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Ranking the Economic Importance of Countries and Industries

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Abstract

In the current era of worldwide stock market interdependencies, the global financial village has become increasingly vulnerable to systemic collapse. The recent global financial crisis has highlighted the necessity of understanding and quantifying interdependencies among the world's economies, developing new effective approaches to risk evaluation, and providing mitigating solutions. We present a methodological framework for quantifying interdependencies in the global market and for evaluating risk levels in the world-wide financial network. The resulting information will enable policy and decision makers to better measure, understand, and maintain financial stability. We use the methodology to rank the economic importance of each industry and country according to the global damage that would result from their failure. Our quantitative results shed new light on China's increasing economic dominance over other economies, including that of the USA, to the global economy.

INTRODUCTION

The growth of technology, globalization, and urbanization has caused world-wide human social and economic activities to become increasingly interdependent [1–13]. From the recent financial crisis it is clear that components of this complex system have become increasingly susceptible to collapse. Integrated models, currently in use, have been unable to predict instability, provide scenarios for future stability, or control or even mitigate systemic failure. Thus, there is a need of new ways of quantifying complex system vulnerabilities as well as new strategies for mitigating systemic damage and increasing system resiliency [14, 15]. Achieving this would also provide new insight into such key issues as financial contagion [16, 17] and systemic risk [18–20] and would provide a way of maintaining economic and financial stability in the future.

It is clear from the recent crisis that different sectors of the economy are strongly interdependent. The housing bubble in the USA caused a liquidity freeze in the international banking system, which in turn triggered a massive slowdown of the real economy costing many trillions of dollars and threatening the financial integrity of the European Union. This demonstrates the high level of dependence between different components in the world economic system. Because strong nonlinearities and feedback loops make economic systems highly vulnerable, we need to understand the behavior of the interacting networks that comprise the economy. How do they interact with each other, and what are their vulnerabilities? One may consider an industry in two countries respectively, for example, electrical equipment industry in China and the USA, and ask which industry is more important to economic stability, electrical equipment in China or that in the USA? Is electrical equipment in China more critical for global economy stability when the production in electrical equipment in China is reduced, and how it will impact the industries within the country and industries abroad.

To answer these questions, we employ recent advances in the theory of cascading failures in interdependent networks [21–23]. In the case of interdependent networks, a malfunction of only a few components can lead to cascading failures and to a *sudden collapse* of the entire system. This is in contrast to single isolated networks, which tend to *collapse gradually* [24]. These recent results indicate the central importance of interconnectivity and interdependency to the stability of the entire system. There have been studies of the complex set

of coupled economic networks [25–28]. However, the importance of countries and industries in the stability of the global economy have not been analyzed, and there is a need for useful methods to quantify and rank their economic importance and influence.

The input-output (IO) model is a technique that quantifies interdependency in interconnected economic systems. Wassily Leontief [29] first introduced the IO model in 1951, for which he received the Nobel Prize in Economics in 1973. It can be used to study the effect of consumption shocks on interdependent economic systems [30–36]. Analysis of IO data is performed using such techniques as the hypothetical extraction method (HEM) [37, 38]. Although HEM can measure the relative stimulative importance of a given industry by calculating output with and without the industry being examined, it does not quantify each industry’s full spectrum of importance to the stability of global economic system. For example, if an industry in a given country collapses completely due to natural disaster or civil unrest it will no longer be able to consume products supplied by other industries. This can cause cascading failure in the economic system if the other industries cannot function when the cash flow from the failed industry is removed. By measuring how widely the damage spreads, we will rank here an industry’s importance within the world-wide economic system.

In this paper we examine the interdependent nature of economies between and within 14 countries and the rest of the world (ROW). We use an “input-output table” [39] and focus on economic activity during the period 1995–2011. From the table we analyze data from 14 countries (Australia, Brazil, Canada, China, Germany, Spain, France, UK, India, Italy, Japan, Korea, Russia, and USA) and from the rest of the world (ROW). The economic activity in each country is divided into 35 industrial classifications. Each cell in the table shows the output composition of each industry to all other 525 industries and its final demand and export to the rest of the world (see Ref. [40]). We construct an output network using the 525 industries as nodes and the output product values as weighted links based on the input-output table, and focus on the output product value for each industry.

