The University Of Sheffield.

Article:

Hu, X., Wang, C., Lim, M.K. et al. (1 more author) (2020) Characteristics and community evolution patterns of the international scrap metal trade. Journal of Cleaner Production. ISSN 0959-6526

https://doi.org/10.1016/j.jclepro.2019.118576

wordcount: 10282

Characteristics and Community Evolution Patterns of the International Scrap Metal Trade

Abstract

To reduce the excessive consumption of metal minerals and boost the development of the circular economy, scrap metals are increasingly recycled across the world. Due to the geographically uneven distribution of scrap metals, most countries are actively participating in the international scrap metal trade. This study collects international trade records on scrap metals from 1988 to 2017 and constructs the annual global scrap metals trade network (GSMTN) to analyze the characteristics and dynamic evolution of the scrap metal trade. The results reveal a globalization trend of the scrap metal trade, the scale-free characteristics of the trade network, and the increasing monopolization of the export market. The international scrap metal trade has experienced a dynamic evolution in the past 30 years and has developed into a complex system with a hierarchical structure that is led by a few core countries. Three relatively stable groups are the main players in the international scrap metal trade: East Asia-America-Oceania, Europe, and South Asia-Middle East. A review of the split and merger process of these communities clearly shows that geopolitics and economic turbulence are important elements in the fragmentation and integration of trade communities. The findings will enable governments to understand the complex trade relationships involved in scrap metals, which can help policy-makers propose effective import-export policies and ensure national resource security.

Keywords: Scrap metal trade; Complex network; Structural characteristics; Community evolution

1. Introduction

Non-ferrous metals, as an important resource for modern manufacturing, play a crucial role in social-economic development (Sverdrup et al., 2017). However, the scarcity of mineral resources has attracted worldwide attention with rapid industrialization (Giurco et al., 2014; Graedel et al., 2015). Fortunately, most metals can be recycled repeatedly without altering their properties, which allows "unlimited manifold recycling" (Ghisellini et al., 2016; Lothar, 2013). More importantly, manufacturers can reduce their production costs by using recycled metals instead of metal ores (Wang et al., 2019).

However, scrap metals are geographically unevenly distributed. For example, the USA, as a post-industrial economy, has an abundant reservoir of copper-bearing scrap products (Spatari et al., 2005). Due to the high recycling cost and increasingly strict environmental regulations, the USA supplies this scrap to the export market. According to the United Nations Commodity Trade Statistics Database, the USA exported approximately one million tonnes of scrap copper to other countries in 2017. In contrast, China, as a newly industrialized country, is facing a serious shortage of mineral resources. The ever-increasing amount of imported scrap provides an effective way to fill the gap. In 2017, the total import of scrap copper in China was approximately 3.56 million tonnes. Therefore, the international scrap metal trade plays a central role in the allocation of scrap metals among countries. A detailed understanding of the import-export relations of the international scrap metal trade is crucial to enable policy-makers to adjust trade policies and ensure resource security.

Although efforts have been made to investigate recycled metals, studies on the international scrap metal trade from the perspective of complex networks are still in their infancy. To the best of our knowledge, previous studies mainly focus on the improvement of recycling technologies as well as economic limitations and challenges (Liu et al., 2017; Reck and Graedel, 2012; Zeng et al., 2017; Zhang and Xu, 2018). A few studies on the scrap metal trade focus on a limited number of countries and commodities (Bosworth and Collins, 2008; Golev and Corder, 2016; Lee and Sohn, 2015; Terao, 2005), but a detailed exploration of global scope is lacking. Therefore, to elucidate the transboundary movement of scrap metals, we collect international trade records on scrap metals and construct the global scrap metals trade network (GSMTN) from 1988 to 2017. Complex network theory is used to analyze the structural properties, detect communities involved in the intricate trade relationships, and identify the dynamic evolution patterns of the GSMTN. Furthermore, we provide policy implications according to the results.

The contributions of this paper are threefold. First, this study reviews the development of the international scrap metal trade in the last three decades from the aspects of the dynamic evolution of trade value, trade relationships, core countries and communities. The globalization progress is revealed, and the characteristics of hierarchical structure and export-monopolization are highlighted. Second, this study describes the effect of geopolitics in the formation of the trade and reveals the important role of different types of political and economic turmoil in the split and merger of the trade communities. These findings will provide policy implications for countries to avoid disruption of the recycling industry and ensure the security of scrap metal resources. Third, in the theoretical research, the international trade system is modeled as a scale-free network (Baskaran et al., 2011). This study further confirms the scale-free assumption empirically from the perspective of the international scrap metal trade.

The remainder of this paper is structured as follows. Section 2 reviews the related literature on metals recycling and international trade networks. Section 3 provides detailed descriptions of the datasets and methods used in this study. Section 4 analyzes the topological properties of the GSMTN, and the dynamic evolution patterns of communities in the GSMTN are described in Section 5. Sections 6 presents the discussion and policy implications. Finally, the conclusion and future research are given in Section 7.

2. Literature review

With the rise of the circular economy, metal recycling has attracted worldwide attention. There are numerous studies on recycling and optimization technologies (Liu et al., 2017; Zhang and Xu, 2018), economic benefits and limitations (Zeng et al., 2017), and closed-loop supply chains (Ghadimi et al., 2019; Reck and Graedel, 2012). Due to the importance of global trade for scrap metals, the related studies have been conducted. A statistical analysis of export-import flows of scrap metals in Australia was conducted to investigate the Australian position in the international cycles of metal production (Golev and Corder, 2016). An empirical study discussed the Sino-US bilateral trade relationships in terms of 67 commodities including scrap metals (Bosworth and Collins, 2008). In addition, Terao (2005) reviewed the trends of import and export on copper scrap, aluminum scrap and lead scrap in Taiwan between 1980 and 2004; examined the controls on international recyclable flows; and provided suggestions on Taiwan's recycling system and recycling industry. Lee and Sohn (2015) identified core trade countries by constructing an international steel scrap trade network from 1990 to 2013 and revealed the relationship between steel scrap utilization and steel production.

The previous studies mainly focused on a limited number of countries and commodities, and the findings in these studies provided specific policy suggestions to the governments and industrial practitioners. However, the results lack universal applicability. In addition, certain important characteristics of the complex GSMTN have not been revealed on a global scale, such as the organizational structure of trade relationships for scrap metals, the level of competition and monopoly in the international trade, trade communities in the intricate trade relationships, the evolution patterns of these trade relationships, and the factors influencing the split and merger of trade communities.

The international scrap metal trade represents the trade relationships among countries, which can be interpreted as a network. A network is a mathematical description of the state of a system at a given point in time in terms of nodes and edges. From the network perspective, the international scrap metal trade is a standard directed and weighted graph. Each node denotes a country/region (hereafter country). Each edge represents the trade relationships between two countries. Directionality identifies the exporter and the importer, and the weight of the edge describes the trade volume. Since the seminal work of Serrano and Boguná (2003), considerable effort has been devoted to understanding the structural properties and evolution patterns of trading networks according to complex network theory (Fan et al., 2014). Specifically, in terms of static features, the scale-free property has been observed in trade networks (Li and Chen, 2003; Serrano and Boguná, 2003). The clustering structure (Fagiolo et al., 2008; Serrano and Boguná, 2003), symmetry (Wang et al., 2009) and disassortative property (Fagiolo et al., 2008) also have been investigated. From the perspective of dynamic evolution, the evolution patterns of the topological properties (Fagiolo et al., 2010; Giorgio et al., 2009) as well as synchronization (Li et al., 2003) and the association (Garlaschelli and Loffredo, 2004, 2005; Garlaschelli et al., 2007) between the trade volume and economic development have been discussed. In addition to the analysis of the aggregate international trade network, complex network theory has also been used to reveal the characteristics of specific commodities, including natural gas (Geng et al., 2014), crude oil (An et al., 2014; Yang et al., 2015) and nonfuel minerals (Dong et al., 2017; Klimek et al., 2015). Numerous studies have proved that the complex network theory enables a better description of the existing heterogeneity in the degrees of connectivity and, hence, of international trade integration (Fagiolo et al., 2010).

Thus, complex network theory is an effective tool to quantitatively investigate the patterns in the international scrap metal trade from a systemic perspective. Due to the identified research gap on the international scrap metal trade according to complex network theory, this study builds the GSMTN and reveals the characteristics of the GSMTN. The findings provide important implications to help governments to cope with political and economic fluctuations and seek effective strategies to maintain scrap metal resource security.

3. Data and methods

3.1 Data description

To explore the international trade for scrap metals, this study collects data from the United Nations Commodity Trade Statistics Database (UN Comtrade, https://comtrade.un.org/). This database contains more than one billion records reported by statistical authorities of approximately 200 countries and is considered the most comprehensive trade database. Each record includes the periods, the reporters and partners, the type of export and import, and the classification of the commodity. The units of measurement are available for weight (kg) and value (US dollar), and each type of commodity has a unique code (called the HS code) based on the interpretation of Harmonized System. This study collects data on 20 categories of scrap and waste metals, including 7204 (Ferrous; waste and scrap), 7404 (Copper; waste and scrap), 7503 (Nickel; waste and scrap), 7602 (Aluminum; waste and scrap), 7802 (Lead; waste and scrap), 7902 (Zinc; waste and scrap), etc. In addition, the period of the data examined in the present study is from 1988 to 2017, and the unit of measurement used is value (ten million US dollars) for the classification of scrap metals. Notably, this study considers mainland China (hereafter China), and the Hong Kong Special Administrative Region of China (hereafter Hong

Kong) separately. In addition, we observe that there is inconsistency in the trade value of import and export reported by these two countries, but it makes no noticeable difference in our main conclusions. As a matter of convenience and unification, we use the maximum value of different reports as the trade value between countries.

