3 shows a modular structure in which the links are significantly inhomogeneous. In particular, the red horizontal lines in the top of Fig. 3(a) represent the economy's heavy dependency on construction sectors. Along with the diagonal, there are clustered sectors which are highly connected with each other. Those sectors represent series of related industrial processes along with the supply chain, such as primary smelting and refining of metals. The bottom of Fig. 3(a) shows dense red horizontal lines, which imply that most of the sectors in the U.S. economy strongly depend on the service sectors. Overall, Fig. 3 shows the existence of strongly bonded sectors in the U.S. economy. This conclusion drawn from the graphical illustration is also supported by statistical evidence. As shown in Fig. 4, only 4.92% of the total 181,050 inter-sectoral connections have dependency coefficients higher than 0.01. Thus the concept of dependency coefficient can be used to identify those non-trivial links in this 426-node network.

We offer a network visualization by superposing all links with a dependency coefficient larger than 0.0945 (see the Appendix for more details). In this clustered network of the U.S. economy (Fig. 5), manufacturing sectors are mainly found in the right side, while other sectors are generally located in the left. The sectors in

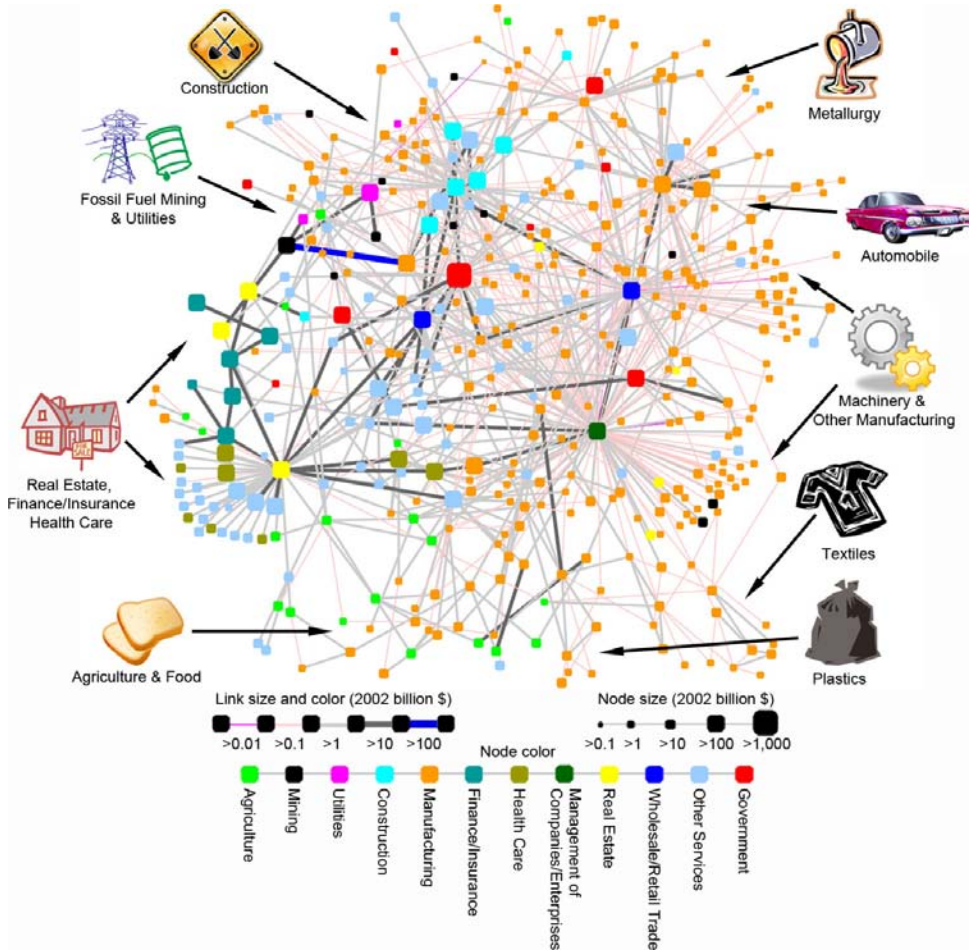


Fig. 5. (Color online) Network visualization of the U.S. economy. Node size represents the economic value of the output of sectors, node color stands for sector classification, and link color indicates strength of economic transactions.

the right of the network, from top to bottom, belong to metallic manufacturing, automobile manufacturing, machinery and other manufacturing, textile manufacturing, and plastic products manufacturing. To the left there are construction, fossil fuel mining and utilities, real estate, finance/insurance and health care, and agriculture and food production, from top to bottom. The clustering of sectors generally agrees with the commonly used Standard Industry Classification (SIC). Yet it provides a different view on how the sectors are connected to each other. For example, automobile manufacturing is next to metallic manufacturing because of the closer supply-demand relationship (i.e. making automobiles needs metals), but far from agriculture and food production because the direct links between the two clusters are relatively weak.

3. Strongest Inter-Sectoral Connection

What are the roles of sectors and links in keeping the economy functional, beyond this intuitive graphical illustration? We use the concept of the strongest inter-sectoral connection to obtain more information for this question. Multiple inter-sectoral connections exist from one sector to another through the economic input–output relationship, including the one directly originating from the upstream sector to the destination sector and all indirect connections through other sectors. To generate a unitary economic output for a destination sector j , each inter-sectoral connection requires a specific amount of input, S_{ijk} , from the particular source sector i ,

$$S_{ijk} = \prod a_{ik_0} a_{k_0k_1} \cdots a_{k_kj}, \tag{2}$$

where $a_{ij} = x_{ij}/X_j$ is the direct requirement from sector i for a unitary economic output in sector j ; and $k = \{k_0, k_1, \dots, k_k\}$ denotes the particular inter-sectoral connection route from sector i to j via k_0, k_1, \dots , and k_k . Among all existing inter-sectoral connection, there is a unique one whose S_{ijk} is the largest, which is not necessarily the one directly connecting the two sectors. This particular inter-sectoral connection is defined as the **strongest inter-sectoral connection** (SSC) from sector i to j , representing the most important economic input–output route to maximize sector i 's production, driven by sector j 's demand. Figure 6 shows an example of SSC from sector 1 to sector 15 for the U.S. economy using the 2002 EIO data. To generate a unitary output for sector 15, the direct input from sector 1 is 0.00034 ($a_{1,15}$). An alternative route is via sector 16. The input required from sector 1 via this alternative route is 0.0012 ($a_{1,16}$ times $a_{16,15}$) which is larger than that of the direct input–output route. In fact, the input from sector 1 on this alternative route is larger than the input from any other existing inter-sectoral connections from sector 1 to sector 15. This particular connection, from sector 1 to sector 15 via 16, is defined as the SSC from sector 1 to sector 15. The notion of SSC reveals the strongest relationship, otherwise hidden, between some sectors through indirect economic input–output connections. For the example in Fig. 6, the *oilseed farming* sector would have a relatively weak link with the *logging* sector as their direct connection is not the strongest. However, if considering indirect links, the