Our goal is to introduce a methodology for quantifying the importance of a given industry in a given country to global economic stability with respect to other industries in countries that are related to this industry. Thus, we study the inflow and outflow of money between each set of 35 industries and the ROW in each of the 14 countries (see the Data section for more detail). We use the theory of cascading failures in interdependent networks to gain valuable information on the local and global influence on global stability of different

economic industries, a methodology that can provide valuable new insights and information to present-day policy and decision makers.

WORLD INPUT-OUTPUT TABLE DATA

The database we use in this study is the World Input-Output Table (WIOT) [40]. It provides data for 27 European countries, 13 other countries, and the rest of the world (ROW) for the period 1995–2011. For our sample, we select the 14 countries with the largest domestic input and the largest import in production in 2011 and also the ROW (adding the remaining 26 countries into the ROW). Using this sample, we construct a new input-output industry-by-industry table. For sake of simplicity, we assume that each industry produces only one unique product. In the WIOT, the column entries represent an industry’s inputs and the row entries represent an industry’s outputs. The rows in the upper sections indicate the intermediate or final use of products. A product is intermediate when it is used in the production of other products (intermediate use). The final use category includes domestic use (private or government consumption and investment) and exports. The final element in each row indicates the total use of each product. The industry columns in the WIOT contain information on the supply of each product. The columns indicate the values of all intermediate, labor, and capital inputs used in production. Total supply of the product in the economy is determined by domestic input plus final demand. The IO table contains negative numbers as outputs for various reasons [39], but their fraction is fairly small and their values are small as well. For simplicity, we set these negative numbers as zero in our analysis.

Based on the supply of the product for each industry, it is possible to construct a directed product supply network. Then we reverse the direction of the links in the network (see schematic representation in Fig. 1), and the network represents the money outflow from one industry to another; e.g., electrical equipment industry is pointing to machinery industry because electrical equipment industry buys a product from machinery industry. The links are weighted according to the value of products from machinery industry as its output electrical equipment industry as its input.

INDUSTRY TOLERANCE

In order to quantify and rank the influence of industries in the stability of this global network, we perform a cascading failure tolerance analysis [21]. Our model is described as follows. Suppose industry A fails, other industries can no longer sell their products to industry A and thus they lose that revenue. The revenue industry B is reduced by a fraction p' , which is defined as industry B's revenue reduction caused by the failure of industry A divided by that industry B's total revenue. The tolerance fraction p is the threshold above which an industry fails. This occurs when reduced revenue fraction p' is larger than tolerance fraction p . Here we assume that (i) p is the same for all industries and that every industry fails when its $p' > p$ and (ii) the failure of an industry in country A does not reduce the revenue of the other industries in the same country A because they are able to quickly adjust to the change.

The methodology can be schematically illustrated as follows: In step 1, industry A in country i fails. This causes other industries in other countries to fail if their $p' > p$. Assume that in step 2 industries B , C , and D fail. The failure of these industries in step 2 will reduce other industries' revenue and cause more industries including those in country i to have a reduced fraction p' . Thus in step 3 there is an increased number of industries whose $p' > p$. Eventually the system reaches a steady state in which no more industries fail. The surviving industries will all have a reduced revenue fraction that is smaller than the tolerance fraction, i.e., $p' \leq p$. Figure 1 demonstrates this process, and the subfigures show the steps in the cascading failure.

To determine how much the failure of each industry would impact the stability of the economic network, we change the tolerance fraction p from 0 to 1 and measure the fraction of surviving industries left in the network. When the tolerance fraction approaches 0, any revenue reduction caused by the failure of one industry can easily destroy almost all the other industries in the network, and the network will collapse. When the tolerance fraction approaches 1, all the industries can sustain a large reduction of revenue and the failure of one industry will not affect the others.

Figure 2(a) shows the failures of electrical equipment industry in China and energy industry in the United States for the 2009 WIOT and shows the fraction of the largest cluster of connected and functional industries as a function of the tolerance fraction p after