3.2 Network construction

To understand the characteristics and dynamic evolution of the international trade for scrap metals, we generate a series of trade networks, which act as snapshots of the international scrap metal trade for the last 30 years. Specifically, the directed and weighted GSMTN is constructed as $G^{[t]} = (V^{[t]}, E^{[t]}, \mathbf{W}^{[t]})$ by using nodes to represent countries and edges to denote the trade relationships between countries. t represents a particular year, and it ranges from 1988 to 2017. The set of countries included in the networks is represented by $V^{[t]} = \{v_1, v_2, \cdots, v_{N^{[t]}}\}$, and $N^{[t]}$ denotes the number of nodes in $G^{[t]}$. The edge set is represented by $E^{[t]} = \{e_{ij} : i, j \in V^{[t]}\}$, where e_{ij} indicates that country i exports scrap metals to country j and $m^{[t]}$ is the number of edges. $\mathbf{W}^{[t]} = \{w_{ij}^{[t]}\}$ is the matrix of weights, and $w_{ij}^{[t]}$ is the export value of scrap metals exported from country i to country j. $G^{[t]}$ is specified by a signal adjacency matrix $\mathbf{A}^{[t]} = \{a_{ij}^{[t]}\}$. When country i exports scrap metals to country j, we have $a_{ij}^{[t]} = 1$; otherwise, $a_{ij}^{[t]} = 0$. For the sake of computing the structural features of the GSMTN, we also construct the weighted and undirected network $G_u^{[t]} = (V_u^{[t]}, E_u^{[t]}, \mathbf{W}_u^{[t]})$, corresponding to $G^{[t]}$.

3.3 Metrics for analyzing the GSMTN

The topological properties of the GSMTN reflect the trade patterns and trade dynamics. This study analyzes the static and dynamic characteristics of the GSMTN from four perspectives, including centrality, distribution patterns, tightness and community evolution. The specific definitions of the indicators are described below.

3.3.1 Centrality

Centrality is one of the most fundamental concepts in complex network theory (Borgatti and Everett, 2006), and it is used to quantify the importance of vertices in networks that exist in different contexts. The term "importance" may have a wide variety of meanings, and a large number of definitions of centrality are proposed in previous studies (Borgatti, 2005; Landherr et al., 2010).

The conceptually simplest definition is node degree, namely, the number of edges linked to a node (Freeman, 1978). A larger degree centrality of a country in GSMTN indicates that the country has more trade relationships than other counties. Thus, when such a country changes its trade policies on scrap metals, it will affect more trade partners in the whole trade network. In terms of the disparity of exports and imports, two separate metrics of degree centrality are defined as in-degree $k_i^{[t]}(in)$ and out-degree $k_i^{[t]}(out)$ as follows:

$$k_i^{[t]}(in) = \sum_{j \in V^{[t]}} a_{ji}^{[t]}, \quad k_i^{[t]}(out) = \sum_{j \in V^{[t]}} a_{ij}^{[t]} \tag{1}$$

The node degree is the sum of node in-degree and node out-degree; specifically, $k_i^{[t]} = k_i^{[t]}(in) + k_i^{[t]}(out)$.

In the definition of node degree, the edge weights are equal. However, edges with different trade values have different impacts on trade networks. Thus, by extending the definition of node degree, the node strength of country i is defined as the aggregation of trade with its trade partners, $s_i^{[t]} = s_i^{[t]}(in) + s_i^{[t]}(out)$. The specific definitions distinguishing the direction of links are shown as follows:

$$s_i^{[t]}(in) = \sum_{(j,i) \in E^{[t]}} w_{ji}^{[t]}, \quad s_i^{[t]}(out) = \sum_{(i,j) \in E^{[t]}} w_{ij}^{[t]} \tag{2}$$

where $s_i^{[t]}(in)$ denotes the in-strength of node i in network $G^{[t]}$ and $s_i^{[t]}(out)$ represents the out-strength of node i. If a country with a larger in-strength is removed from the trade network, then the total trade value will be dramatically reduced and the international scrap metal trade will be subject to a great shock.

The node degree and node strength are mainly affected by the number of edges. However, the quality of partners is not considered in the above measurements, which would result in unreasonable outcomes. For example, if a node connects to three nonsignificant nodes and another node links to one important node, then the evaluation based on the degree and the strength cannot distinguish the difference between these two nodes. Therefore, the PageRank algorithm is also applied in this study (Page et al., 1999). This algorithm uses the number of links and the quality of partners to estimate how important the node is. Comparing to the above metrics, i.e., in-degree, out-degree, in-strength and out-strength, the PageRank value represents a comprehensive evaluation of nodes. Specifically, PageRank satisfies the following equation:

$$\mathbf{p}^{[t]} = \alpha \mathbf{Ad}^{[t]} \mathbf{p}^{[t]} + \frac{1-\alpha}{N^{[t]}} \mathbf{e} \tag{3}$$

where the element $p_i^{[t]}$ of vector $\mathbf{p}^{[t]}$ is the PageRank value of each node. $\mathbf{Ad}^{[t]}$ denotes the adjacent matrix of network $G^{[t]}$ with the weight matrix $\mathbf{W}^{[t]}$, and the variable $Ad_{ij}^{[t]}$ of the adjacent matrix is defined as $w_{ij}^{[t]} \Big/ \sum_j w_{ij}^{[t]}$. α is the damping factor and is always set to the empirical value of 0.85. $N^{[t]}$ is the number of nodes in networks, and $\mathbf{e} = \mathbf{1}$. The PageRank calculation is performed according to the power iteration method, and the iteration will stop after the maximum number of iterations or the error tolerance has been reached. Specifically, the parameters of the maximum number of iterations and the error tolerance are set as the empirical value 100 and 1.0e-6, respectively.

In addition, betweenness centrality is calculated in this study, which is proposed to quantify the ability of one node to control the connections between other nodes (Freeman, 1977). Betweenness centrality is calculated as the sum of the fraction of all-pairs shortest paths that pass through the given node (Brandes, 2001) as follows:

$$b_i^{[t]} = \sum_{j,k \in V_u^{[t]}} \frac{\sigma^{[t]}(j,k \mid i)}{\sigma^{[t]}(j,k)} \tag{4}$$

where $\sigma^{[t]}(j,k)$ is the number of the shortest paths between nodes j and k in network $G^{[t]}$. $\sigma^{[t]}(j,k \mid i)$ is the number of the shortest paths passing through node i other than j and k. If $j = k, \sigma^{[t]}(j,k) = 1$, and if $i \in j,k, \sigma^{[t]}(j,k \mid i) = 0$.

3.3.2 Distribution patterns

The distribution analysis of trade networks is an effective tool to identify the trade patterns of the global scrap metal trade. This approach provides an intuitive and quantitative understanding of heterogeneity. The degree distribution is the simplest way to reflect the patterns of trade relationships. The degree distribution $P(k^{[t]})$ is defined as the proportion of nodes having degree $k^{[t]}$ in the network; that is, $P(k^{[t]}) = n_k^{[t]} / N^{[t]}$, where $n_k^{[t]}$ is the number of nodes with degree $k^{[t]}$ in the network $G^{[t]}$ and $N^{[t]}$ is the number of nodes. The cumulative distribution $P(k^{[t]} \geq k_0)$ is calculated by summing the proportion of nodes with a degree that is not less than k_0 in the networks and is represented as $P(k^{[t]} \geq k_0) = \sum_{k^{[t]}=k_0}^{k_{\max}^{[t]}} P(k^{[t]})$, where $k_{\max}^{[t]}$ is the maximum degree of the nodes in the network $G^{[t]}$. Similarly, strength distribution and strength cumulative distribution are defined as $P(s^{[t]})$ and $P(s^{[t]} \geq s_0)$, respectively, by considering the trade value on the basis of degree distribution. If the degree distribution of a network is well approximated with $P(k^{[t]}) \sim (k^{[t]})^{-\gamma}$, it is called a power-law distribution (Barabási, 2016).

The heterogeneity in the networks indicated by degree distribution and strength distribution has not been characterized directly. Estrada (2010) proposed a unique indicator of heterogeneity, $h^{[t]}$, which is defined as the sum total of the differences in a given function of the node degrees for linked nodes. This indicator is easily calculated with the following equation:

$$h^{[t]} = \frac{N^{[t]} - 2\sum_{(i,j)\in E^{[t]}} (k_i^{[t]} k_j^{[t]})^{-1/2}}{N^{[t]} - 2\sqrt{N^{[t]} - 1}} \tag{5}$$

where $N^{[t]}$ is the number of nodes in the network $G^{[t]}$. A larger $h^{[t]}$ means that most of the trade value for scrap metals is concentrated in a few countries.

In addition, the degree of monopoly in the export trade and the degree of trade competition are measured by an indicator, namely, degree centrality, which is calculated as follows

(Freeman, 1978):

$$c^{[t]}(in)=\frac{\sum_{i\in\mathcal{V}^{[t]}}(k_{\max}^{[t]}(in)-k_i^{[t]}(in))}{(N^{[t]}-1)^2},\quad c^{[t]}(out)=\frac{\sum_{i\in\mathcal{V}^{[t]}}(k_{\max}^{[t]}(out)-k_i^{[t]}(out))}{(N^{[t]}-1)^2} \tag{6}$$

where $k_{\max}^{[t]}(in)$ denotes the maximum in-degree of nodes and $k_{\max}^{[t]}(out)$ represents the maximum out-degree of nodes in the network $G^{[t]}$.

