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Scaling of global input–output networks

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HIGHLIGHTS

- Four distributions can better describe scaling patterns of input–output networks.
- Global input–output networks do not follow power law distributions.
- Dataset choice has limited impacts on the observed scaling patterns.

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ABSTRACT

Examining scaling patterns of networks can help understand how structural features relate to the behavior of the networks. Input–output networks consist of industries as nodes and inter-industrial exchanges of products as links. Previous studies consider limited measures for node strengths and link weights, and also ignore the impact of dataset choice. We consider a comprehensive set of indicators in this study that are important in economic analysis, and also examine the impact of dataset choice, by studying input–output networks in individual countries and the entire world. Results show that Burr, Log-Logistic, Log-normal, and Weibull distributions can better describe scaling patterns of global input–output networks. We also find that dataset choice has limited impacts on the observed scaling patterns. Our findings can help examine the quality of economic statistics, estimate missing data in economic statistics, and identify key nodes and links in input–output networks to support economic policymaking.

1. Introduction

An economy comprises industrial activities (called industries in this study) exchanging goods and services with each other. An industry (or sector) uses products from other industries as inputs to produce products consumed by other industries and final consumers (e.g., households and government), as described by the System of National Accounts (SNA) [1]. In a real-world economy, an industry may be densely connected through the exchange of products with particular industries,

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but weakly connected with others. Such interactions among industries, often referred as industrial interdependence or inter-industrial linkage [2–4], represent the structure of an economy [2].

Economies are networks in the sense that industries as nodes are linked with the exchanges of products between industries [5–10]. As the structure of a network often determines its functions [11], examining the network structure of economies can help better understand the workings and evolution of the economies at the industry level. In particular, how does an IO network change over time? What do different IO networks have in common? Does the choice of datasets matter? These are important questions to be answered in order to reveal the structural patterns of economic networks [12].

In this study we model economies as input–output networks using economic input–output (IO) models [9,13]. We focus on scaling patterns of IO networks, which means the distribution patterns of indicators measuring nodes and links in a network [14]. Examining scaling patterns of IO networks can reveal patterns shared by economies [7] and provide targets for statistical models [7] (e.g., missing link prediction models and data quality examination models). Previous studies have examined scaling patterns of a variety of networks, including World Wide Web [14–16], actor collaboration networks [14], power grid [14], brain functional networks [17], neuronal avalanches [18], and social networks [19]. Specifically, several studies examined scaling patterns of IO networks in order to identify common structural features shared across economies. McNerney et al. [7] found that link weights measured by intermediate economic flows of individual countries follow the Weibull distribution, and node strengths measured by industrial economic outputs follow the exponential distribution. Cerina et al. [6] found that the weights of links in the global economy follow the Log-normal distribution. Despite these limited studies, there are still three research gaps to be filled.

First, previous studies use intermediate flows (i.e., the value of exchanged products between industries in a given year) to measure the weights of links [6,7]. Industrial interdependence of an IO network, however, can be more than just the direct exchanges of products [2–4]. For example, a supply chain between two nodes shows a path starting from one node, passing through certain intermediate nodes, and ending at the other node. Thus, two nodes of an IO network are interdependent through not only directly exchanged products but also supply chains. Such supply chain-based interdependence is equally important to economic analysis as direct exchanges of products.

Second, existing studies use industrial total outputs to measure nodes of an IO network [7]. There are other indicators popularly used in economic studies to measure nodes (e.g., industrial final demands and value added) [13]. Using those indicators as node strengths can potentially reveal additional insights on the structure of IO networks.

Third, different datasets have different region and industry resolutions (i.e., the number of regions and industries an economy is divided into) which can significantly impact the results of some economic analyses [20,21]. It is not clear whether the structure of IO networks depends on dataset choice or not. In theory, we want to identify structural properties that are shared by IO networks across a wide range of datasets.

This study addresses these research gaps on three fronts. First, we use additional commonly used indicators to measure node strengths (i.e., industrial total outputs, industrial final demands, and industrial value added) and link weights (i.e., direct requirement coefficients, total requirement coefficients, and intermediate inter-industrial flows). Second, we examine the scaling of the global IO network at both the individual country scale and the global scale. Third, we test whether dataset choice impacts the scaling of the global IO network.