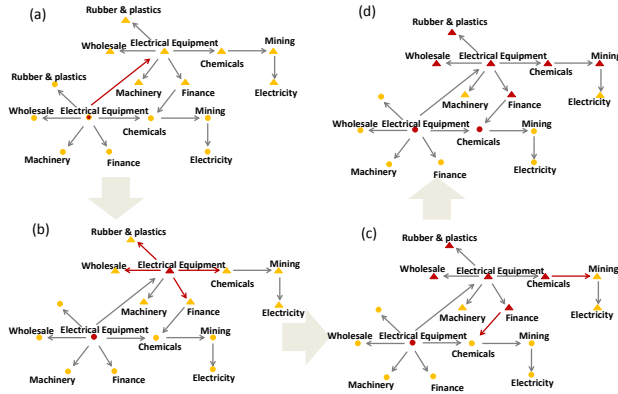


FIG. 1: Schematic representation of each step in the cascading failure propagation in the world economic network. We present an example of two countries, where circle nodes represent country 1, and triangles represent country 2. Both countries have the same industries, and the arrow between two nodes points in the direction of money flow. (a) There is a failure in electrical equipment industry in Country 1 (circle) which causes a failure of electrical equipment industry in Country 2. In (b) the failure of electrical equipment industry in Country 2 will cause rubber and plastics, wholesale, finance and chemicals in Country 2 to fail. (c) Shows mining in Country 2 and chemicals in Country 1 to fail further. (d) The network reached a steady state. The red nodes represent the failing industries and the yellow nodes stand for the surviving industries.

the Chinese electrical equipment industry becomes malfunction and is removed from the network due to a large shock to this industry. The shock could result from different causes, such as natural environmental disaster, government policy changes, insufficient financial capability. The removal of China electrical equipment industry will cause revenue reduction in other industries because China electrical equipment industry is not able to buy products and provide money to other industries. When p is small, the industries are fragile and sensitive to the revenue reduction, causing most of the industries fail, and the number of the surviving industries is very small. When p is large, the industries can tolerate large revenue reduction and are more robust when revenue decreases. The number of the surviving industries tends to increase abruptly at a certain $p = p_c$ value as p increases. Figure 2(b) shows the number of cascading steps that elapse before a stable state is reached as a function of tolerance fraction p after removing the Chinese electrical equipment industry or the USA