3.3.3 Tightness and stability

The tightness of the trade networks measures the trade relationships between countries. It indicates the stability of the scrap metal trade in terms of trade ties and structure. Density is used to evaluate the overall tightness among countries in a trade network (Fischer and Shavit, 1995). The countries in a network with greater density are closer to each other. Density is defined as the fraction of edges to the maximal number of possible edges and is calculated as follows:

$$d^{[t]}=\frac{m^{[t]}}{N^{[t]}(N^{[t]}-1)} \tag{7}$$

If the weight of edges is introduced to evaluate the tightness, the geometric average of the subgraph edge weights is proposed, which is defined as a weighted clustering coefficient to measure tightness (Saramäki et al., 2007):

$$wcc_i^{[t]}=\frac{1}{k_i^{[t]}(k_i^{[t]}-1)}\sum_{i,j,k\in\mathcal{V}^{[t]}}(\hat{w}_{ij}^{[t]}\hat{w}_{ik}^{[t]}\hat{w}_{jk}^{[t]})^{1/3},\quad \overline{wcc^{[t]}}=\frac{1}{N^{[t]}}\sum_{i\in\mathcal{V}^{[t]}}wcc_i^{[t]} \tag{8}$$

where $\hat{w}_{ij}^{[t]}$ is the edge weight that is normalized by the maximum weight in the network $G^{[t]}$ and $\hat{w}_{ij}^{[t]}=w_{ij}^{[t]}\big/\max(w^{[t]})$. The average weighted clustering coefficient of the nodes in network $\overline{wcc^{[t]}}$ is used to evaluate the tightness of the network.

In addition, the average path length is calculated as the average length of the shortest paths for all possible network node pairs in the GSMTN (Watts and Strogatz, 1998), which intuitively reflects the distance between countries that have trade relationships:

$$l^{[t]}=\frac{1}{N^{[t]}(N^{[t]}-1)}\sum_{i,j\in\mathcal{V}^{[t]}}d^{[t]}(i,j) \tag{9}$$

where $d^{[t]}(i,j)$ denotes the shortest distance between nodes i and j in the network $G^{[t]}$. When node i is out of reach of node j or $i=j$, we set $d^{[t]}(i,j)=0$.

In addition to the average path length, the core number of the trade network is another way to measure the distance between nodes. This approach is used to evaluate the depth of the entire network by revealing the hierarchical structure (Batagelj and Zaversnik, 2003). A *k*-core is the maximal subgraph in the network $G^{[t]}$ that contains nodes of degree $k^{[t]}$ or more, and the core number of a node is the largest value $k^{[t]}$ of a *k*-core containing that node. Therefore, the core number of a network is defined as the maximum core number of nodes. A network with a smaller core number is less hierarchical and more easily controlled.

Furthermore, a change in the countries involved in the scrap metal trade can be detected by using a simple metric to measure the member stability of the GSMTN. This metric is defined as the fraction of unchanged nodes in the trade network from t_i to t_{i+1} and is calculated as follows:

$$ms^{[t_i]} = \frac{|V^{[t_i]} \quad V^{[t_{i+1}]}|}{|V^{[t_i]} \quad V^{[t_{i+1}]}|} \tag{10}$$

where $V^{[t_i]}$ is the node set in time t_i.

3.3.4 Community structure

Community structure reveals the group organizations and indicates the distribution of the edges (Fortunato, 2010; Girvan and Newman, 2002), which is an important feature of networks. Community structure is not only globally inhomogeneous but also locally inhomogeneous and includes high concentrations of links between nodes in certain special communities and low concentrations between nodes in other groups (Fortunato, 2010). In the GSMTN, countries in the same community have close relationships with each other, indicating the regional characteristics of the GSMTN. In addition, the dynamic evolution of these communities plays a vital role in understanding the trends in the scrap metal trade.

To detect the community structures of the GSMTN, this study employs an information theoretical approach named *Infomap* (Rosvall and Bergstrom, 2008). The algorithm is based on the idea of describing a network using the least amount of information. *Infomap* converts the problem to optimally compress the coding length for the probability flow of random walks. To find the best partition $M^{[t]}$ of the network $G^{[t]}$, which is also the optimization objective, the average description length is given by the sum of the entropy of the movement between communities and the entropy of movements within communities:

$$L(M^{[t]}) = q^{[t]} H(\theta^{[t]}) + \sum_{i=1}^{|M^{[t]}|} \rho_i^{[t]} H(\varsigma_i^{[t]}) \tag{11}$$

where $q^{[t]}$ denotes the probability of a random walk from one community to another community and $H(\theta^{[t]})$ is the entropy of the community names. $\rho_i^{[t]}$ stands for the sum of the percentage of intragroup walks in community i and movements leaving community i. $|M^{[t]}|$ represents the number of communities in partition $M^{[t]}$. $H(\varsigma_i^{[t]})$ is the entropy of intragroup walks in community i. The *Infomap* algorithm can be calculated by the MapEquation software packages, which are available at https://www.mapequation.org.

To further analyze the difference in the size of communities in each year, we use the indicator diversity, which is defined as $diver^{[t]} = \frac{1}{|M^{[t]}|} \sum_{i}^{|M^{[t]}|} r_i^{[t]} \log(r_i^{[t]})$, where $M^{[t]}$ is the set of communities divided by the algorithm and $|M^{[t]}|$ is the number of communities. $r_i^{[t]}$ is the ratio of the size of the community i to the number of countries in the network $G^{[t]}$. $diver^{[t]}$ ranges from 0 to 1, and a higher value indicates a more uniform size of communities.

4. Topological properties of the GSMTN

4.1 Overview of the GSMTN

Figure 1 reviews the changes of the international scrap metal trade from 1988 to 2017. Figure 1(A) clearly shows that the number of countries in the GSMTN presented an upward trend during the last three decades and reached a peak in 2017 with 235 countries. Between 1988 and 2000, the number of countries grew dramatically from 133 countries to 224 countries, mainly due to the inclusion of developing countries in Africa and Latin America. After this period, the number of countries climbed slightly and remained stable since 2010. Similarly, the number of trade relationships increased since 1988, as shown in Figure 1(B). This number fluctuated from 2007 to 2011 but declined slightly after 2012. We find that each country maintained trade relationships with an average of 40 countries in 2017, as shown in Figure 1(C). The growth in the number of countries and trade relationships indicates that more countries now participate in the scrap metal trade.

However, the trade value of scrap metals shows a significantly different variation tendency. Figure 1(D) and (E) show that the trade value increased sharply in 2000 and peaked in 2012. For the following five years, the trade value gradually decreased and then returned to its original level in 2007. This decline in trade value might be impacted by the depressed international economy. Notably, the international financial crisis and the European debt crisis started in 2007. The stagnant economy reduced the demand for scrap metals. Hence, the trade value for scrap metals decreased to a certain extent. In addition, the import trade value of China declined sharply in the last seven years, and the 34% reduction of the trade value worldwide was a result. This reduction was caused by Chinese policies on the restriction of importing scrap metals. In addition, the member countries have remained stable in recent years, as shown in Figure 1(F).

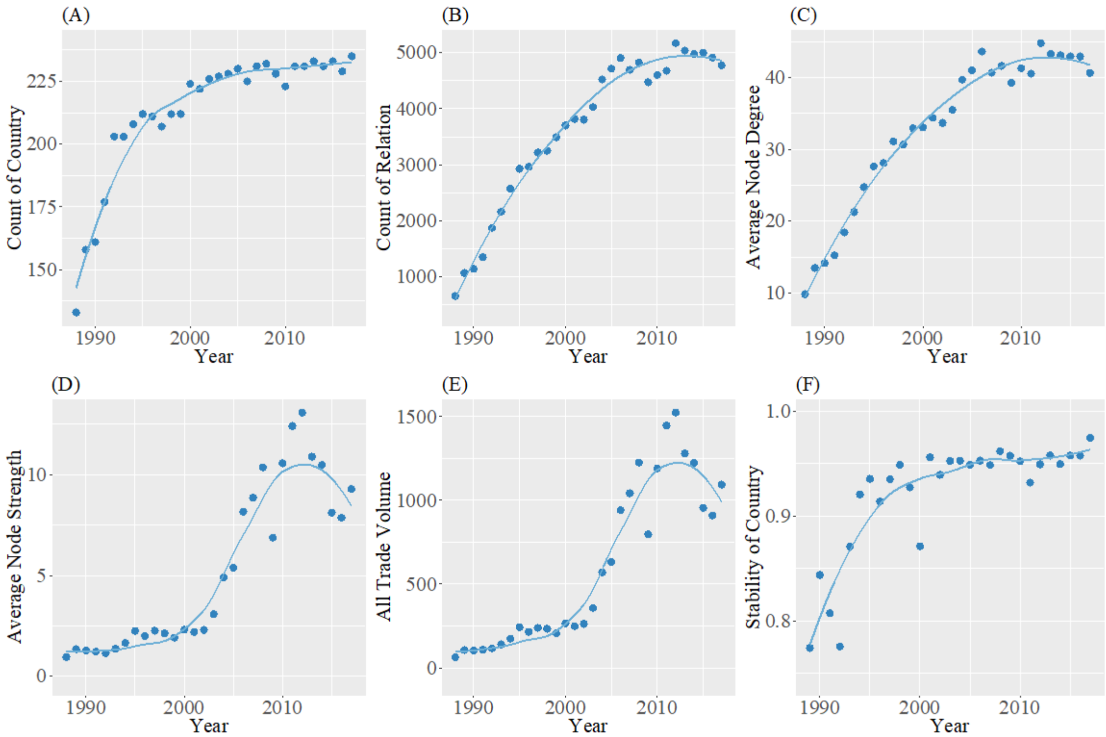


Figure 1. Basic information on the GSMTN from 1988-2017.