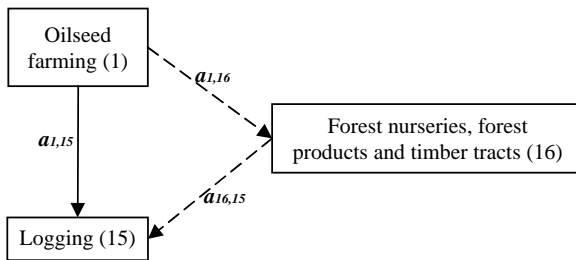


Fig. 6. The SSC from sector 1 to sector 15.

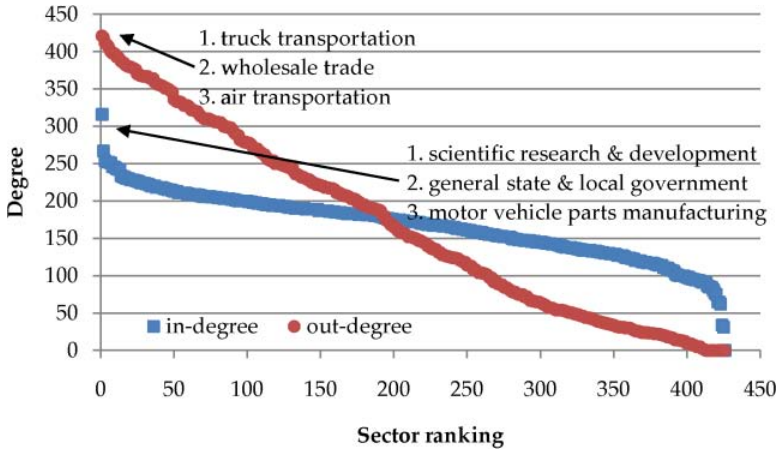


Fig. 7. Sectors ranking by in-degree and out-degree.

two sectors are much more closely connected in the way that the *oilseed farming* sector provides significant support to the sector of *forest nurseries, forest products and timber tracts* (sector 16) which in turn has a strong link with the *logging* sector. Thus the concept of SSC can quantify the true strength of the connection between two sectors from a full life cycle perspective by considering not only the direct link.

An SSC network is constructed for the U.S. economy by eliminating links that are not within any SSC. This network contains 71,234 directional links, representing 47.09% of the total existing links in the U.S. economy. Several metrics are chosen to analyze this network. First, define in-degree as the number of links directing to a sector and out-degree as the number of links directing from a sector. The ranking of in-degree and out-degree for each sector, as shown in Fig. 7, implies a network far from homogeneous. In particular, out-degrees are distributed among sectors in a wider range than in-degrees most of which are between 50 and 250. It implies that sectors are more diverse when selling their products/services to others than buying products/services from others. On one hand, the diversity of sectors as suppliers agrees with the way these sectors are classified which is based on specialization. On the other hand, the relative homogeneity of sectors in terms of in-degrees reveals the fact that most sectors actually depend on a large number of other sectors for inputs rather than just a few particular ones. Ranking top in out-degree, *truck transportation, wholesale trade, and air transportation* are critical for facilitating inter-sectoral transactions by providing services to fulfill other sectors' demand. Ranking top in in-degree, *scientific research and development, general state and local government, and motor vehicle parts manufacturing* are important in driving other sectors' production.

An SSC's step is defined as the number of its constitutional links. Table 2 shows the number and value of SSCs ranging from 1 to 6 steps. From an economic value point of view, all SSCs contribute 43.95% of the total output of the U.S.

Table 2. Number and value of SSCs with different steps.

SSC step	Number of SSCs	Share in total SSCs	Value of SSCs (million \$)	Share in total economic output
1	71,234	40.78%	7.70	40.17%
2	84,908	48.61%	0.68	3.56%
3	16,684	9.55%	0.041	0.22%
4	1,737	0.99%	0.0015	0.0076%
5	120	0.07%	0.000028	0.00015%
6	5	0.003%	0.00000017	0.0000009%

economy in 2002. SSCs with one step, meaning the source and destination sectors are directly connected, accounts for 40.78% of the total SSCs and 40.17% of the total economic output. Although SSCs with two or more steps only contribute less than 4% of the total economic output, they actually represent more than 59.22% of the total SSCs, implying that the strongest inter-sectoral connections between most sector pairs are indirectly facilitated by other sectors. In other words, some sectors play more important roles than others as intermediates to facilitate inter-sectoral transactions. We use betweenness as an indicator to capture this notion. Note that betweenness has been previously used to characterize the centrality of fully connected EIO networks [29, 30], but not for the abstracted EIO network based on the concept of SSC.

The betweenness of a sector is defined as the number of SSCs in the economy passing through it. The higher a sector's betweenness is, the more SSCs it occurs in and the more important it is in bonding sectors together as an economy. In the U.S. economy, *food services and drinking places* has the highest betweenness (12,379), meaning it exists in 12,379 SSCs, among all sectors. Given that the second highest betweenness is only 6,622 (*management of companies and enterprises*), *food services and drinking places* is significantly more critical than any other sector in facilitating inter-sectoral transactions in the economy. This partially implies the intuitive fact that the economy would not work in any way without feeding people. More importantly, although people can still make food by themselves, this also reveals the role of *food services and drinking places* as an economic sector in providing the entire economy an important service. Other sectors ranking top in betweenness include *general state and local government services*, *non-residential maintenance and repair*, and *wholesale trade*, as shown in Fig. 8. Note that the SSCs facilitated by *food services and drinking places*, which has the highest betweenness among all sectors, only represent 7.09% of all SSCs. Thus the constitution of SSCs in the U.S. economy does not highly depend on those sectors with higher betweenness, but relies on a variety of sectors in a distributed and diversified manner.