2. Methods and data

2.1. Input–output (IO) networks

IO data describe an economy as a set of industries (i.e., nodes in IO networks) connected by inter-industrial product flows (i.e., links in IO networks) [13,22–24]. Fig. 1 uses a three-industry example to illustrate product flows among industries within an economy. An industry uses products from other industries for its production, and then provides its products to satisfy final demand and the production of other industries. Value added is created during the production of this industry. Final demand means the amount of products being directly consumed by final users (i.e., household consumption, government expenditure, fixed capital formation, inventory changes, and exports). Value added is the net additions to the wealth of an economy (i.e., employee compensation, depreciation of fixed assets, net tax on production, and net operating surplus).

Product flows among industries in Fig. 1 are named intermediate flows. Intermediate flows of an industry includes its intermediate inputs (i.e., product inputs from itself and other industries) and its intermediate outputs (i.e., products allocated to the production of itself and other industries).

For a particular industry, the sum of its intermediate outputs and final demand equals to its total output, and the sum of its intermediate inputs and value added equals to its total input. Moreover, an industry's total output equals to its total input.

We can get a matrix A representing *direct requirement coefficients* [13] based on industrial total outputs (defined as the output vector x representing the total output of each industry) and intermediate flows (defined as the direct requirement matrix Z representing product flows among industries), as shown in Eq. (1).

$$A = Z(\hat{x})^{-1}. \quad (1)$$

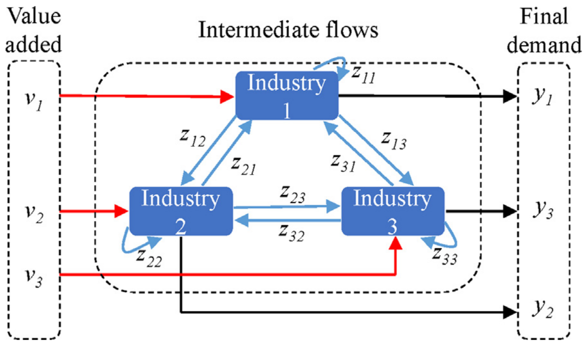

Fig. 1. Product flows among industries within a three-industry economy. Taking industry 2 for example, z_{12} means product flow from industry 1 to industry 2, z_{22} means product flow from industry 2 to itself, and z_{21} means product flow from industry 2 to industry 1. The notation v_2 means value added created by industry 2 which are primary inputs (e.g., labors and capital) for the production of industry 2, and y_2 means final demand of product from industry 2.

The element a_{ij} in matrix A represents direct product flow from industry i to produce unitary total output in industry j. The hat ˆ on x means diagonalizing the vector x.

We can express total outputs x as a function of final demands y by

$$x = (I - A)^{-1}y \tag{2}$$

where y is the final demand vector representing final demand of products produced by each industry.

The matrix $(I - A)^{-1}$ is called *total requirement coefficients* or *Leontief Inverse* matrix [13], element l_{ij} in which represents both direct and indirect inputs from industry i to produce one unit of finally consumed products in industry j. I is the identity matrix. Total requirement coefficients between two industries represent the dependence of one industry on another throughout the entire supply chains.

We use three indicators including industrial total outputs (i.e., total output vector x), industrial final demands (i.e., final demand vector y), and industrial value added (i.e., value added vector v) to measure node strengths. Three indicators including intermediate flows (i.e., direct requirement matrix Z), direct requirement coefficients (i.e., direct requirement coefficient matrix A), and total requirement coefficients (i.e., total requirement coefficient matrix L) are used to measure link weights. Distributions of these six indicators are fitted against various distribution functions, such as *Power Law* distributions [16,25–27], Log-normal distribution [6,7], and Weibull distribution [7,28]. We consider 18 types of distribution functions in total (listed in the Supporting Information (SI)) in this study to cover a wide range of possible scaling patterns.

We first calculate the frequency of each data, and then fit data values and their frequencies against various distributions.