We further analyze the distribution patterns of the trade network. The distribution patterns of the GSMTN are shown in Figure 2, indicating the diversity of countries involved in the international scrap metal trade. The cumulative degree distribution and the cumulative strength distribution of the GSMTN obey the power-law form. As shown in Table 1, the power-law exponent of the cumulative degree distribution $-\gamma_k$ remains within the range [-0.87, -0.61]. The imitative effect of the function evaluated by R_k^2 is good, and the parameters are sufficiently significant. In addition, in terms of the trade value, the fitting coefficients of the cumulative strength distribution $-\gamma_s$ have been relatively stable over past 30 years, remaining within the range of [-0.25, -0.20]. The cumulative degree distribution and the cumulative strength distribution in 1988, 2003 and 2017 (as examples) are shown in Figure 2 (A)-(F). We intuitively observe the shape of the long tail on the cumulative distribution, which can verify the results presented in Table 1. These results demonstrate that the international scrap metal trade is dominated by a few countries. In contrast, we find that the estimated parameter of the power-law function on the cumulative strength distribution $-\gamma_s$ is greater than that on the cumulative degree distribution $-\gamma_k$. This result indicates that the distribution of trade value is more nonuniform than that of trade relationships. This result is verified by the steeper distribution curve of strength, as shown in Figure 2(D)-(F).

Figure 2(G) illustrates the variation in in-degree centrality from 1988 to 2017, which reflects the level of monopolization and competition in the international trade in scrap metals. Clearly, the out-degree centrality increased gradually in the first 20 years and drastically in the last decade from 44.4% to 79.7%. The out-degree centrality in 2017 is more than twice as high as that in 1988, at 79.7% and 32.1%, respectively. In addition, the top five exporting countries occupied approximately 39.4% of the trade value of the total export value. Competition is measured by the in-degree centrality, and the competition among importing countries gradually increased from 1988 to 2000 and then slightly decreased. Recently, competition in the import market remained at approximately 60%. A comparison of the in-degree centrality and out-degree centrality shows that there is more intense competition among the importing countries than among the exporting countries. Furthermore, Figure 2(H) shows the substantial decline of the heterogeneity of the GSMTN in the past 30 years. In 2017, the heterogeneity of the GSMTN reached a relatively low level of 39.2% but was still higher than 11% in the Barabási–Albert network (Estrada, 2010), indicating that the GSMTN is more uneven than the network generated by preferential attachment.

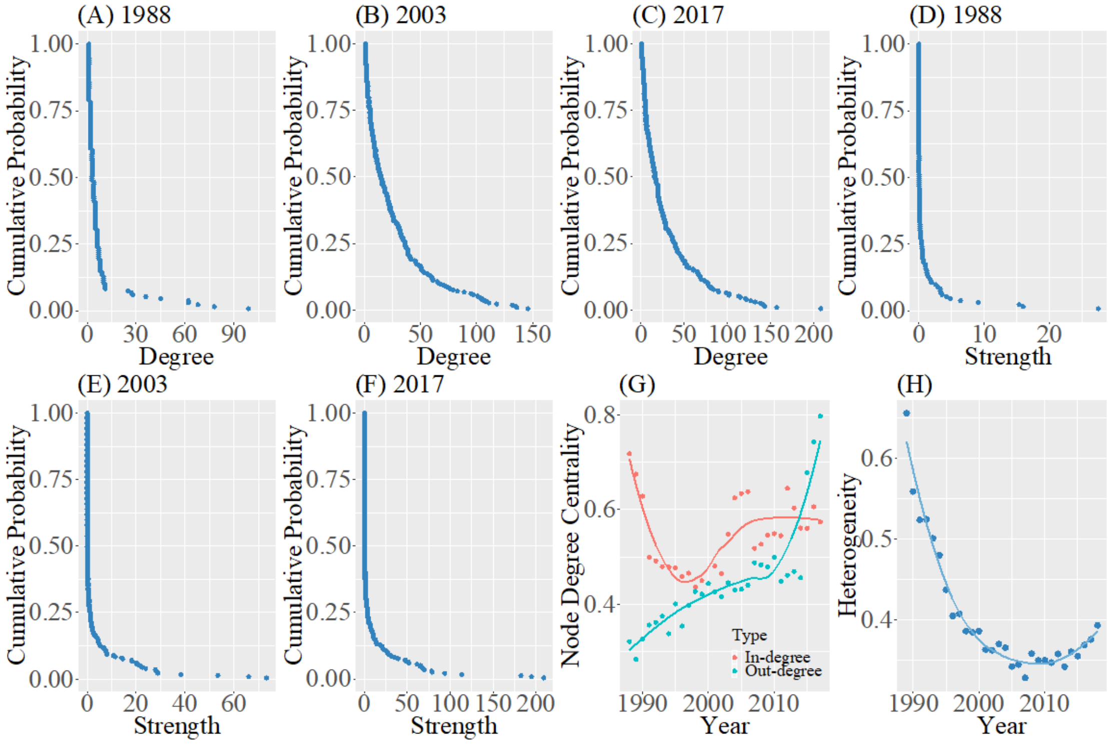


Figure 2. Distribution patterns of the GSMTN.

Table 1. The fitting result of the cumulative distribution of the GSMTN.

Year	Degree		Strength		Year	Degree		Strength	
	$-\gamma_k$	R_k^2	$-\gamma_s$	R_s^2		$-\gamma_k$	R_k^2	$-\gamma_s$	R_s^2
1988	-0.87***	0.94	-0.25***	0.80	2003	-0.62***	0.75	-0.23***	0.77
1989	-0.72***	0.90	-0.25***	0.83	2004	-0.63***	0.73	-0.23***	0.76
1990	-0.73***	0.90	-0.24***	0.81	2005	-0.61***	0.71	-0.23***	0.74
1991	-0.69***	0.89	-0.25***	0.84	2006	-0.66***	0.73	-0.25***	0.78
1992	-0.65***	0.86	-0.25***	0.83	2007	-0.62***	0.73	-0.22***	0.72
1993	-0.67***	0.85	-0.25***	0.83	2008	-0.65***	0.74	-0.23***	0.72
1994	-0.68***	0.84	-0.25***	0.81	2009	-0.64***	0.74	-0.24***	0.76
1995	-0.68***	0.81	-0.25***	0.81	2010	-0.66***	0.74	-0.25***	0.77
1996	-0.64***	0.79	-0.25***	0.80	2011	-0.63***	0.74	-0.24***	0.77
1997	-0.67***	0.78	-0.25***	0.80	2012	-0.65***	0.72	-0.25***	0.76
1998	-0.61***	0.76	-0.24***	0.80	2013	-0.65***	0.74	-0.24***	0.74
1999	-0.63***	0.75	-0.24***	0.77	2014	-0.64***	0.73	-0.23***	0.73
2000	-0.62***	0.75	-0.22***	0.76	2015	-0.64***	0.75	-0.21***	0.72
2001	-0.65***	0.77	-0.24***	0.77	2016	-0.66***	0.76	-0.24***	0.77
2002	-0.62***	0.76	-0.23***	0.76	2017	-0.65***	0.77	-0.20***	0.72

Note: $-\gamma_k$ and $-\gamma_s$ stand for the exponents of power law to fit the cumulative degree distribution and cumulative strength distribution, respectively. R_k^2 and R_s^2 evaluate the imitative effect. *** indicates that the significance of the parameter is less than 0.001.

We use four indicators presented in Sub-section 3.3.3 to analyze the tightness of the trade relationships in the GSMTN and draw the following results. As illustrated by Figure 3, the density of the trade network gradually increased and the average shortest path length decreased over the past 30 years. In particular, the relatively low value of the average shortest path length in 2017, approximately 1.96, indicates that most countries can conduct trade with each other directly without third countries acting as intermediary agents. Nevertheless, when the trade value is used to evaluate the tightness in the weighted clustering coefficient, the opposite result is obtained, as demonstrated in Figure 3(C). The downward tendency of the weighted clustering coefficient illustrates that the disparity in the trade value expanded the distance among countries, although increasing numbers of trade relationships were established. Figure 3(D) depicts the variation in the core number of countries in the GSMTN. A hierarchical structure is obvious in the GSMTN, and the number of layers was increasing during the past three decades. Therefore, in terms of the organizational structure, countries have an increasingly loose connection with each other in the trade network in a longitudinal perspective.