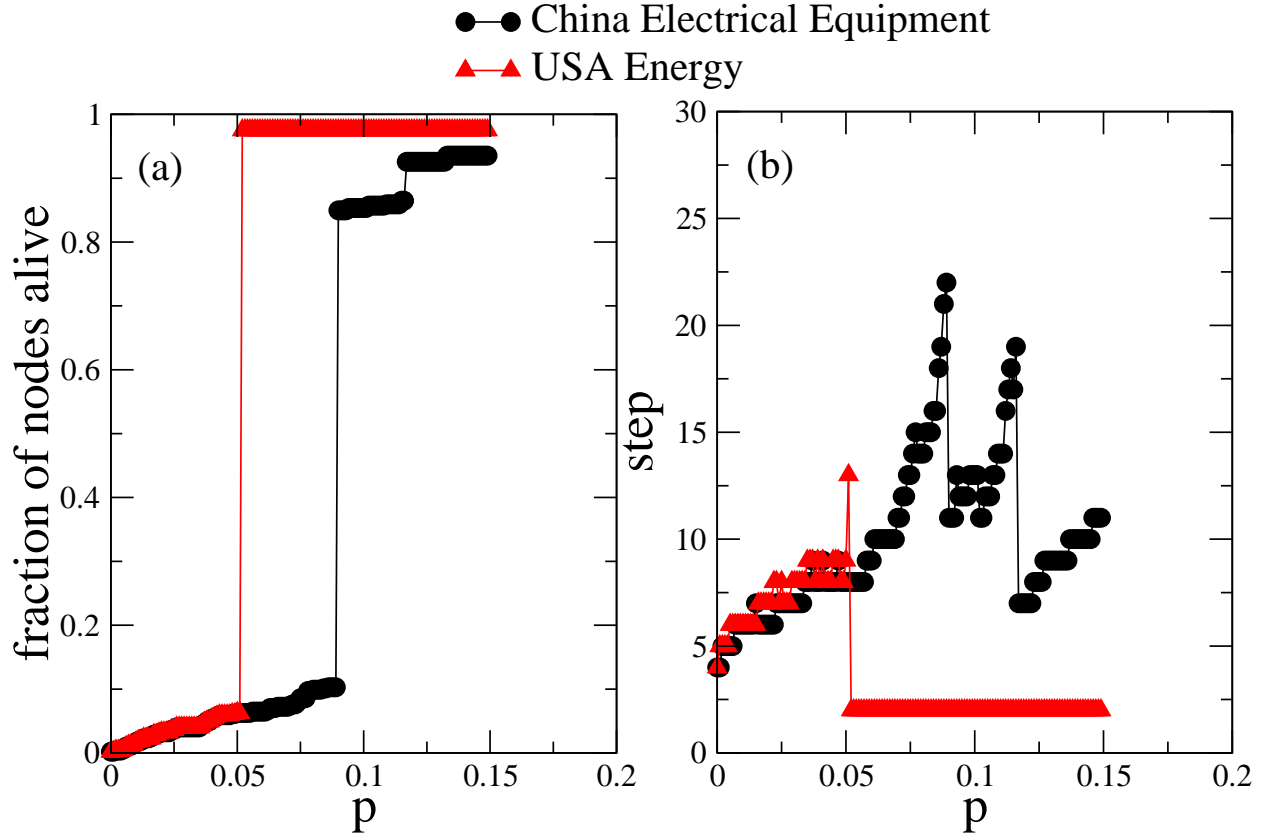


FIG. 2: Typical examples of industry tolerance threshold p_c . Tolerance threshold p_c shows the importance of each industry in the international industry networks. In (a) the black curve shows the fraction of surviving industries as a function of tolerance threshold for the case when the electrical equipment industry in China fails in year 2009 and the red curve represents the case of the failure of energy industry in 2009 in the USA. (b) Shows the number of failure steps as a function of p corresponding to (a). The total number of steps is the number of cascades it takes for the network to reach a steady state after certain initial failure. The peaks in (b) are corresponding to the abrupt jumps in (a), which means that large numbers of cascade steps are associated at p_c with a dramatic failures in the industry network. Each step in the cascading process in (b) is demonstrated in Figure 1.

energy industry. The number of steps reaches a peak when p approaches criticality p_c [24].

Here we analyze for each of the 525 industries this important parameter, the critical tolerance threshold p_c . Our goal is to determine the threshold p_c at which global network subject to collapse becomes stable and most of the industries in the network survive after initial failures. To this end, we assume that the p_c is the critical threshold below which less

than 30% of industries survive. When $p > p_c$, more than 30% of the remaining industries survive after the failure cascade in the system is over. When $p < p_c$, the survival rate of the remaining industries is 30% or less. The higher this threshold, the higher the impact of a failing industry will be on the vulnerability of the global network. Without losing generalization, we also take different fraction of surviving industries to set p_c in simulations. For example, when the p_c is the threshold below which 50% of industries survive, the importance of industries and countries maps are shown as in supplementary information. The correlation of p_c values in simulations using 50% fraction of surviving industries and 30% surviving industries is 1 and the p_c are identical in both scenarios. Thus, we find that the critical threshold p_c is not sensitive to the chosen fraction in this industry network, for values below 50%. The following p_c in this study is defined as the critical threshold below which less than 30% of industries survive.

We use this methodology to test how the failure of an individual industry in a given country impacts the stability of the entire system. Thus, p_c of an industry is our measure of the importance of this industry in the global economic network.

Using the tolerance threshold p_c , we can quantify and rank the economic importance of each industry. We measure the tolerance threshold of 35 industries in 14 countries between 1995 and 2011. We calculate the tolerance of each industry according to how much it affects the entire network, i.e., all 35 industries in all 14 countries.

IMPORTANCE OF COUNTRY AND INDUSTRY

The proposed methodology provides the means to quantify and rank the importance of each industry to the stability of the global economic network or the importance of each country in the global economic network.

We define the importance of each country by averaging all the 35 industries p_c within the country for a specific year,

$$I_{country}(i) \equiv \frac{1}{n} \sum_{k=1}^n p_c(i, k) \quad (1)$$

where n is the number of industries. To rank the importance of a given country, we average the tolerance across industries as shown in Eq. 1.

Figure 3(a) shows the importance of all countries for different years where the average in