2.2. Data sources

We use three databases in this study: the STAN Input–Output Database from the Organisation for Economic Co-operation and Development (OECD, 2006 edition) [29], the World Input–Output Database (WIOD, released in November 2013) [30,31], and the Eora database (versions v199.82 and v199.324) [32]. We use the OECD and WIOD databases for distribution fitting, and compares distribution fitting based on the Eora database with that based on the WIOD to examine the impact of dataset choice on scaling patterns. The OECD database includes only domestic IO data for isolated individual countries, while the WIOD and Eora databases provide IO data for the entire world. In particular, Eora v199.82 (Eora-original) describes each country by the original industry classifications from government statistics, while Eora v199.324 (Eora-26) aggregate the data to a unified 26-industry format (i.e., every country has the same 26 industries).

For OECD data, we use basic-price industry-by-industry IO data for domestic economic transactions of 29 individual countries. Each country is divided into 48 industries (Table S1). These IO tables are generally for the years of 1995, 2000, and 2005, with minor variations for several countries (Table S2). We convert all current-price IO data using the 2005 constant price by price indexes from OECD and World Bank databases [33,34] in order to make time-series IO data comparable. For the power law distribution fitting, because IO data for different countries are in different currencies, we convert all IO data using US Dollars (USD) by exchange rates also from OECD [35]. We use exchange rates instead of purchasing power parity in order to be consistent with compilation methods of the WIOD database [30,31].

For WIOD data, we use basic-price industry-by-industry IO data for the world economy from 1995 to 2009. WIOD covers 40 major countries/regions (i.e., 27 European Union countries and 13 other major countries/regions in the world) and the Rest of the World (RoW). Each country/region is uniformly divided into 35 industries (Table S3). Thus, WIOD data for one year include product exchanges between 1435 industries in 41 countries/regions in the world. We convert 15 sets of current-price IO data from 1995 to 2009 using the 1995 constant price by price indexes also from WIOD [30,31].

In order to examine the impact of dataset choice on scaling patterns, we compare probability density distributions of the global IO network described by WIOD, Eora-original, and Eora-26 using 2011 as the baseline year. In particular, WIOD