The definition of betweenness only considers the number of SSCs, representing the heterogeneity or diversity of sectors, but neglects the heterogeneity of links (value of economic transactions between sectors). Thus, the weighted betweenness is computed by assigning each SSC a weight of embodied value $w_{ij} = X_j S_{ij-SSC}$,

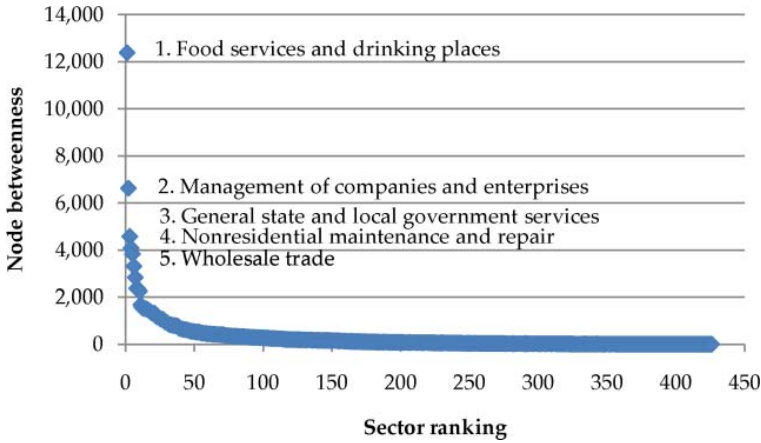


Fig. 8. Sector ranking by betweenness.

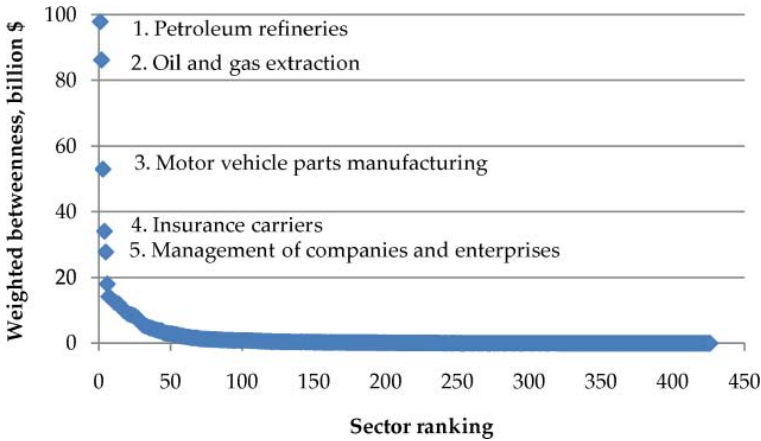


Fig. 9. Sector ranking by weighted betweenness.

where S_{ij-SSC} stands for the amount of input from sector i to produce a unitary output of sector j through the SSC. The weighted betweennesses among sectors are highly heterogeneous as shown in Fig. 9. Only five of the total 426 sectors have weighted betweennesses higher than \$20 billion (in 2002 \$, same hereinafter), including *petroleum refineries* (\$98 billion), *oil and gas extraction* (\$86 billion), *motor vehicle parts manufacturing* (\$53 billion), *insurance carriers* (\$34 billion), and *management of companies and enterprises* (\$28 billion). These sectors are critical for the U.S. economy as they facilitate those inter-sectoral connections with high embodied value. However, given that the largest weighted betweenness (*petroleum refineries*) only represents less than 1% of the U.S. gross domestic production (GDP) in 2002, the economy as a whole obviously does not entirely depend on this particular group of sectors with high weighted betweenness.

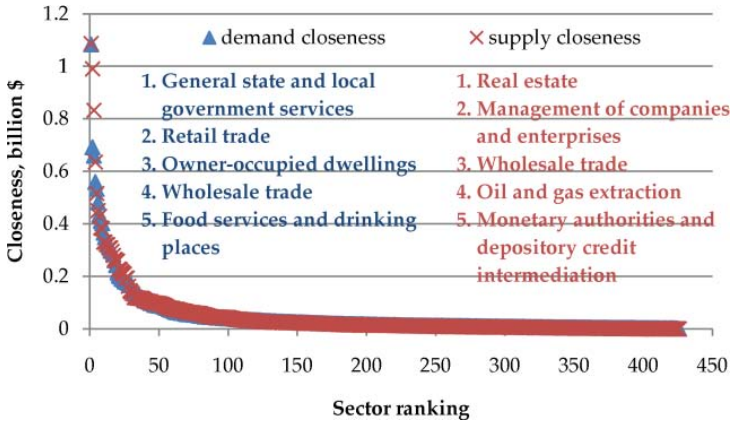


Fig. 10. Sector ranking in demand closeness and supply closeness.

A sector can receive (or demand) inputs from some sectors and also supply its outputs to other sectors. The concept of closeness is used to understand a sector's role as either demander or supplier in the economy. In particular, a sector's demand closeness is defined as the average of embodied values of all SSCs ending at this sector, while its supply closeness is the average of embodied values of all SSCs originating from it. Higher demand closeness implies that the sector is closer to other sectors and more important to the economy in terms of driving other sectors' production as a sector receiving inputs. On the other hand, higher supply closeness indicates that the sector is more important to the economy as a supplier to provide its products or services for other sectors. As shown in Fig. 10, sectors with higher demand closeness are those that provide products or services to the final consumers, including *general state and local government services* (\$1.1 billion), *retail trade* (\$0.7 billion), *owner-occupied dwellings* (\$0.7 billion), *wholesale trade* (\$0.6 billion), and *food services and drinking places* (\$0.5 billion). Higher supply closeness appears in sectors where products or services are mainly processed to other sectors as intermediate inputs, rather than consumed by the final consumers, such as *real estate* (\$1.1 billion), *management of companies and enterprises* (\$1.0 billion), *wholesale trade* (\$0.8 billion), *oil and gas extraction* (\$0.6 billion), and *monetary authorities and depository credit intermediation* (\$0.5 billion).