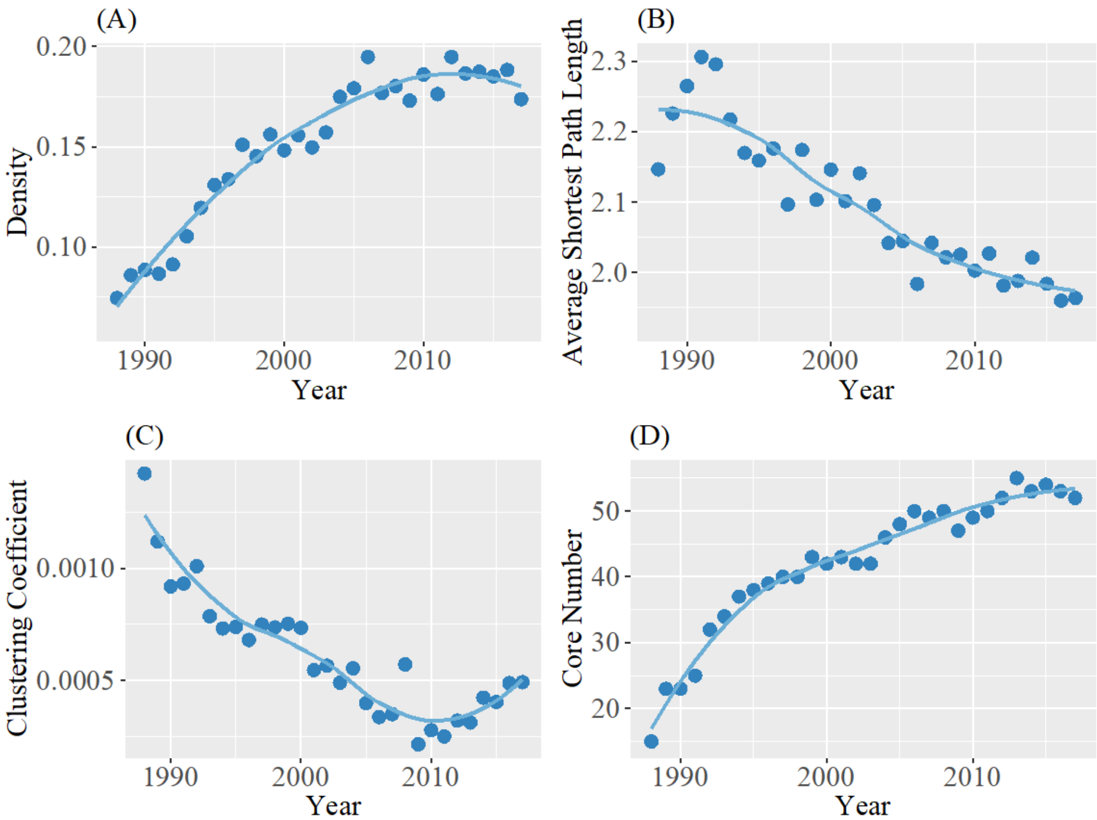


Figure 3. Relation between countries in the GSMTN from 1988-2017.

4.2 Core countries in the GSMTN

The core countries occupy the central positions in the GSMTN and have important influences on global trade. To understand the dynamics of global trade, this sub-section discusses the core countries in 1998, 2003 and 2017, provides a snapshot of the trade network in Table 2, and shows the evolution of the top ten countries during the past 30 years in Figure 4.

Table 2 lists the top ten core countries from different perspectives quantified by the indices in-degree $k_i(in)$, out-degree $k_i(out)$, in-strength $s_i(in)$, out-strength $s_i(out)$, betweenness b_i and PageRank value p_i in 1988, 2003 and 2017. The ten core countries identified by using in-degree and in-strength are mainly geographically concentrated in Europe and Asia. Over time, the import relationships of the core countries increased remarkably and the composition of the major hubs altered. More specifically, China and the USA occupied the central positions in the GSMTN, but certain European countries gradually disappeared from the top list. Table 2 and Figure 4(A) show that China remained the most important importing country from 2002 to 2017. Thus, the policy disturbances in China will lead to drastic variations in the international scrap metal trade. As shown in Figure 4(A), the major importing countries during the past 30 years remained relatively stable.

With regard to the major exporting countries as measured by out-degree and out-strength, the top ten exporters accounted for 20.2% of the scrap metals trade in 2017. Notably, Hong Kong is always an influential exporter and remained in the top 15 in terms of trade volume over 30 years, as shown in Figure 4(B). Due to its free-port status, Hong Kong is the important transshipment station of the scrap metals important mainland China. In 2017, Hong Kong was the third biggest exporter of scrap metals to mainland China, just behind the USA and Japan. The other important exporting countries also remain relatively stable, including the USA, Germany, the UK, the Netherlands and France. In addition, the USA has had the largest export volume over the past three decades.

Figure 5 illustrates the changes in the import and export trade value over 30 years in certain core countries. The import and export trade values in these countries showed distinctly different patterns. In some countries, such as China, India, South Korea, Turkey and Italy, the import trade value is much higher than the export value. The considerable import trade value of the newly industrialized countries China and India indicates that they have urgent and immense resource needs for industrialization. In contrast, the USA, France and Australia prefer to ship the scrap metals to other countries due to the expensive recycling cost in these countries. Thus, their export values are far higher than their import values. Moreover, countries such as Canada and Germany have relatively balanced import and export trade values.

We use the indicator betweenness, b_i, to measure the countries that play the role of bridges in the trade network. As shown in Table 2, in the early stage, the bridge countries were mainly located in Europe and Asia, including Finland, Germany, Thailand, Italy and Japan. Over time, certain African countries and Gulf states, such as Botswana, Tanzania and Oman, emerged as new core bridges connecting the scrap metal trade in 2017. These frequent changes in bridge countries indicate the dynamic evolution of the GSMTN.

The PageRank value measures the significance of nodes in the networks and involves two assumptions regarding quantity and quality. In Table 2, countries in Europe and Asia, including Germany, Italy, China, Japan and South Korea, are in the central positions obviously quantified by the PageRank value. As shown in Figure 4(C), the United Arab Emirates (UAE) gradually improved its status during the past 30 years and emerged as a major hub from 2013 to 2017. The main reason is the ideal geographical location of UAE, which is convenient to import scrap from Africa and Europe, refine or sort it and then re-export it within the region as well as into China, India and Pakistan.

Table 2. Top 10 countries in 1988, 2003, 2017 by different indicators.

Rank	In-degree						Rank	Out-degree					
	1988		2003		2017			1988		2003		2017	
	Country	Value	Country	Value	Country	Value		Country	Value	Country	Value	Country	Value
1	Germany	99	India	141	Netherlands	154	1	Germany	47	USA	118	Netherlands	206
2	Japan	75	Germany	118	India	151	2	Switzerland	32	Germany	96	USA	116
3	India	66	UK	113	South Korea	138	3	Australia	26	UK	94	China	97
4	South Korea	60	China	112	Germany	136	4	Japan	25	France	88	UK	95
5	Switzerland	50	Netherlands	105	Spain	121	5	Finland	20	Italy	86	Germany	82
6	Thailand	44	USA	104	Pakistan	120	6	Portugal	20	Spain	72	Italy	81
7	Australia	28	South Korea	100	USA	120	7	South Korea	17	India	63	India	76
8	Greece	25	Italy	90	China	118	8	India	14	Belgium	63	Spain	73
9	Finland	22	Belgium	89	Belgium	115	9	Greece	11	UAE	63	France	71
10	Portugal	18	Spain	87	UK	111	10	Belgium-Luxembourg	10	South Africa	62	Australia	69

Rank	In-strength						Rank	Out-strength					
	1988		2003		2017			1988		2003		2017	
	Country	Value	Country	Value	Country	Value		Country	Value	Country	Value	Country	Value
1	Germany	15.5	China	49.8	China	169	1	USA	15.8	USA	54.6	USA	146
2	Japan	14.2	Germany	30.8	Germany	99.7	2	Germany	12.0	Germany	35.2	Germany	94.7
3	South Korea	8.88	Turkey	19.2	Turkey	65.7	3	Netherlands	4.33	UK	21.7	Japan	69.9
4	India	4.80	South Korea	18.6	USA	61.3	4	Australia	3.18	France	18.5	UK	65.5
5	Italy	3.80	Switzerland	18.2	India	55.8	5	France	2.62	Japan	18.1	Netherlands	53.9
6	Thailand	3.22	USA	17.9	South Korea	55.4	6	UK	2.53	Russia	17.9	France	53.4
7	Belgium-Luxembourg	2.23	Italy	16.7	Italy	49.0	7	Hong Kong	1.87	Netherlands	17.8	Canada	41.0
8	Netherlands	2.06	UK	16.6	Belgium	46.7	8	Switzerland	1.76	Hong Kong	15.6	Australia	33.9
9	Sweden	1.48	Belgium	15.7	Japan	42.6	9	Singapore	1.44	Canada	11.5	Belgium	31.4
10	France	0.94	Spain	15.5	Switzerland	38.4	10	USSR	1.30	Belgium	8.16	Hong Kong	30.6

Rank	Betweenness						Rank	PageRank					
	1988		2003		2017			1988		2003		2017	
	Country	Value	Country	Value	Country	Value		Country	Value	Country	Value	Country	Value
1	Finland	0.29	Aruba	0.31	Netherlands	0.76	1	Germany	0.18	China	0.11	China	0.09
2	Germany	0.21	Colombia	0.31	Botswana	0.26	2	Japan	0.17	Germany	0.08	Germany	0.08
3	Thailand	0.20	Cyprus	0.25	Germany	0.26	3	South Korea	0.10	Japan	0.06	India	0.06
4	Australia	0.18	Austria	0.24	Tanzania	0.20	4	Italy	0.05	South Korea	0.05	Japan	0.05
5	Italy	0.13	Italy	0.22	Oman	0.20	5	Thailand	0.04	Italy	0.04	South Korea	0.05
6	Japan	0.11	Russia	0.21	Canada	0.19	6	India	0.04	Switzerland	0.04	UAE	0.04
7	India	0.11	Canada	0.20	Switzerland	0.19	7	Belgium-Luxembourg	0.03	France	0.04	USA	0.04
8	Switzerland	0.10	Costa Rica	0.20	China	0.19	8	Netherlands	0.03	UK	0.04	Belgium	0.04
9	South Korea	0.09	France	0.16	Czechia	0.16	9	USA	0.03	Hong Kong	0.04	Italy	0.04
10	Portugal	0.07	Latvia	0.16	Brazil	0.15	10	Sweden	0.02	USA	0.03	Turkey	0.03