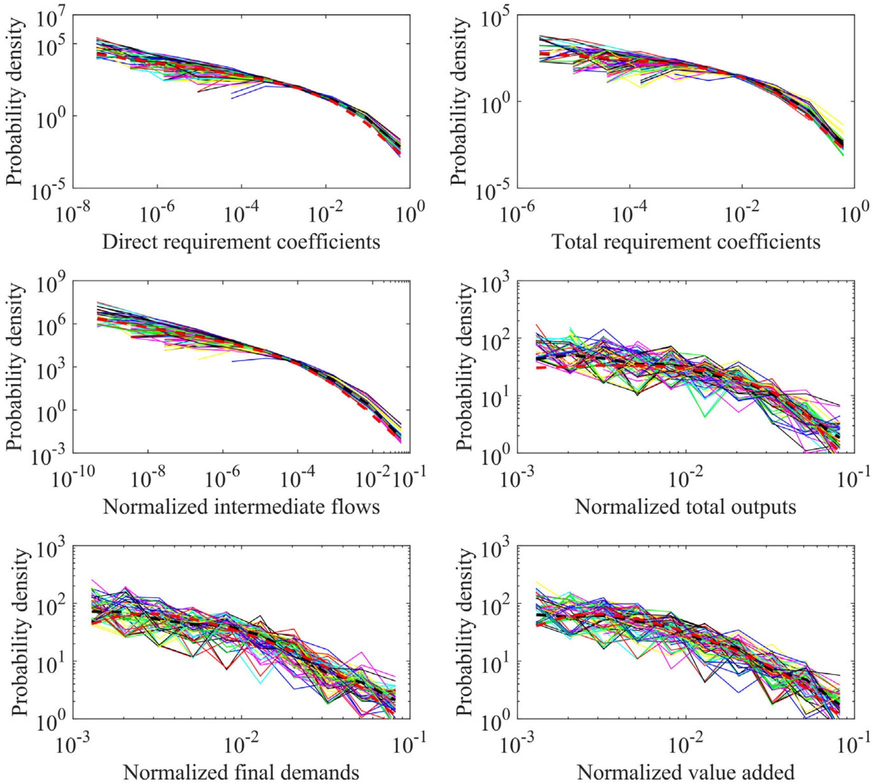

Fig. 2. Probability density distribution fits of pooled economic data for 29 individual countries from the OECD database. The black dashed line represents the pooled data, and the red dashed line represents the best-fit distribution to the pooled data. Each solid line represents a country. Intermediate flows and industrial total outputs are normalized by total through-flow of the economy which is the sum of all industrial total outputs. Industrial final demands are normalized by the sum of all industrial final demands representing total final demand of the economy. Industrial value added is normalized by the sum of all industrial value added representing gross domestic products (GDP) of the economy. As the OECD data have fewer number of links and nodes which may not be sufficient enough for deriving probability density distributions, we also plot cumulative distributions for better illustration, as shown in Figure S3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and Eora data are significantly different from each other in terms of country and industry resolutions. WIOD divides the world economy into 1435 industries in 41 countries/regions [30,31], while Eora-original and Eora-26 have 9812 industries in 190 countries/regions and 4873 industries in 187 countries/regions, respectively [21,32]. Note that the original Eora data are in the format of Supply-Use Tables (SUTs), instead of the industry-by-industry format used by OECD and WIOD data. We convert SUTs into the industry-by-industry format for Eora-original and Eora-26 according to methods of Miller and Blair [13]. Details on the conversion processes are shown in the SI.

3. Results

3.1. Distribution fitting

We calculate probability densities of node strengths and link weights. We then fit these probability densities with particular distributions according to log-likelihood. Higher log-likelihood value indicates better fit [7]. Fig. 2 shows probability density distribution fits of pooled IO data for 29 individual countries from the OECD database. Probability density distributions of node strengths and link weights are heavy-tailed and have significant curvature on the log–log axes. Distributions of different datasets are similar to one another. The best fit for link weights is the Burr distribution (Table S4). For node strengths, the best fit for industrial total outputs is the Gamma distribution, while for industrial final demand and value added it is the Birnbaum–Saunders distribution (Table S4). According to log-likelihood values in Table S4, four types of distributions are similar to one another and can be used to model probability densities of node strengths and link weights, including Burr, Log-Logistic, Log-normal, and Weibull distributions.

In particular, as data samples for three indicators for node strengths (i.e., industrial total outputs, industrial final demands, and industrial value added) are relatively small (i.e., 48 industries for each country), the fitted distributions behave worse at two ends than the middle range.

McNerney et al. compared Weibull distribution and Log-normal distribution for intermediate flows (which is *flow weight* in their study) based on the OECD database, and found that Weibull distribution performs better than Log-normal