Generally, betweenness and closeness measure a sector's centrality within a network. The more central a sector is, the more important it is to the entire economy network in facilitating inter-sectoral transactions. Similarly, one can define a measure of link betweenness to measure the centrality of a specific link within a network. Formally, a link's betweenness is the number of SSCs it passes through. In particular, a link is passed through by an SSC if, and only if, its source sector is not the SSC's source and its destination sector is not the destination of the SSC. As shown in Fig. 11, among all 71,234 directional links in the SSC network, only two links' betweennesses are higher than 1,000, meaning only two links appear in over

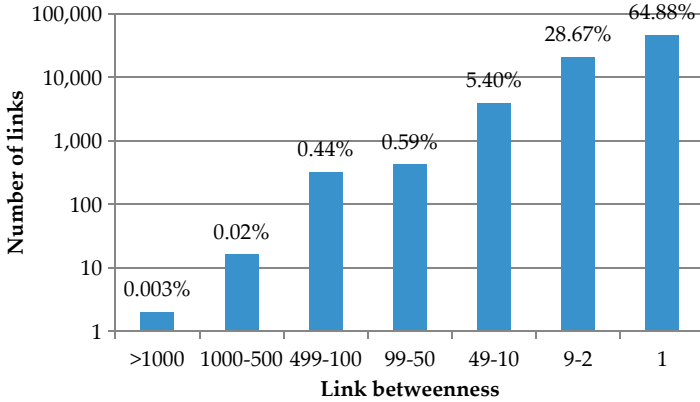


Fig. 11. Distribution of link betweenness.

1,000 SSCs. They are the link from *oil and gas extraction* to *petroleum refineries* (1,376) and the link from *general state and local government services* to *iron and steel mills* (1,122). Interestingly, the two links following them in betweenness ranking are from *cheese manufacturing and poultry processing* both to *food services and drinking places* (671 and 670, respectively). This agrees with the role of *food services and drinking places* in the economy described by sector betweenness. Note that the SSCs connected by these four links only represent 2.20% of all SSCs. Most links only appear in one or less than ten SSCs. In other words, the U.S. economy relies on almost all existing links to facilitate SSC transactions in a diversified way, rather than only depending on a few selected critical links.

Weighted by embodied values of all SSCs passing through, links' weighted betweennesses show a lognormal-like distribution in Fig. 12. Most links (76.54%) have weighted betweennesses ranging between \$0.1 million and \$100 million. Only

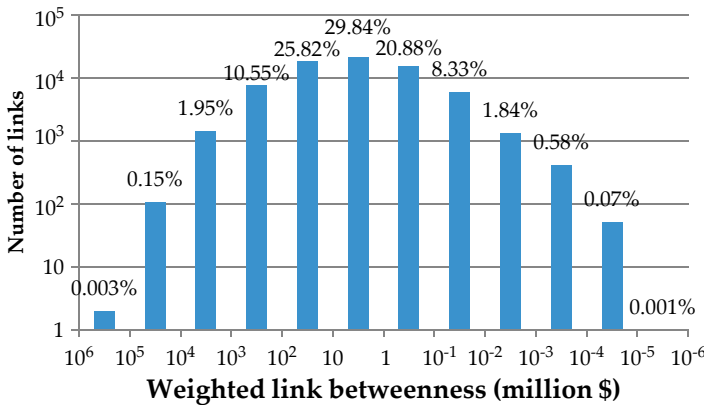


Fig. 12. Distribution of weighted link betweenness.

two links' weighted betweennesses are higher than \$100 billion. They are the link from *oil and gas extraction* to *petroleum refineries* (\$278 billion), which also ranks the first in unweighted betweenness (Fig. 11), and the link from *insurance agencies, brokerages and related* to *insurance carriers* (\$135 billion). The links following them in the ranking of weighted betweenness basically connect sectors related to energy extraction and distribution, finance, and automobile manufacturing. The distribution of weighted link betweenness also reveals that the U.S. economy does not depend on a particular group of links but relies on more diversified inter-sectoral transactions.

The study on the SSC network compares sectors' relative importance to the U.S. economy. Despite the fact that particular sectors are significantly more critical than others, the economy as a whole in fact does not solely depend on those particular sectors but highly relies on the diversified interconnectedness. Next, we design an analysis to understand how the diversified interconnectedness affects the resilience of the economy.

4. Resilience of the U.S. Economy

Resilience is often described as a system's inherent ability to remain functional in the face of various challenges [31]. We measure the economy's resilience by simulating its responses to failures in different sectors through the complex input-output interconnectedness. In particular, the economy's responses to changes in sectors are characterized by the changes of average SSC value which is defined as,

$$V = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij}}{n(n-1)}, \quad (i \neq j), \quad (3)$$

where w_{ij} represents the embodied value for the SSC from sector i to sector j . Thus V , essentially the arithmetic mean of embodied values for all SSCs, describes how strongly sectors in an economy are bonded with each other. In other words, the higher V is, the closer are sectors connected and the more are values created from inter-sectoral transactions. The 2002 U.S. economy's average SSC value was \$46.56 million, indicating that \$46.56 million was created in each SSC transaction on average. To compare sectors' roles in enhancing the resilience of this economy network, we first study the changes in V when disabling one sector's transactions with others, representing a crisis occurring in that sector. In general, preventing any sector's participation in the economy forces those SSCs facilitated by that sector to change to alternative routes with less embodied values, thus reducing the average SSC value (V) of the entire economy. However, the economy responds differently to the removal of different sectors (Fig. 13). The value of V is reduced by less than 1% if any of 380 sectors out of the total 426 is removed, indicating the economy's resilience against downturns in most sectors. The economy responds more sensitively (V decreasing by 1–8%) to removal of any of the remaining 46 sectors, including *management of companies and enterprises*, *real estate*, and *wholesale trade*. Overall, the economy is



Fig. 13. Ranking in average SSC value (V) after removing each sector.

generally resilient against the meltdown in a randomly selected sector. Even when the meltdown happens in intentionally selected more important sectors (e.g. those ranking top in Fig. 13), the economy is still relatively resilient given that the value of V does not decrease by more than 8% in any case.