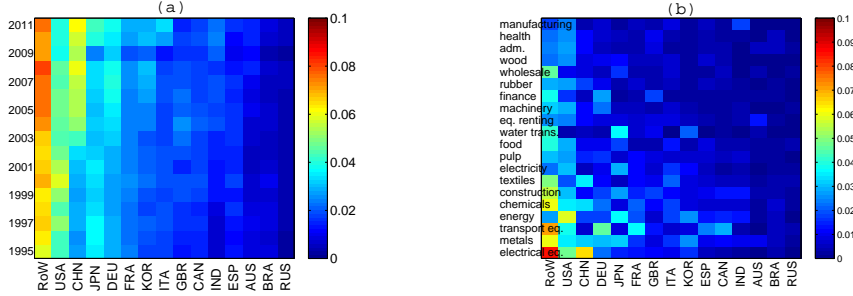


FIG. 3: Ranking the importance of individual industries or countries. (a) Map of averaging industry tolerances for each country, $I_{country}$. The average tolerance p_c is calculated by averaging the largest four p_c for each country in one year. The color represents the strength of the tolerance, ranging from blue for low tolerance, to red for high tolerance. (b) Averaging industry tolerance over 17 years (1995-2011). The average tolerance p_c is calculated by averaging the industry tolerance over 17 years for each country (for presentation sake, we plot only the top 20 industries with respect to their $I_{industry}$ value). The values are represented using the same color code.

Eq. 1 is taken over the four largest p_c values, in order to consider the strongest industries. Note that the rest of the world (RoW) is the most important "country" since it includes many countries other than the 14 countries included in the sample. Countries in RoW provide products that are crucial inputs to these 14 countries and their industries. We also define the importance of the individual industries in terms of the average of their p_c ,

$$I_{industry}(i) \equiv \frac{1}{T} \sum_{j=1}^T p_c(i, t), \quad (2)$$

where T denotes years. Figure 3(b) shows the average tolerance of industry over all years (1995-2011) for the individual countries. For the sake of clarity, we plot only the top 20 industries with respect to the average of $I_{industry}$ values for all the countries. Note that the electrical equipment industry is the most important when we average the tolerance fraction p_c across 17 years. The energy industry p_c in the United States, for example, is relatively high because the United States is the world's largest energy consumer.

ROBUSTNESS AND STABILITY OF ECONOMIC STRUCTURE

We use the critical tolerance threshold p_c to measure the importance of each industry in the global economic network. We can also rank each industry according to their tolerance $p_c(i, k)$ for each separate country—the tolerance of industry i in country k . By comparing industry order rankings for different years, we can study the similarity in economic environment across a period of 17 years.

To do this we use the Kendall τ coefficient [41], which measures rank correlation, i.e., the similarity in data orderings when ranked by each quantity. Let $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ be a set of observations of the random variables X and Y respectively. Any pair of observations (x_i) and (y_i) is concordant if the ranks for both elements agree, that is if $x_i < x_j$ and $y_i < y_j$ or if $x_i > x_j$ and $y_i > y_j$. Otherwise the pair is discordant. If $x_i = x_j$ or $y_i = y_j$, the pair is neither concordant nor discordant. The Kendall τ coefficient is defined as

$$\tau = \frac{n_+ - n_-}{\frac{1}{2}n(n-1)}, \quad (3)$$

where n_+ is the number of concordant pairs and n_- is the number of discordant pairs. The coefficient τ is in the range $-1 \leq \tau \leq 1$. When the agreement between the two rankings is perfect, the coefficient is 1. When the disagreement between the two rankings is perfect, the coefficient is -1 . If X and Y are independent, the coefficient is approximately zero.

We use the Kendall τ to investigate the evolution of the economic structure of each country in our sample. For each year, we rank the industries in each country according to their tolerance values, and calculate the Kendall τ for every year pair. Figure 4 shows the values of the Kendall τ for all pairs of years, for China (Fig. 4(a)), USA (Fig. 4(b)), and Germany (Fig.4(c)), using a color code ranging from blue, for low similarity, to red, for high similarity (see Supplementary Information for all other countries). For these three countries, we find different behaviors in terms of the stability and consistency of the economic structures. For the case of China, we observe that the structure changes significantly, with high values of the Kendal correlation (represented using red) only presenting for previous 2~3 years (as can be observed from the diagonal of elements of Fig. 4(a)). However, in the case of the USA, it is possible to observe three periods in terms of stability of the economic structure: 1995-1999, 2000-2007, and 2008-2011 (see Fig. 4(b)). The first marks the period leading to the "dot.com" crisis, which was followed by a significant change in the