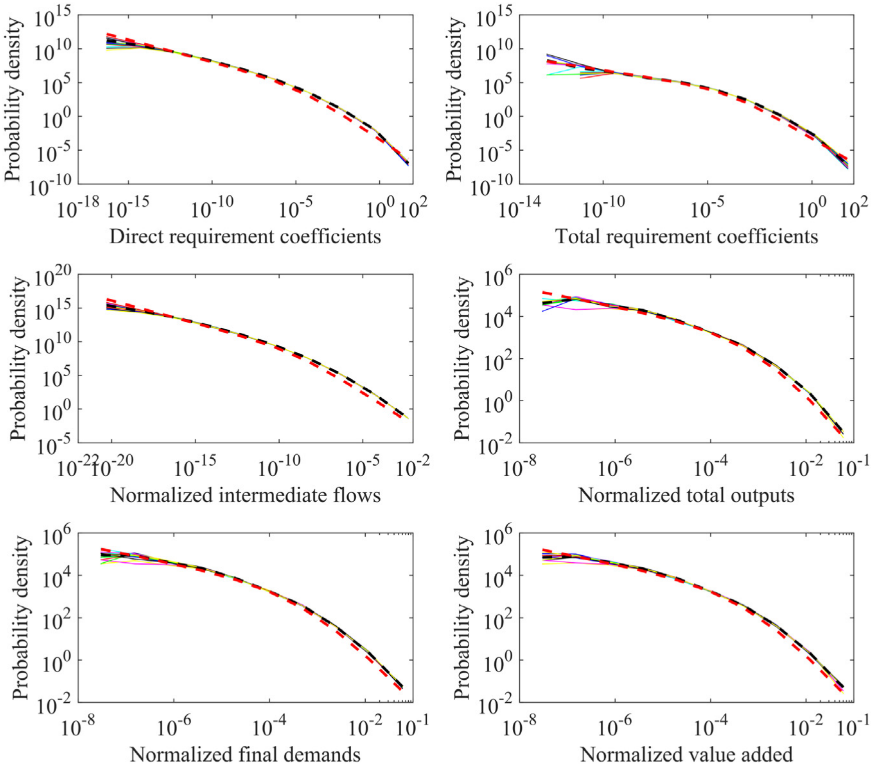

Fig. 3. Probability density distribution fits of pooled global economic data from WIOD during 1995–2009. The black dashed line represents the pooled data, and the red dashed line represents the best-fit distribution to the pooled data. Each solid line represents a country. Intermediate flows and industrial total outputs are normalized by total through-flow of the economy which is the sum of all industrial total outputs. Industrial final demands are normalized by the sum of all industrial final demands representing total final demand of the economy. Industrial value added is normalized by the sum of all industrial value added representing gross domestic products (GDP) of the economy. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

distribution for pooled data [7]. Our results agree with their findings, as Weibull distribution has larger log-likelihood value (1,087,370) than Log-normal distribution (1,085,760).

Fig. 3 shows probability density distribution fits of pooled IO data from WIOD during 1995–2009. Unlike the OECD data, WIOD considers international trade flows among countries and treats countries as parts of an integrated global economic system. Similarly, probability density distributions of node strengths and link weights are heavy-tailed and have significant curvature on the log–log axes. Distributions of different datasets are similar to one another. The best fit for probability density distributions of node strengths and link weights is Burr distribution (Table S5). Again, we find that four types of distributions are similar to one another and can be used to model probability densities of node strengths and link weights, including Burr, Log-Logistic, Log-normal, and Weibull distributions.

Figs. 2 and 3 show that nodes and links are highly heterogeneous in global economy. This calls for further investigation on different roles that nodes and links play in the global economy, which represents a useful future research avenue.

Power law distributions have been found in many real-world networks [16]. Figure S1 shows power law distribution fits of pooled IO data for 29 individual countries from the OECD database. Industrial total outputs measuring node strengths follow a power law distribution, while the other five indicators do not. Figure S2 shows power law distribution fits of pooled IO data from WIOD during 1995–2009. Direct requirement coefficients measuring link weights follow a power law distribution, while the other five indicators do not. There is no indicator following power law distributions based on both the OECD and WIOD databases. However, the observed power-law distributions for specific indicators seem to describe only ∼1% of the data. Thus, six indicators generally do not follow power law distributions. Details about the power law fitting are shown in the SI.

In general, whether for individual countries or the entire world, probability density distributions of node strengths and link weights can be approximated by Burr, Log-Logistic, Log-normal, and Weibull distributions. The global IO networks indeed show significant scaling patterns. In particular, the Log-normal distribution indicates that, for the growth of nodes (i.e., industries) and links (i.e., inter-industrial exchanges) in IO networks, their relative growth rates are independent of node strengths and link weights [36].