An economy always fluctuates by experiencing growth and downturns in different sectors. To simulate a more general situation, how an economy responds to downturns in multiple sectors, we designed a Monte Carlo experiment to show the response of the economy, measured by the change of V , after randomly removing sectors one by one. As shown in Fig. 14, the value of V gradually decreases as more sectors are removed until only 11 sectors are left, meaning removing as much

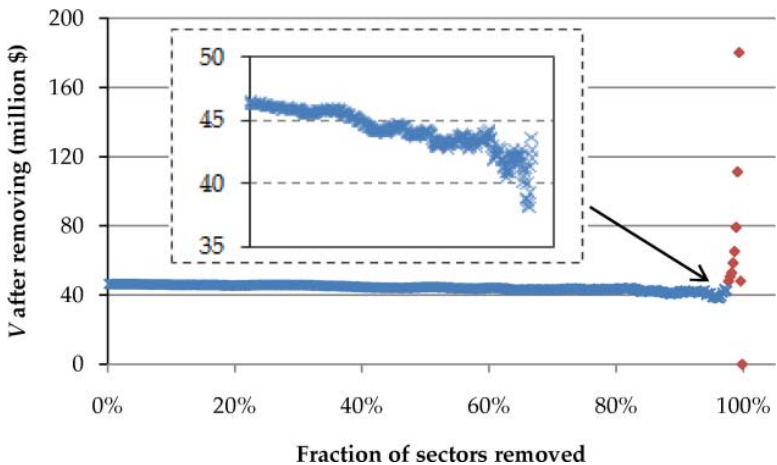


Fig. 14. Average SSC value (V) after randomly removing sectors in the Monte Carlo simulation. The inset shows the change of V for removing sectors until 11 remain.

as 97% of the sectors can only reduce the average SSC value by less than 8.4%. The fewer the sectors remaining, the greater the possibility that an individual SSC with a large embodied value could dominate the value of V which could increase by as much as 287% (red dots in Fig. 14). Despite this irregular increase when few sectors remain, the result reveals that redundant linkages among sectors are not trivial, as the economy can always find alternative routes to connect sectors without sacrificing significant loss on SSC values. In other words, in the U.S. economy, sectors' upstream inputs and downstream outputs are well diversified so that alternative suppliers and/or demanders always exist, even if the most important ones face severe downturn. As a comparison, Albert *et al.* [32] studied the connectivity of the random network, measured by its average length of the shortest paths between any two nodes, by intentionally and randomly removing its nodes. The result showed a linear relationship between the decreasing network connectivity and increasing portion of removed nodes, implying that nodes in the random network are homogeneous. Although metrics used in this research are different from the measure used by Albert *et al.* [32], Figs. 13 and 14 clearly show sectors in the U.S. economy are far from homogeneity and the economy network itself is far from random. It must be remembered that this conclusion is valid at the level of sectors, not necessarily in situations where a critical bottleneck in an important technology exists (say, where there is only one plant producing chips required in a number of electronic products).

5. Similarity

The economy's resilience benefits from diversified interconnectedness and redundant links, which act as alternatives for maximizing economic values embodied in intersectoral transactions. Similarly, can sectors replace each other during meltdowns in particular industries to keep the economy functional? If two sectors receive inputs from similar upstream sectors and provide outputs to similar downstream sectors, it implies that they require similar technology, infrastructure, resources, market, or combinations thereof. Thus it is relatively easy for them to produce products or provide services originally specialized by the other sector. Using this conceptual notion, we introduce the measure of similarity between two sectors. In particular, the supply similarity of two sectors is defined as,

$$ss_{ij} = ss_{ji} = \sqrt{\frac{1}{n} \sum_{k=1}^n (a_{ki} - a_{kj})^2}, \quad (4)$$

while the demand similarity is defined as,

$$ds_{ij} = ds_{ji} = \sqrt{\frac{1}{n} \sum_{k=1}^n \left(\frac{x_{ik}}{X_i} - \frac{x_{jk}}{X_j} \right)^2}. \quad (5)$$

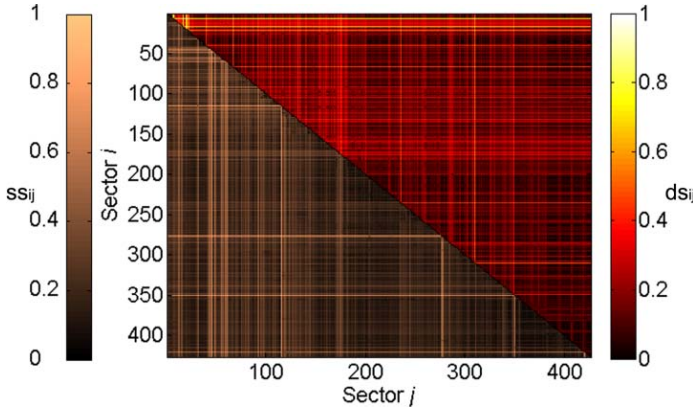


Fig. 15. (Color online) Matrix of supply similarity (left) and demand similarity (right) normalized between 0 and 1.

Supply similarity and demand similarity measure how similar two sectors are in terms of receiving inputs from upstream sectors and providing outputs to downstream sectors, respectively. The lower the similarities are, the more similar the two sectors are. In other words, it is more likely for similar sectors to be able to take over each other’s responsibility in the economy by receiving other sectors’ products/services (supply similarity) or providing products/services for other sectors (demand similarity). Figure 15 illustrates the matrix of ss_{ij} and ds_{ij} normalized between 0 and 1. Bright color represents sectors relatively different from each other, while dark color indicates sectors that are relatively similar to each other. Figure 15 shows a textured surface composed by bright lines with dark background. In general, bright lines imply that the corresponding sectors are dissimilar from most of the other sectors in either supply or demand.