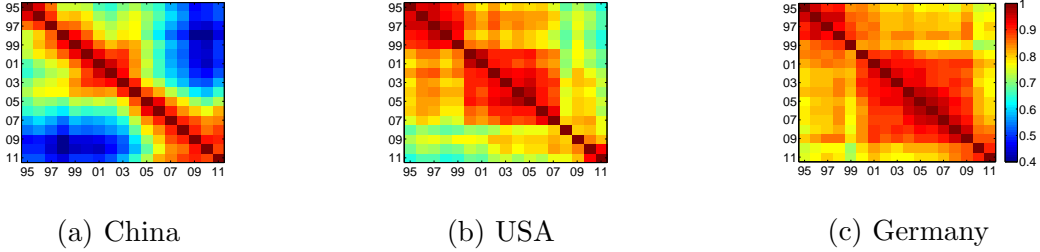


FIG. 4: Kendall correlation coefficient heat map shows the industry rank correlation coefficient between each pair of years from 1995 – 2011. Using Kendall correlation coefficient τ , we investigate the evolution of the economic structure of the investigated countries. For each year, we rank the industries in each country according to their tolerance values, and then calculate the Kendall τ for every pairs of years. We plot the values of the Kendall τ for all pairs of years, for China (top), USA (middle), and Germany (bottom), using a color code ranging from blue, for low similarity, to red, for high similarity (see Supplementary Information for all other countries).

US market structure. The second marks the period leading unto the financial crisis, which again was followed by a significant change in the US market structure. Finally, the third marks the period following the financial crisis, which shows no stable period in terms of market structure. Finally, in the case of Germany, we observe only two periods: 1995-1999, and 2000-2011 (see Fig. 4(c)). The first period can be also attributed to that apparent in the case of the USA, however possibly to a lesser extent and also resulting from the introduction of the Euro currency. However, in the case of Germany we do not observe a change in structure following the recent financial crisis, which highlights the degree of stability in the German economy.

THE RISE OF CHINA

Due to the fact that economic influence is dynamic across time, we ask whether the methodology presented here can provide new information on the increase or decline of economic importance. In each year we calculate the individual industry tolerance as described above. We then calculate the average tolerance of each country for a given year. Figure 5 shows the average of p_c of country for the 17-year period investigated. In Figure 5(a), we show the largest tolerance p_c in China, the USA and Germany along 17 years. Figure 5(b)

shows the average of 4 largest industries p_c , and Figure 5(c) shows the average of 8 largest p_c in each country.

We find that the average tolerance p_c of China becomes larger than that of the USA after 2003, which is most pronounced in Figure 5(b). The USA tolerance p_c first increases from 1995 to 2000, then decreases from 2000 to 2009, with a slight increase in 2010-2011. Germany's tolerance p_c in general increase in the investigated period and shows certain fluctuations between 2000 and 2005. Note that for the USA the change across time is minor but that the economic importance of China increases significantly. The economic importance of China relative to that of the USA shows a consistent increase from year to year, illustrating how the economic power structure in the world's economy has been changing during time.

To further validate these results, we compare the total product output (see Figure 6, red triangle) and average tolerance p_c (see Figure 6, black circles) for China, USA, and Germany, as a function of time. The product output (see Figure 6, red triangle) value is the total money flow a country supplies to the other countries plus value added in the products, which also indicates its total trade impact on foreign countries. Studying Figure 6, we find that generally speaking the total outputs of the three investigated countries grows throughout time, with that of the USA and China being higher in value than that of Germany (see Figure 6, right y-axis). However, by comparing the tolerance p_c , we find three different behaviors. First, for the case of China (Figure 6(a)), we find that both the tolerance p_c and total outputs are growing in time, and observe that in the early 2000's there was a jump in the tolerance p_c , following by a sharp increase in the total output. Secondly, for the case of the USA (Figure 6(b)), we find that while the total output is increasing in time, the tolerance p_c is in a decreasing trend. Finally, for the case of Germany (Figure 6(c)), we find that while the total import is increasing in time, the tolerance p_c is rather stable with small fluctuations.

This provides further evidence into the change in influence of these three important economies - that of China is increasing, that of the US is declining, and that of Germany is rather constant across time. Comparing the total output to the tolerance p_c provides further evidence that the tolerance measurement of country's impact reveals the underlying economic evolving dependencies which is not obvious from the simple measurement of total output capability.