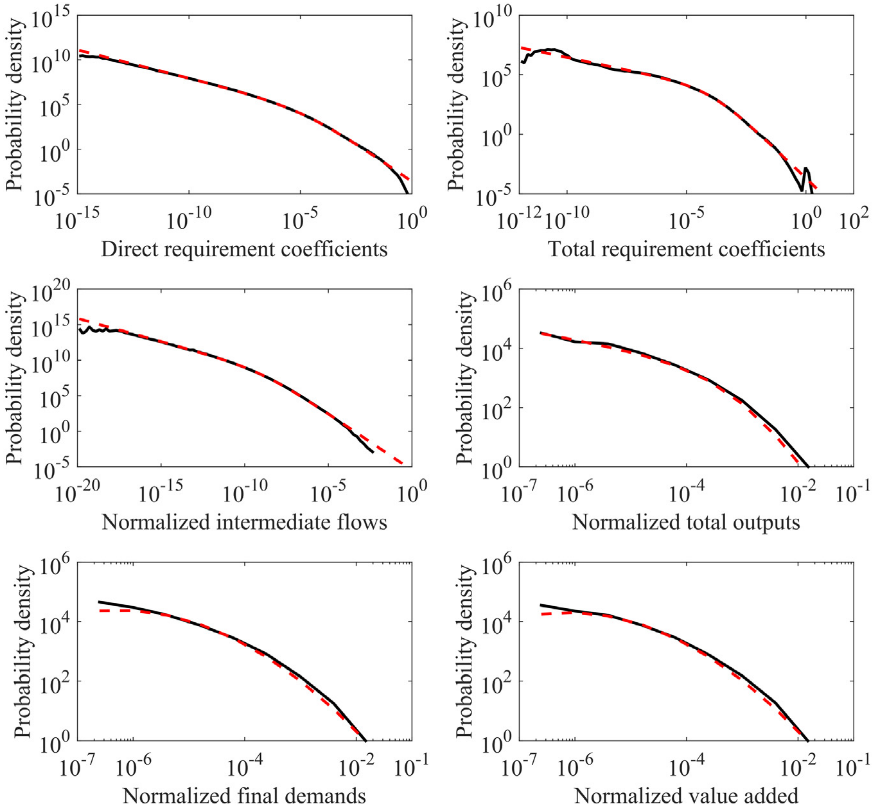

Fig. 4. Probability density distribution fits of global economic data from WIOD in 2011. The black dashed line represents the global economic data, and the red dashed line represents the best-fit distribution to the data. Intermediate flows and industrial total outputs are normalized by total through-flow of the economy which is the sum of all industrial total outputs. Industrial final demands are normalized by the sum of all industrial final demands representing total final demand of the global economy. Industrial value added is normalized by the sum of all industrial value added representing gross domestic products (GDP) of the global economy. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2. Impacts of dataset choice

We compare scaling patterns of the global economy derived from WIOD and Eora data in 2011 to examine how much impact dataset choice has on the results. Figs. 4, 5, and 6 show probability density distribution fits of IO data from WIOD, Eora-original, and Eora-26, respectively, in 2011.

For WIOD data, the best fit for probability density distributions of link weights is Burr distribution (Table S6). For node strengths, the best fit for industrial total outputs is Burr distribution, while for industrial final demands and value added it is Log-normal distribution. This is generally consistent with results shown in Fig. 3. In particular, we observe that fitted distributions for WIOD behave better for link weights than for node strengths (Fig. 4), as there are more data samples for the former.

Best fits based on the Eora data (Tables S7 and S8) are different from those based on WIOD data. For Eora-original, the best fit for direct and total requirement coefficients is Log-normal distribution, while that for the other four indicators is Burr distribution. For Eora-26, the best fit for direct and total requirement coefficients, industrial total outputs, and industrial final demands is Log-normal distribution, and that for intermediate flows and industrial value added is Burr distribution.

We also find that, according to log-likelihood values in Tables S6, S7, and S8, whether based on WIOD or Eora data (including Eora-original and Eora-26), four types of distributions (i.e., Burr, Log-Logistic, Log-normal, and Weibull distributions) are similar to one another. This indicates that dataset choice has limited impacts on the scaling pattern of the global economy.

Moreover, WIOD data performs better than Eora data for fitted distributions of link weights. Previous studies comparing WIOD and Eora data found that a main difference between these two databases is the *Leontief Inverse* (i.e., total requirement coefficients) which is calculated essentially based on intermediate flows [21]. The Eora database takes IO data for 2000 as the initial estimate and derives 2011 data based on large-scale optimization with a set of real-world constraints (e.g., the US GDP is equal to a certain value according to economic statistics) [32]. It aggregates the world into about 190 countries/regions, but only 74 countries/regions have their IO data directly obtained from statistical agencies [32]. On the other hand, WIOD estimates the 2011 world IO data based on the nearest year (which is more recent than 2000) in which IO data of more countries are available [30]. WIOD then aggregates the world into 40 countries/regions, for most of which IO data are