To compare sectors’ overall similarity with other sectors, we define a sector’s average supply similarity as

$$SS_i = \frac{1}{n} \sum_{j=1}^n ss_{ij}. \tag{6}$$

Sectors ranking top in SS_i are those requiring specific supplies from upstream sectors, such as *petroleum refineries, soybean and other oilseed processing, funds, trusts and other financial vehicles*, etc. On the other hand, sectors providing general services to the whole economy have fewer SS_i , such as *wholesale trade, commercial and industrial machinery and equipment repair and maintenance, amusement parks, arcades and gambling industries*, etc. Similarly, average demand similarity is defined as

$$DS_i = \frac{1}{n} \sum_{j=1}^n ds_{ij}. \tag{7}$$

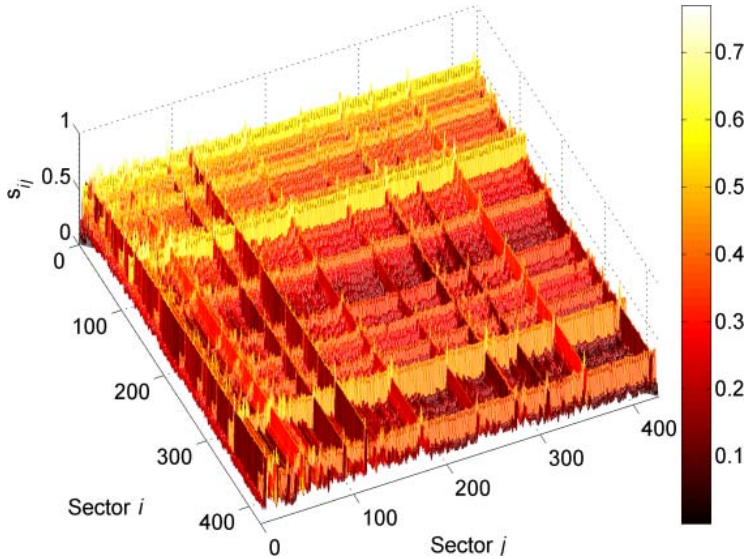


Fig. 16. (Color online) Matrix of similarity S_{ij} .

Sectors ranking top in DS_i generally require specialized downstream processing, such as *tobacco farming*, *fishing*, *oil and gas extraction*, and so on. Sectors ranking bottom in DS_i are those providing products or services to a wide range of industries, such as *automotive repair and maintenance*, *primary battery manufacturing*, *food services and drinking places*, etc.

Finally, we combine the two measures together to provide an overall measure for sectors' similarity with each other, taking both inputs and outputs into account. Formally, a sector's similarity is defined as

$$s_{ij} = s_{ji} = \sqrt{\frac{1}{2}(\overline{\overline{ss}}_{ij} + \overline{\overline{ds}}_{ij})}, \quad (8)$$

where $\overline{\overline{ss}}_{ij}$ and $\overline{\overline{ds}}_{ij}$ are ss_{ij} and ds_{ij} normalized between 0 and 1. Figure 16 illustrates the matrix of similarity in a symmetric way. Bright color represents higher s_{ij} indicating sectors are not similar with each other. Interestingly, there are several sectors which are not similar with most sectors in the economy, illustrated by the wall-like structure in Fig. 16. These sectors either require specific upstream inputs, such as *petroleum refineries*, *soybean and other oilseed processing*, or *leather and hide tanning and finishing*, or provide specialized products or services to downstream sectors, such as *tobacco farming*, *fishing*, or *oil and gas extraction*.

6. Uncertainty

The inherent uncertainties of the EIO data include aggregation, time-lag, and homogeneity of products. Although detailed uncertainty analysis from these aspects is rarely done primarily due to lack of information within EIO tables, theoretical

analysis on uncertainties has been extensively discussed [33]. For this research in particular, first, more disaggregated data would provide more insights on the complexity of the economy. On the other hand, more aggregated data would reduce the accuracy of the result and eventually the usefulness of this study when randomness becomes significantly large (e.g. the red outliers in Fig. 14). In other words, the more aggregated the data are, the less appropriate the network approach becomes for studying a national economy. Second, the EIO data essentially treat sectors as functionally equivalent in the way that the uniqueness of the function a sector specializes is not recognized. As a result, the network representation fails to characterize the potential importance of a particular sector whose economic output is relatively trivial but whose function is critical to a particular supply chain. For example, a small chip in a computer might have trivial value in the whole supply chain but the computer would not work without it. However, this study uses the heterogeneity of a sector's upstream inputs and downstream outputs as proximity for its functional heterogeneity. The result shows that sectors are almost equally important for the whole economy (Figs. 13 and 14). Last but not least, this study only considers domestic transactions among sectors, but not taking into account international trade. Indeed, as an open economy, the U.S. receives significant amount of products/services (e.g. manufactured products) from other countries and provides products/services to other countries. Although this study does not capture the effect of international trade, it clearly is a promising direction for future research.

7. Conclusion

The economic crisis of 2008 has instigated a great deal of research intended to reveal the causes and consequences of the crisis by using macroeconomic [34, 35], financial [36], and cultural [37] arguments. While also inspired by similar questions, this study seeks to understand how the economy works from a more systematic point of view by examining the interconnectedness of economic sectors utilizing macroeconomic data. The detailed network structure derived from EIO data and shown here strongly suggests that sectors, categorized by specialties in providing products/services, play very different roles in forming inter-sectoral connections within the economy. Critical sectors, such as *management of companies and enterprises*, *wholesale trade*, *real estate*, *oil and gas extraction*, *petroleum refineries*, and *motor vehicle parts manufacturing*, and a variety of financial sectors, are seemingly more important to the economy than others as they are closer to the center of the clusters in the economy network. However, when it comes to resilience of the economy as a whole, all sectors play non-trivial, if uneven, roles by facilitating alternative input-output routes in case of crisis in single or multiple sectors.