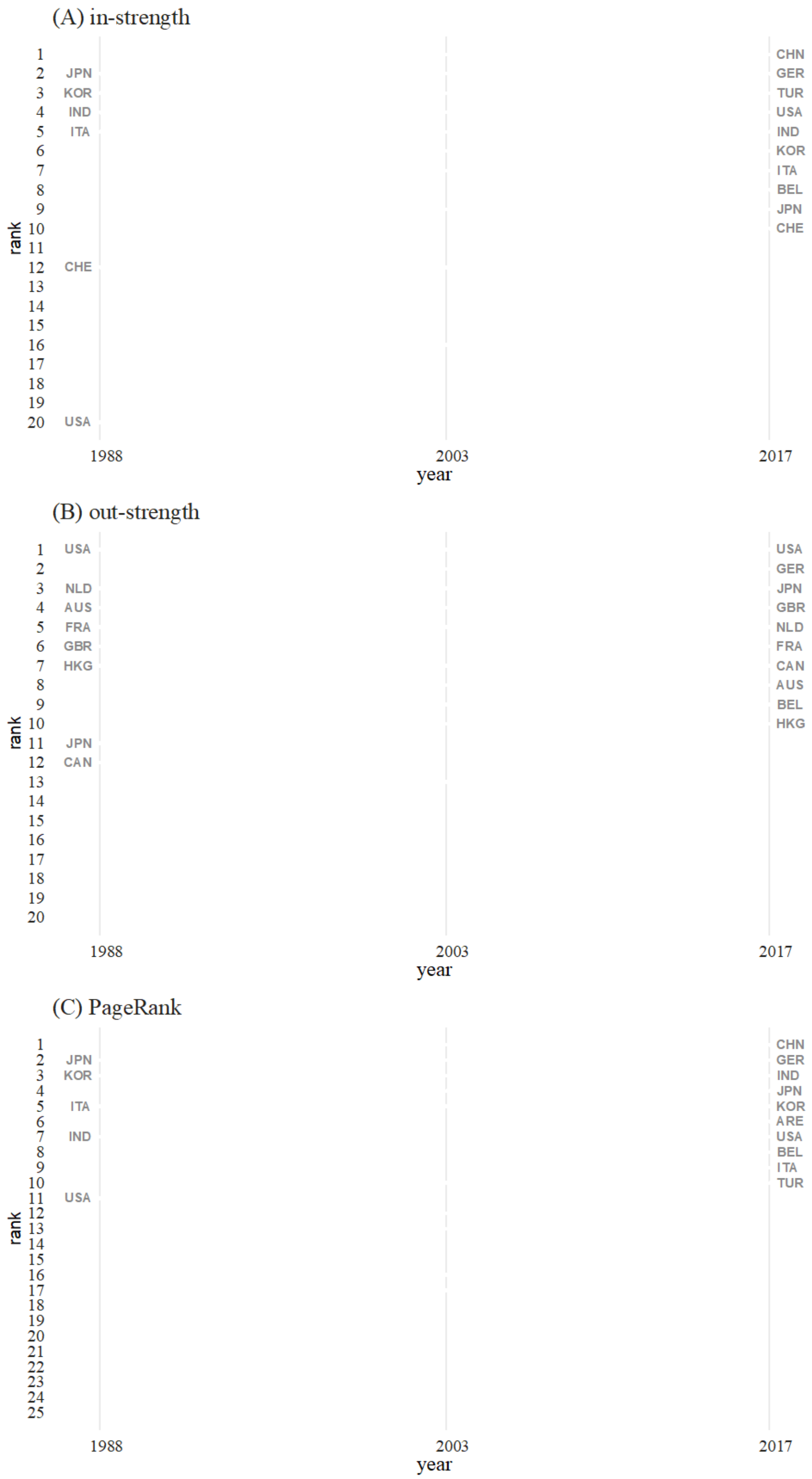
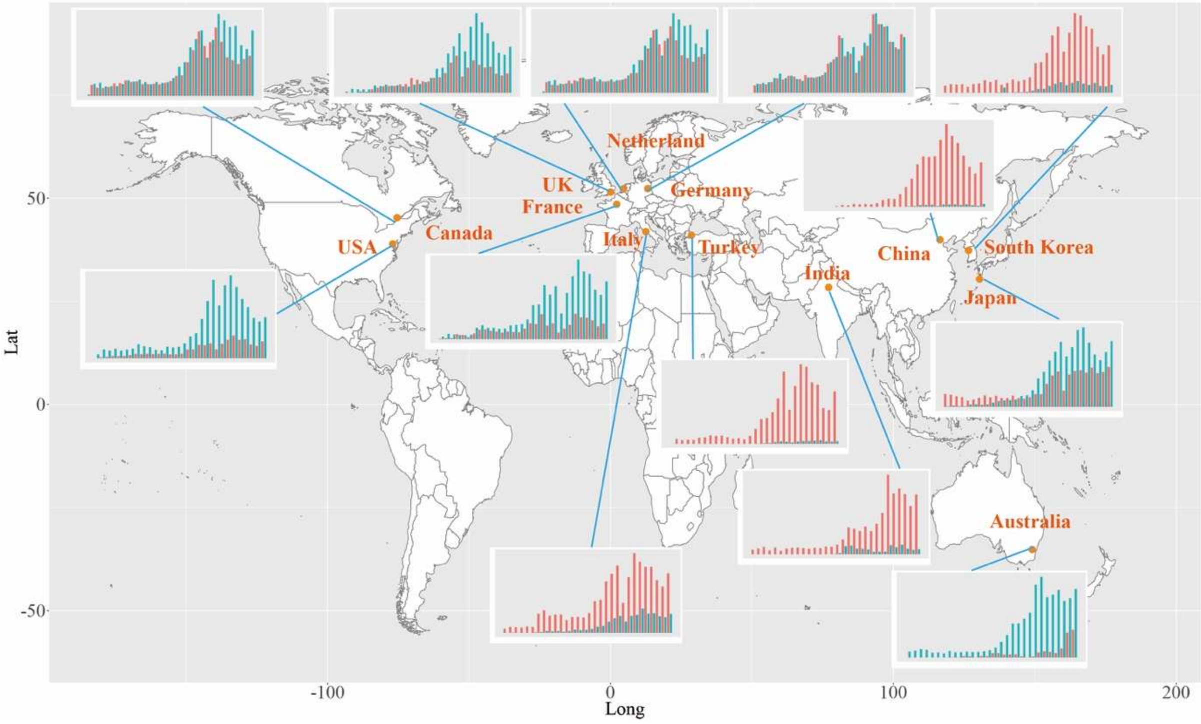


Figure 4. Changes in the top 10 countries from 1988-2011 by different metrics.



Notes: We show changes in the import and export trade value in certain core countries during the past 30 years. The core countries are selected from top 10 countries as ranked by in-strength and out-strength. The red bars and green bars indicate the trade value of imports and exports, respectively.

Figure 5. Changes in the import and export trade value in core countries from 1988 to 2017.

5. Community structure and evolution

So far, we have explored the structural characteristics and core countries in the international scrap metal trade over the past 30 years. The above analysis is mainly based on a holistic perspective, but the trade networks have clear regional patterns due to their geographical distribution and the cultural and historical relationships among countries. Therefore, this section applies the *Infomap* algorithm (Rosvall and Bergstrom, 2008) to detect communities in the GSMTN and discusses the dynamic evolution of these communities.

5.1 Overview of the communities

Figure 6(A) shows the basic features of the communities and changes that occurred over the past 30 years. The number of communities ranges from 4 to 9, and since 2010, it has remained at a relatively high level. The size of the communities is described in Figure 6(B), which shows that the average size of the communities over the past 30 years has remained within a certain range, approximately 25 to 50. The smallest communities each year are composed of approximately two countries. Due to the geographic positions and limited trade volume, these smallest communities are formed, which mainly consist of countries from Latin America. For instance, Paraguay and Uruguay constituted the smallest community in 1990. The results indicate that although many countries have participated in the scrap metal trade and established close trade ties, some individual countries are still separate from the close global trade.

To further analyze the difference in the size of communities in each year, Figure 6(C) depicts the diversity of communities, $diver$, annually. We observe a dramatic downward tendency from 2005 to 2010, and the diversity in terms of size reaches its lowest level in 2009. The results suggest that most countries are connected closely within the largest community, and a few countries are dispersed in small communities, as shown in Figure 6(B).

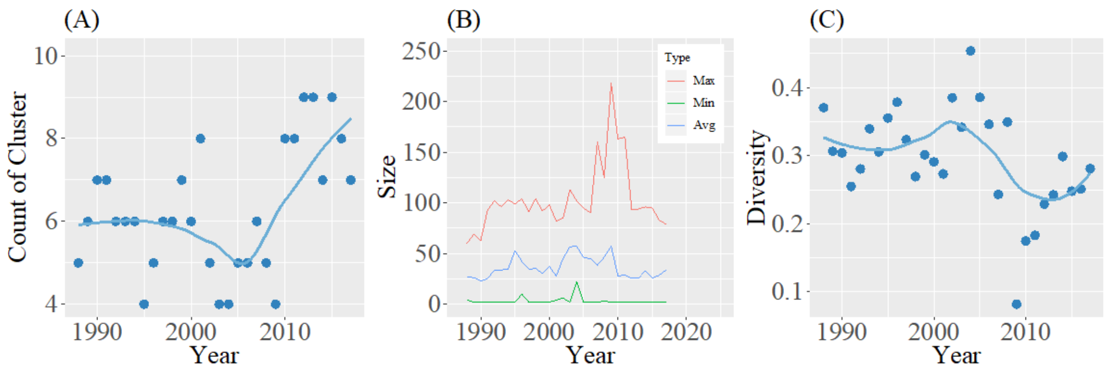


Figure 6. Basic information on communities in the GSMTN from 1988-2017.