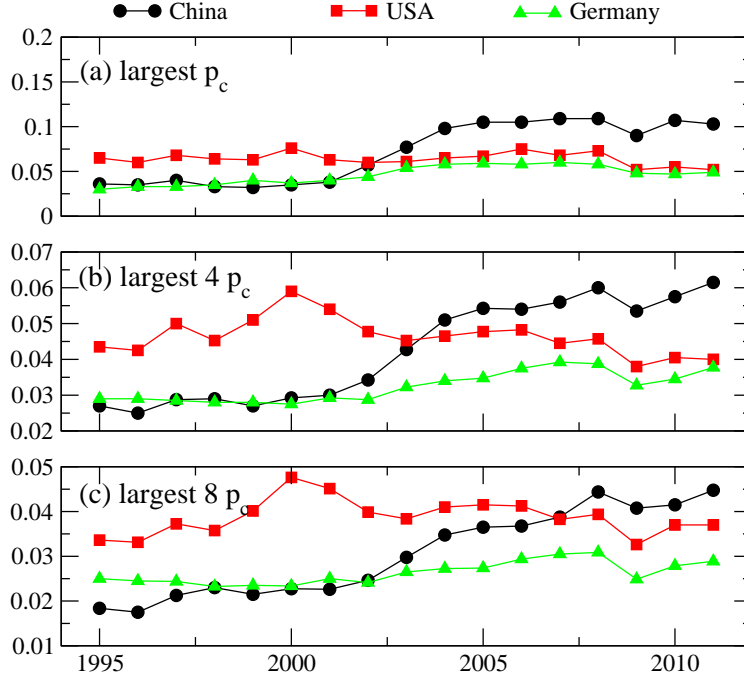


FIG. 5: Tolerance p_c changes of China, the USA and Germany for 17 years. We show that the average tolerance p_c increases from 1995 to 2011. In (a), we shows the largest tolerance p_c in China, the USA and Germany along 17 years. (b) Shows the average of 4 largest p_c in each country. We can see the p_c of China becomes larger than the USA after 2003. (c) Shows the average of 8 largest p_c in each country. The difference between the average p_c of China and that of the USA is smaller compared to that in (b) in years 2005-2011. This is because the average includes more industries with small p_c and mainly the importance of large industries increase. The USA tolerance p_c first increases from 1995 to 2000, then slightly decreases from 2000 to 2009, with a small increase in 2010-2011. Germany's tolerance p_c in general slightly increases in the 17-year period and shows small fluctuations between 2000 and 2005.

CONCLUSIONS

We developed a framework to quantify interdependencies in the world industrial network and measure risk levels in global markets. We use the methodology to rank the economic importance of each industry and country according to the global damage that would result from their failures. Using network science to investigate input-output data of money flows between different economic industries, it becomes possible to stress test the global economic

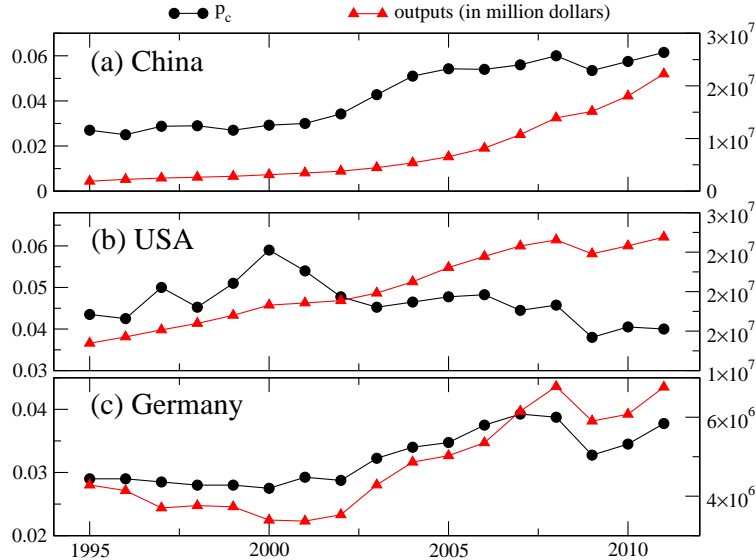


FIG. 6: Tolerance p_c of China, the USA and Germany comparing to the total product output value. For each country, the p_c is an average of the largest four industry p_c of this country (black circles). The product output (red triangle) value is the money flow a country supplies to the rest of the countries, which also indicates its impact to foreign countries. In (a) and (c), the trends of the p_c and output value are similar, which indicate that China and Germany become more influential to the world economy. In (b), the p_c of the USA increases in the period of year 1995 to year 2000, and decreases from 2000 to 2011, while the output value increases from 1995 to 2011 in general.

network and identify vulnerabilities and sources of systemic risk. Our quantitative results shed new light on China’s increasing economic influence over other economies, including that of the USA. The resulting information will enable policy and decision makers to better measure, understand, and maintain financial stability.

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