These findings have implications for economic policy because they suggest that incentives to promote development in, and stabilize, sectors located near the center of the economy network may be more important and effective in maintaining economic resilience than more general policies aimed at the economy as a whole. Yet the model also warns against overly favoring sectors, near the center or not, in the

allocation of scarce resources. Although there are critical sectors, this is balanced by the role that all sectors play in the resilience and stability of the underlying network structure that characterizes highly developed economies; diversity in specializations is the truly important characteristic when it comes to resilience of the economy.

In addition, this use of network theory illustrates more broadly the principle that looking at complex systems from a variety of perspectives, including very different kinds of models, often reveals more than reliance on any particular model alone. In this case, the translation of EIO architecture and data into a network model provides a new perspective on economic structure, with policy ramifications that previously may only have been vaguely and intuitively understood. For example, saving large automobile companies where were at risk in the economic downturn in the U.S. appears to have been justified by the critical role of automobile parts manufacturing which emerges from this analysis.

Finally, we see this study as developing a novel analytical framework to understand the interconnectedness within an economic system. Building upon this framework, we anticipate future research in two main directions. On one hand, comparative studies utilizing either historical EIO data for the U.S. or EIO data for other economies would be useful to analytically understand how the economic system has been evolving or functioning differently in different countries from the network perspective. On the other hand, it would also be interesting to study a particular sector or industry by mapping its whole supply chain using the network representation. By doing this, one could identify critical input–output relationships for the sector or industry under study and discuss policy implications. This is particularly important for sectors or industries which are essential for sustainability (e.g. the energy sector or the automobile industry).

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Appendix A. Economic Input–Output (EIO) Model

Each row of the EIO table (Table 1) represents the output of the corresponding sector in the way that the sum of intermediate output and final demand is equal to the total output. That is,

$$\sum_{j=1}^n X_{ij} + Y_i = X_i. \quad (\text{A.1})$$

Each column represents the input of the sector in the way that the sum of intermediate input and value-added equals the total input. That is,

$$\sum_{i=1}^n X_{ij} + V_j = X_j. \quad (\text{A.2})$$

Define a_{ij} as the proportion of input of sector i to the total output of sector j . That is,

$$a_{ij} = \frac{x_{ij}}{X_j}. \quad (\text{A.3})$$

Let X denotes the vector of total output, Y denotes the vector of final demand, and A represent the $n \times n$ matrix of $\{a_{ij}\}$ which is known as technical coefficient matrix or direct requirement coefficient matrix. Therefore,

$$AX + Y = X. \quad (\text{A.4})$$

Rearrange it,

$$X = (I - A)^{-1}Y, \quad (\text{A.5})$$

where I denotes the $n \times n$ identity matrix. The matrix $(I - A)^{-1}$ is known as the Leontief inverse matrix or the total requirement coefficient matrix. It represents the total, including direct and indirect, requirements for products in all sectors caused by unitary changes of final demand. Details about the EIO model and its extensions can be found in reputable publications (e.g. [21]).

Appendix B. 2002 U.S. EIO Account

In the U.S., the Bureau of Economic Analysis (BEA) has been publishing national benchmark EIO accounts at the detailed level (around 500 sectors) according to the Standard Industry Classification (SIC) codes in each five years since 1967. The emerging industries that are beyond the scope of SIC system are included in BEA's national EIO accounts after 1999 by adopting the North American Industry Classification System (NAICS) which is updated every five years to reflect the changes in the composition of the economy. This research utilizes the 2002 U.S. benchmark EIO account, which is the most recent data released and contains 426 sectors. The classification of the U.S. sectors can be found from the website: <http://sitemaker.umich.edu/mingxu/eio/>.

Appendix C. Network Visualization of the U.S. Economy

Figure 2 shows the “skeleton” of the economy network by keeping the strongest input link of each sector while discarding all other links. In other words, for each sector j , its link with sector k can be kept if and only if $x_{kj} = \max\{X_{ij}\}$. This abstracted network has 426 nodes and 425 links. To appropriately generate a network visualization, important links in the economy should be identified. The important links are defined as those links whose representing dependency coefficients are

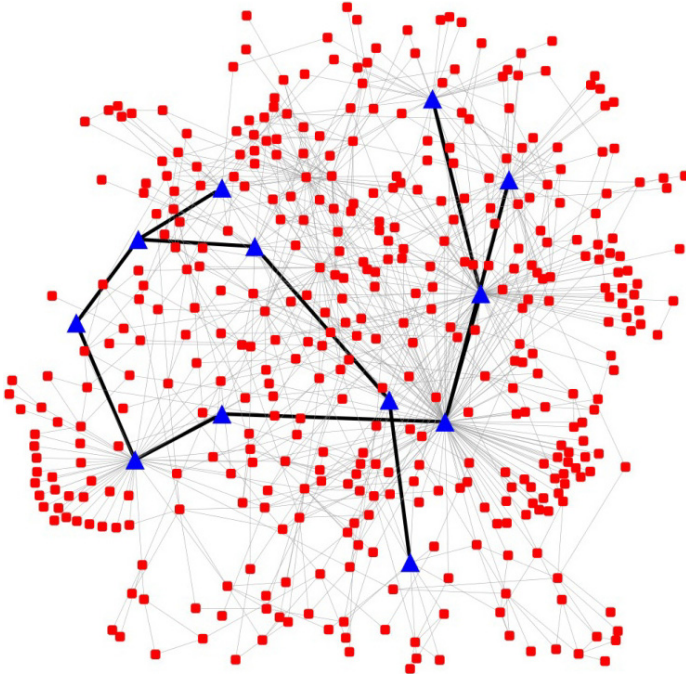


Fig. A.1. (Color online) Network structure of the U.S. economy with $d_m = 0.0945$. Blue triangles and dark links connecting them indicate the backbone of the network.

higher than a threshold d_m . As a rule of thumb, an average degree of 4 gives a good network visualization, which is equivalent to the number of links is twice the number of nodes. In this case, the number of links should be around 850 in order to generate a good network visualization. When $d_m = 0.0945$, the number of links in this abstracted network is 852 which is able to provide a good network visualization. Figure A.1 shows this network structure of the U.S. economy. The layout is determined by a spring embedded algorithm. In particular, nodes are treated as physical objects repel each other such as electrons. Links are treated as metal springs connecting nodes. These springs attract their end nodes according to a force function. The layout is determined by minimizing the sum of forces in the network. Based on that, the final network visualization is generated by painting nodes and links according to their characteristics and economic performances.