5.2 Community structure

This sub-section explores the regional topological features and dynamic patterns of the communities. Schematic diagrams are used to provide an intuitive and visual representation of the community structure. The countries within a community are labeled by the same color. The size of the nodes in the schematics denotes the strength of the countries. The weight of the edges represents the trade volume between two countries. Four snapshots of the international scrap metal trade networks (1988, 1993, 2005 and 2017) are selected to reflect four different and typical topological structures of trade clusters, which are illustrated in Figure 7.

In the early stage, four distinct communities appeared in 1988, as seen in Figure 7(A). Generally, the star structures within the same communities are noticeable, indicating that certain countries act as hubs and have established trade relationships with other countries to form a community. Except for the core countries, other countries in the same communities did not build strong trade connections with each other. Within the trade communities, the trade relationships were very sparse. For example, in the communities labeled by green nodes and edges, several trade connections were established between the hub countries, such as the USA, South Korea and Japan. In contrast, the peripheral countries in this community, such as Vietnam, Qatar, Iran, and Syria, did not build strong trade connections. In addition, these communities display geographically regional characteristics. In particular, European countries constituted the biggest community, with Germany, Switzerland and Finland acting as the major hubs. To a certain degree, this community was formed due to the strong geographical and cultural ties of the member countries. The second largest community was composed of most Asian and American countries, and the central countries included Japan, South Korea, India, and the USA. Similarly, Australia, a core country, and its peripheral island countries such as Fiji and Vanuatu were integrated due to their close geographical relationships. Notably, China joined with Thailand and certain geographically distant American countries, including Canada, Brazil and Argentina, to make up a small community with 14 members.

The communities in 1993 show a different structural characteristic compared to those in 1988. As illustrated in Figure 7(B), the hubs still played a vital role in connecting countries within the communities. However, there were tight intracommunity relations that differed from the typical star structure. In addition, the core countries in the different communities established close trade relationships. For example, there were large trade values in USA-China and USA-UK, and these countries belonged to different communities. The Asia region was split into two communities. One is the East Asia region with China, Japan and Singapore acting as hubs. The other is the Middle East and the South Asia region with India and the UAE acting as hubs. This change in the communities reflects the fast growth of emerging countries in Asia, such as China and India. In addition, the Americas, led by the USA, formed the third largest community. However, this community was smaller than the European community and the East Asian community. Despite the many changes that occurred between 1988 and 1993 shown in Figure 7(A) and (B), two communities remained relatively stable: Europe and Oceania remained the first and the fourth largest communities, respectively.

Due to the increasing attention to recycling scrap metals, trade ties, especially among countries in the same communities, became closer in 2005, as shown in Figure 7(C). In contrast to 1993, in 2005, the East Asia region, Americas and Oceanic countries merged to form the largest community, where China and the USA were the core countries. The trade value between China and the USA was far higher than that for other country pairs. The European region was split into two communities: UK and Germany were the hubs for the large community, and the small community was composed of Russia and other European countries surrounding the Black Sea. The community constituting South Asia and the Middle East with India, Saudi Arabia and UAE remained relatively stable. Figure 7(D) shows that until 2017, the community structure had a trend in which the three major communities, the East Asia-America community, the European community and the South Asia-Middle East community, were fairly equal. Meanwhile, the size of the community led by Russia clearly decreased.

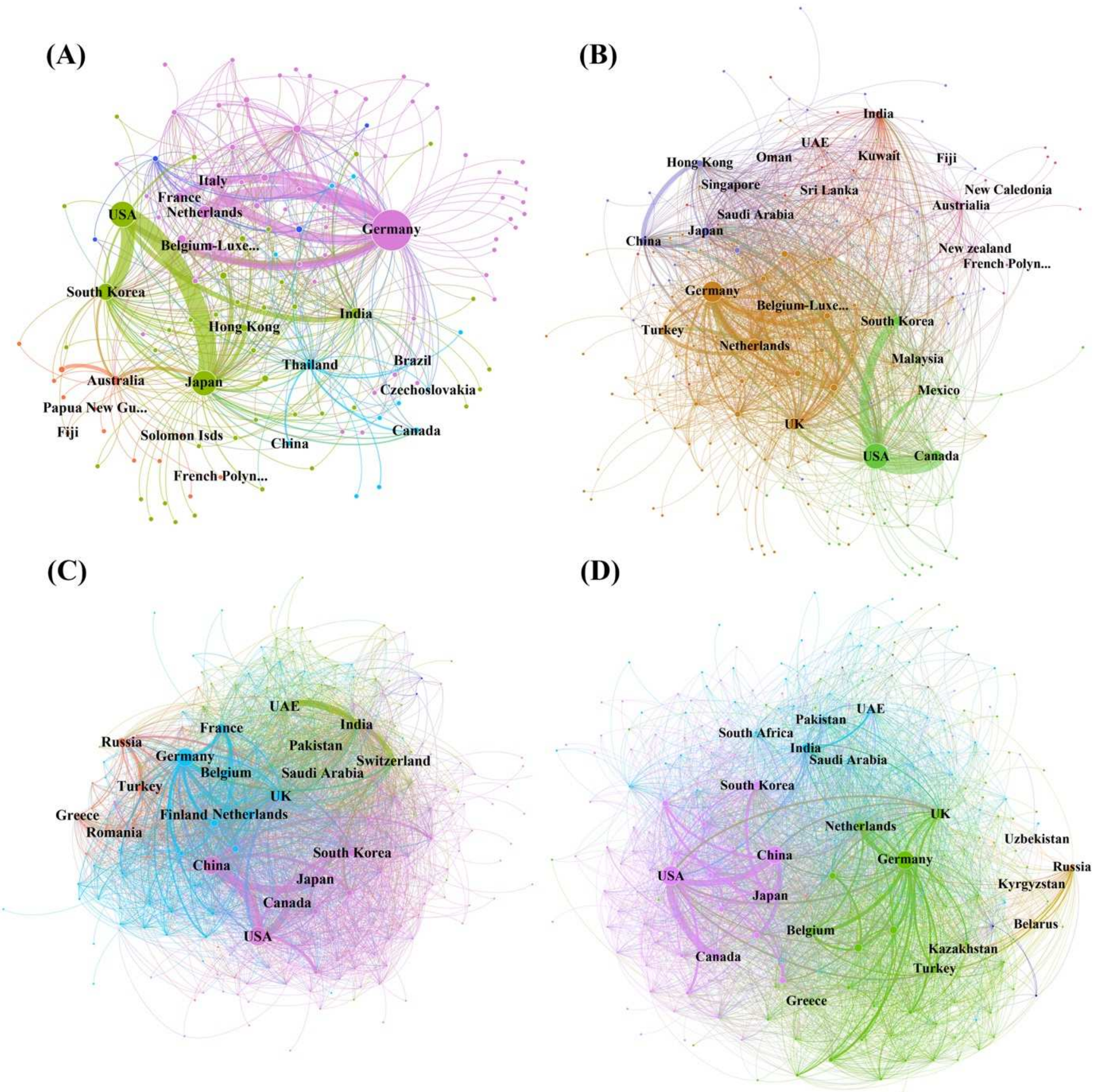


Figure 7. Communities of the GSMTN in 1988, 1993, 2005, and 2017.

5.3 Community evolution

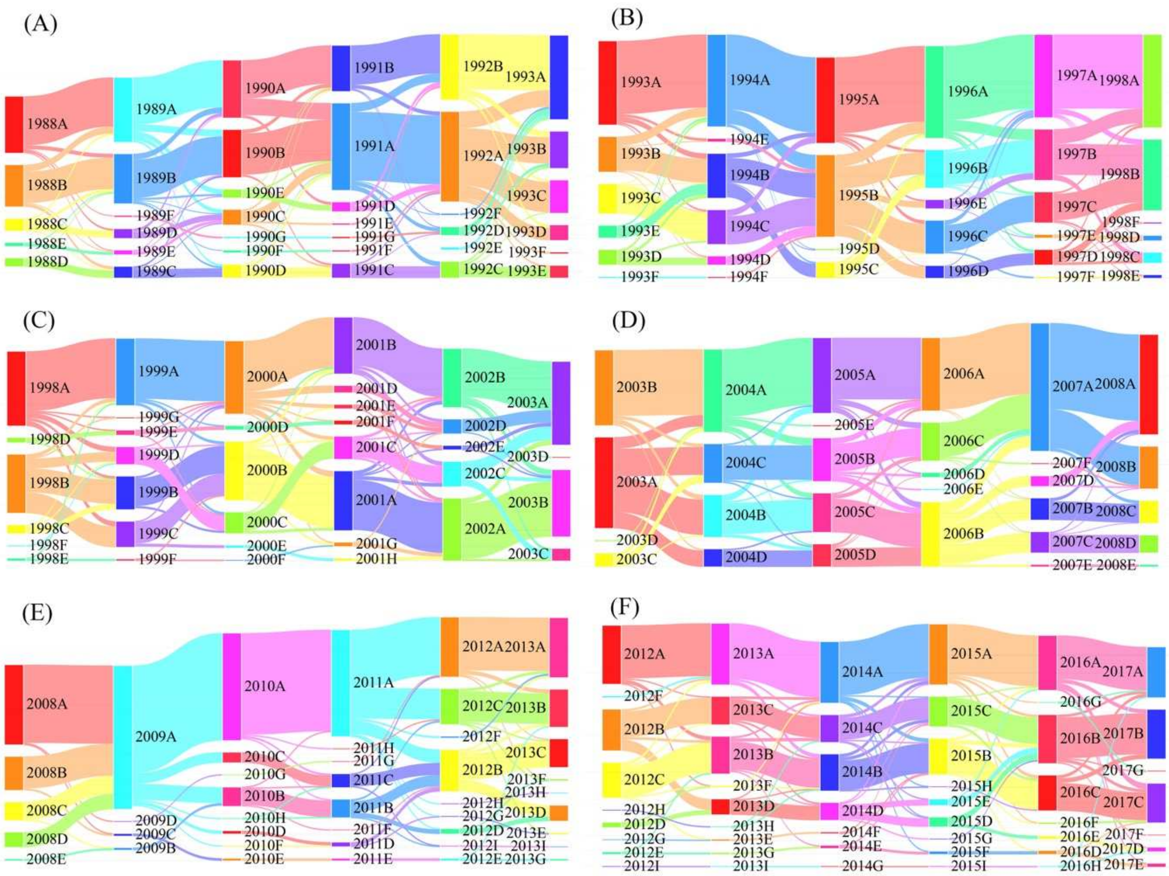
To understand the dynamics of the communities, this sub-section analyzes the stability and evolution of the communities to show how the communities split and merge. The results are shown in Figure 8.