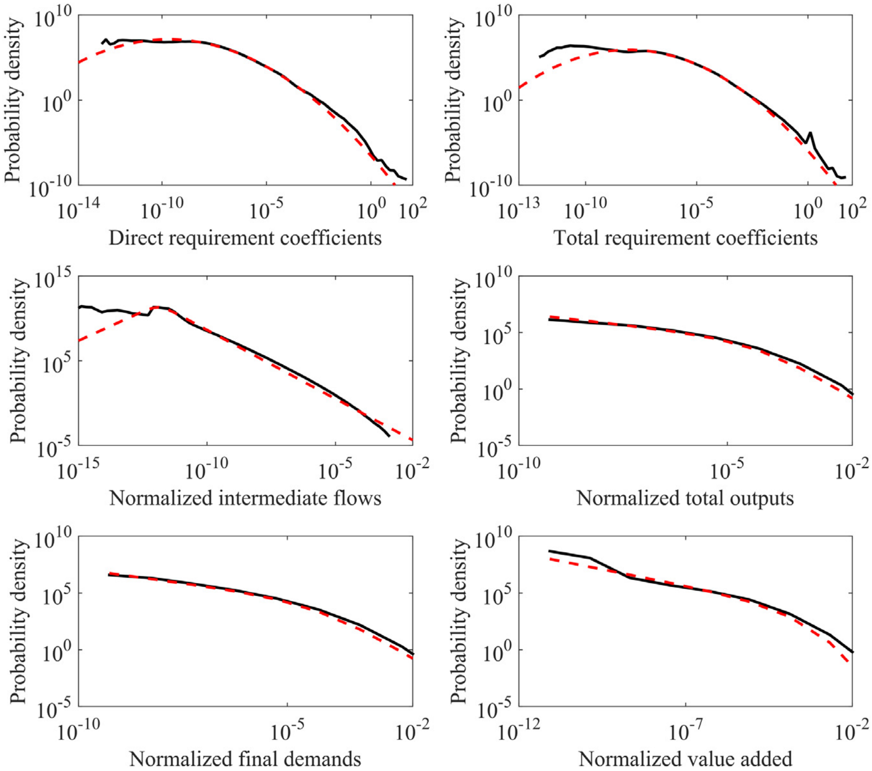

Fig. 5. Probability density distribution fits of global economic data from Eora-original in 2011. The black dashed line represents the global economic data, and the red dashed line represents the best-fit distribution to the data. Intermediate flows and industrial total outputs are normalized by total through-flow of the economy which is the sum of all industrial total outputs. Industrial final demands are normalized by the sum of all industrial final demands representing total final demand of the global economy. Industrial value added is normalized by the sum of all industrial value added representing gross domestic products (GDP) of the global economy. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

available directly from statistical agencies (e.g., National Statistical Institutes, OECD, and UN National Accounts statistics) [30,31]. Thus, it is generally expected that the quality of data for WIOD is better than that for Eora. This perhaps explains why WIOD performs better in distribution fits of link weights than Eora data.

In general, we find that dataset choice has limited impacts on the scaling pattern of the global economy, whether based on databases compiled by different organizations (i.e., WIOD versus Eora) or based on databases compiled by the same organization (i.e., Eora-original versus Eora-26). We also find that different compiling methods may result in different quality of IO data, but have limited impact on the scaling pattern of the global economy.

4. Discussion and conclusions

We examine scaling patterns of the global IO networks in this study. Probability density distributions of node strengths and link weights can be approximated by Burr, Log-Logistic, Log-normal, and Weibull distributions. We find that the best fits for probability densities of node strengths and link weights vary from different datasets. However, these four types of distributions generally perform well across all datasets. It is clear that global IO networks indeed have significant scaling patterns. Moreover, dataset choice has limited impacts on the observed scaling patterns. There are several real-world implications of this study.