References

- [1] Watts, D. J. and Strogatz, S. H., Collective dynamics of “small-world” networks, *Nature* **393** (1998) 440.
- [2] Barabási, A.-L. and Albert, R., Emergence of scaling in random networks, *Science* **286** (1999) 509.
- [3] Newman, M. E. J., Barabási, A.-L. and Watts, D. J., *The Structure and Dynamics of Networks* (Princeton University Press, Princeton, 2006).

- [4] Caldarelli, G., *Scale-Free Networks: Complex Webs in Nature and Technology* (Oxford University Press, New York, 2007).
- [5] Schweitzer, F., Fagiolo, G., Sornette, D., Vega-Redondo, F., Vespignani, A. and White, R. D., Economic networks: The new challenges, *Science* **325** (2009) 422.
- [6] Schweitzer, F., Fagiolo, G., Sornette, D., Vega-Redondo, F. and White, D. R., Economic networks: What do we know and what do we need to know? *Adv. Complex Syst.* **12** (2009) 407.
- [7] Eagle, N., Macy, M. and Claxton, R., Network diversity and economic development, *Science* **328** (2010) 1029.
- [8] May, R. M., Levin, S. A. and Sugihara, G., Complex systems: Ecology for banks, *Nature* **451** (2008) 893.
- [9] Arthur, W. B., Complexity and the economy, *Science* **284** (1999) 107.
- [10] Matutinović, I., Organizational patterns of economies: An ecological perspective, *Ecol. Econ.* **40** (2002) 421.
- [11] Foster, J., From simplistic to complex systems in economics, *Cambridge J. Econ.* **29** (2005) 873.
- [12] Samuelson, L., Perspectives on the economy as an evolving complex system, in *The Economy as an Evolving Complex System, III: Current Perspectives and Future Directions*, Blume, L. E. and Durlauf, S. N. (eds.) (Oxford University Press, New York, 2006).
- [13] Snyder, D. and Kick, E. L., Structural position in the world system and economic growth, 1955–1970, *Am. J. Sociol.* **84** (1979) 1096.
- [14] Smith, D. A. and White, D. R., Structure and dynamics of the global economy: Network analysis of international trade 1965–1980, *Soc. Forces* **70** (1992) 857.
- [15] Hidalgo, C. A., Klinger, B., Barabási, A.-L. and Hausmann, R., The product space conditions the development of nations, *Science* **317** (2007) 482.
- [16] Hidalgo, C. A. and Hausmann, R., The building blocks of economic complexity, *Proc. Natl. Acad. Sci.* **106** (2009) 10570.
- [17] Benson, J. K., Interorganization network as a political economy, *Admin. Sci. Quart.* **20** (1975) 229.
- [18] Achrol, R. S. and Kotler, P., Marketing in the network economy, *J. Marketing* **63** (1999) 146.
- [19] Kirman, A., The economy as an evolving network, *J. Evol. Econ.* **7** (1997) 339.
- [20] Leontief, W. W., *Input-Output Economics* (Oxford University Press, New York, 1986).
- [21] Miller, R. E. and Blair, P. D., *Input-Output Analysis: Foundations and Extensions*, 2nd edn. (Cambridge University Press, New York, 2009).
- [22] Warner, M. and Liu, Z.-L., The importance of child care in economic development: A comparative analysis in regional economic linkage, *Econ. Dev. Q.* **20** (2006) 97.
- [23] Ghertner, D. A. and Fripp, M., Trading away damage: Quantifying environmental leakage through consumption-based life-cycle analysis, *Ecol. Econ.* **63** (2007) 563.
- [24] SEC, *Standard Industrial Classification (SIC) Code List*, <http://www.sec.gov/info/edgar/siccodes.htm> (U.S. Securities and Exchange Commission, Washington, DC, 2008).
- [25] BEA, *Benchmark Input-Output Accounts*, <http://www.bea.gov/industry/index.htm> (Bureau of Economic Analysis, Washington, DC, 2010).
- [26] OMB, *North American Industry Classification System: United States, 2007* (Office of Management and Budget, Washington, DC, 2007).
- [27] BEA, *2002 Benchmark Input-Output Data*, http://www.bea.gov/industry/io_benchmark.htm#2002data (Bureau of Economic Analysis, Washington, DC, 2008).

- [28] Albert, R. and Barabási, A.-L., Statistical mechanics of complex networks, *Rev. Mod. Phys.* **74** (2002) 47.
- [29] Fisher, E. O'N. and Vega-Redondo, F., The linchpins of a modern economy, *Proceedings of the 2007 American Economic Association Annual Meeting* (Chicago, IL, January 5–7, 2007).
- [30] Blöchl, F., Theis, F. J., Vega-Redondo, F. and Fisher, E. O'N., Vertex centralities in input–output networks reveal the structure of modern economies, *Phys. Rev. E* **83** (2011) 046127.
- [31] Allenby, B. and Fink, J., Toward inherently secure and resilient societies, *Science* **309** (2005) 1034.
- [32] Albert, R., Jeong, H. and Barabási, A.-L., Error and attach tolerance of complex networks, *Nature* **406** (2000) 378.
- [33] Lenzen, M., Errors in conventional and input–output based life-cycle inventories, *J. Ind. Ecol.* **4** (2000) 127.
- [34] Adam, C. and Vines, D., Remaking macroeconomic policy after the global financial crisis: A balance-sheet approach, *Oxford Rev. Econ. Pol.* **25** (2009) 507.
- [35] McKibbin, W. J. and Stoeckel, A., Modeling the global financial crisis, *Oxford Rev. Econ. Pol.* **25** (2009) 581.
- [36] Fatas, A. and Mihov, I., Why fiscal stimulus is likely to work, *Int. Finance* **12** (2009) 57.
- [37] Hayward, M., The economic crisis and after, *Cult. Stud.* **24** (2010) 283.