First, scaling patterns of an economy are useful to examine the quality of economic statistics. Reliable economic data are the basis of economic analysis and decision-making. Our results show that four types of distributions (i.e., Burr, Log-Logistic, Log-normal, and Weibull distributions) can be used to model probability densities of node strengths and link weights of IO networks. If probability densities of certain data in economic statistics significantly diverge from these distributions, special attentions should be paid to the quality of these data. In addition, compiling economic statistics using survey-based approaches for countries and the global economy is a challenging job. As an alternative to survey-based methods, non-survey methods, e.g., gravity model [37], augmented gravity model [38], and RAS method [39], are developed to compile IO data. Assumptions and constraints of those non-survey methods produce significant uncertainties. Scaling patterns observed in this study can direct the emphases for improving the quality of non-survey data. For example, because the Eora database is probably of lower data quality than the WIOD database as discussed in the above section, distribution fitting results of the

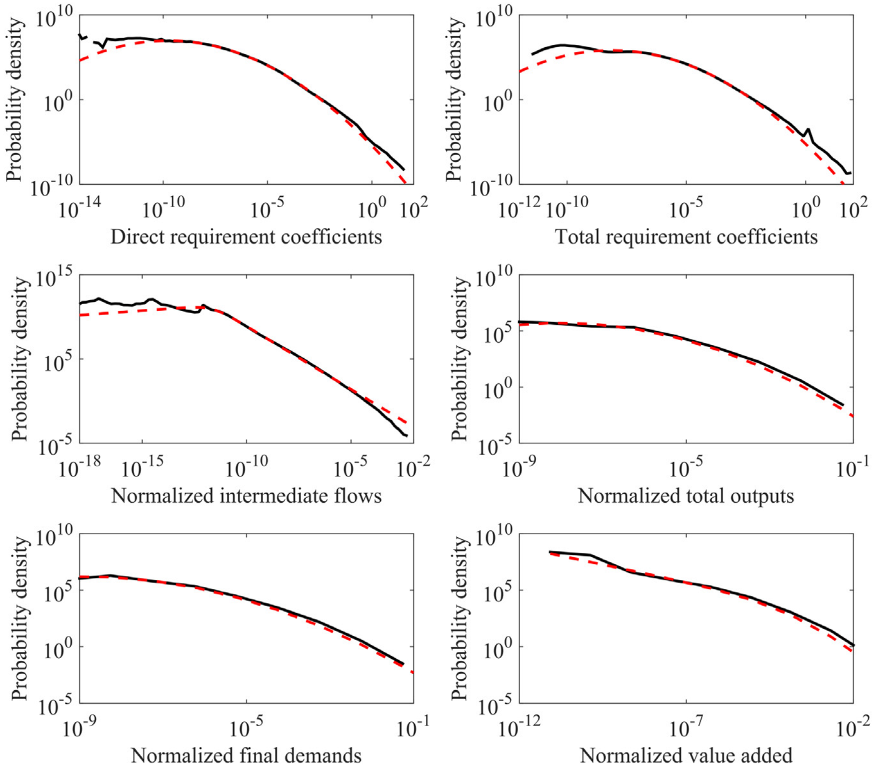

Fig. 6. Probability density distribution fits of global economic data from Eora-26 in 2011. The black dashed line represents the global economic data, and the red dashed line represents the best-fit distribution to the data. Intermediate flows and industrial total outputs are normalized by total through-flow of the economy which is the sum of all industrial total outputs. Industrial final demands are normalized by the sum of all industrial final demands representing total final demand of the global economy. Industrial value added is normalized by the sum of all industrial value added representing gross domestic products (GDP) of the global economy. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

WIOD database can be used to assist data quality improvement of the Eora database in future. Specific data points in the Eora database that are outliers of the four types of distributions (i.e., Burr, Log-Logistic, Log-normal, and Weibull distributions) should be given special attention in future database improvements.

Second, scaling patterns of an economy are useful to predict missing data in economic statistics, using observed probability density distributions as the objective or a function of missing data prediction methods (e.g., linear optimization models [40]).

Third, scaling patterns of an economy show significant heterogeneity of nodes and links in an economy. This enables further investigation on identifying key nodes and links in IO networks and providing decision support for economic policies [2,3].

This study examines scaling patterns of global IO networks based on three widely used databases (i.e., OECD, WIOD, and Eora databases). Although these three databases are compiled by different organizations and have uncertainties to different extents, we found four common distribution functions to describe probability densities of their node strengths and link weights. This in turn proves that these common patterns are relatively robust. It is interesting to incorporate more global economic datasets in future studies.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.physa.2016.01.090.

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