Generally, two large communities were dominant in the GSMTN before 2012: the European community with Germany and the UK as hubs and the East Asia-America community led by the USA and China. After 2012, the South Asia-Middle East community was formed. These three communities have formed a situation of tripartite confrontation. A distinct integration occurred, and most countries were in the same community in 2009. One considerable reason for the emergence of a large community is the financial crisis in 2007-2008, which reduced the worldwide consumption of metals products and the demand for scrap metals. In effect, the countries that originally belonged to the small communities diversified risk by establishing trading connections with countries from different communities, and thus, a large community was formed.

In terms of the specific communities, the European community remained the largest community from 1988 to 2000. However, this community has not ranked in the first position in terms of size since 2004. Some countries in the Black Sea-Mediterranean Sea regions and in the regions near Russia split from the European community and formed an independent community led by Russia and Turkey in 2002. This community was unstable throughout the study period and occasionally joined the European community again. In 2010 and 2011, this community expanded the scale of members and even became the second largest community. However, after 2013, it collapsed and the countries in Black Sea-Mediterranean Sea regions gradually returned to the European community.

The East Asia region is closely related to the Americas in terms of community structures. In the early stage, these regions were split into two communities: the large one was composed of most Asian and American countries led by the USA and Japan, and the small one consisted of a few Asian and South American countries led by Thailand and Brazil until 1991. These countries repartitioned into two communities based on the geographical positions: the East Asia community represented by China and Japan and the America community with the USA and Canada as hubs in 1993-1994, 1996-1997 and 1999. The changes in communities are in line with the important historical events. The Asian financial crisis had serious repercussions in 1997, and Brazil’s financial crisis led to economic turmoil in Latin American countries in 1999. Compared with the global economic crisis of 2007-2008, these two events have notable regional features. Hence, these two communities split in terms of the geographical position of the member countries to reduce the risk contagion. It is clear that the split and merger of trade communities are affected by the stability of the economic and political environment. These two communities merged into one community with the USA, Japan and China as hubs, which has remained the largest community since 2005. Australia joined with its neighbors to form the Oceania community. This community was the third or the fourth largest from 1988 to 1995, and then it was integrated into the East Asia-America community in 1996.

In addition to the two large communities discussed above, some countries split from the East Asia-America community in 1993 and gradually formed a South Asia-Middle East community that included India and the UAE. In the early years, the South Asia-Middle East community was not stable and occasionally was integrated into the East Asia-America community. After 2012, the countries in the South Asia-Middle East community remained relatively stable. In addition, this community and the European community became the second or the third largest community, respectively.



Notes: The communities are labeled in capital form and ordered by the size. For example, the largest community in 1988 is labeled 1988A, and the smallest community is labeled 1988D. In addition, the links between communities in two years reflect the migration of community members. The weight of the links denotes the scale of overlapping community members.

Figure 8. Community evolution from 1988-2017.

6. Discussion and policy implications

(1) The globalization of international trade for scrap metals

The globalization of the international scrap metal trade gradually increased over the past

30 years due to the increasing number of trade countries and trade relationships. The number of countries involved in the international scrap metal trade mainly increased between 1988 and 2000, and most of the new entrants were developing countries in Africa and Asia. This growth indicates that a growing number of countries recognize the benefits of scrap metal trade. However, the latest trend in trade contrasts to its previous growth trend from 1988 to 2008 and shows a prominent downward trend in the past seven years. This change may result from the unstable world economic situation and the restrictive policy in core importing countries such as China. As shown in Figure 1(D), the 34% reduction of the total world trade value was caused by China's import decline.

The findings suggest that the trade relationships with respect to scrap metals will remain relatively stable. The total trade volume experienced a decline in the past five years, and it is expected to continue to drop. In particular, China, as the biggest importing country, has enforced strict market surveillance since 2017 because of the environmental degradation and structural transformation.

(2) Scale-free characteristic of trade networks

Global scrap metal trade networks have scale-free properties in which a few countries hold the most trade value and the largest number of trade relationships. In particular, the degree of monopolization in exporting countries presented a steady upward trend from 1988 and grew sharply in the last five years as shown in Figure 2. For the importing countries, competition was increasingly intense in the early stage and then decreased slightly to reach a medium level over the past decade. In addition, heterogeneity in the trade network is prominent, although its degree dropped and reached a low level in 2017. Based on the world economic situation and prospects in 2019 from the United Nations, the global economic growth will become more imbalanced. This change will result in a more prominent scale-free characteristic, i.e., a higher proportion of trade value occupied by a few core countries.

Due to the scale-free characteristic, the following policy suggestions are provided for importing countries and exporting countries. The importing countries, especially those whose metal production is heavily dependent upon imported scrap, are suggested to decentralize import channels to avoid stock-out due to the political turmoil of core exporting countries. In addition, the countries with huge import volumes are encouraged to promote domestic recycling markets and improve the scrap metal recycling rate. For the exporting countries, the policy turmoil in the core importing countries deserves attention. With increasing importing countries banning imports of low-grade scrap metals, the metal recyclers in the exporting countries are suggested to upgrade the quality of export scrap metals by employing existing purification technologies.

(3) Clustering and hierarchical structure of the trade relationships

In Figure 3, the characteristics of clustering structure in the GSMTN are revealed. Specifically, the increased density and the decreased average shortest path length denote that an increasing number of trade relationships among countries was established. However, the low level of the weighted clustering coefficient reveals that the tight connections were still concentrated in a few countries.

Moreover, the trade relationships show a clearly hierarchical structure, which is dominated by certain hubs. In the early stage, the developed countries were the core countries. Because of the unprecedented growth in newly industrialized countries, China and India have become the core importing countries. Despite these changes, in general, the core countries in the trade networks have remained relatively stable in the past 30 years. Due to the substantial influence of core countries on the trade network, the non-hub countries are suggested to pay close attention to the changes in import and export policies of these hubs.

(4) Community evolution patterns

The community structure in the GSMTN undergoes a continuously dynamic evolution. In terms of the intracommunity, the community structure has changed from the original star pattern to a dense structure with closer trade relationships as shown in Figure 7. This change indicates that countries attempt to expand their trade relationships to decrease their dependence on a few hubs, which will improve their trade security. Certain countries still play vital roles, and the trade value among these hubs within the same communities occupies a large proportion of intracommunity trade.

The effect of geopolitics is evidenced in the formation of the communities because the regional trade communities have lower transportation costs and closer cultural and historical ties. In addition, the community evolution is distinctly influenced by political and economic disturbances. There are two kinds of typical turning points during which the stability of communities fluctuates widely. The first one is a regional economic crisis, such as the Asia financial crisis in 1997 and the Brazil financial crisis in 1999, which led to the disintegration of the East Asia-America community and the formation of the East Asia community and the America community. The other turning point was the global economic crisis in 2007-2008, which resulted in the integration of most countries. Therefore, it is suggested that regional crises tend to promote the separation of communities and that global crises tend to facilitate the integration of communities.

The findings on the important effect of geopolitics imply that the trade countries should pay attention to the policy directions of the hub countries within their communities. For example, in the East Asia-America-Oceania community, the movements of USA and China are the issues of greatest concern, which will directly affect the fragmentation and integration of the close-knit trade group. To relieve the negative impacts of the regional economic crisis, it is better for countries to downsize the trade volume with the countries involved in the crisis to avoid the risk contagion. In dealing with the global economic crisis, the reallocation of trade volume and strengthening of connections with countries in different communities is an efficient way to handle risk.

7. Conclusion and future research

Metal resources are one of the most important raw materials for industrial manufacturing, but the geological scarcity of minerals has attracted widespread concern. Because creating products from recycled metals instead of virgin ore saves energy, decreases greenhouse gas emissions, and reduces production cost, recycled metals play a vital role in relieving the shortage of metal resources. The geographically uneven distribution of scrap metals promotes an increasing number of countries to participate in the international scrap metal trade. In the context of the intricate trade relationships, it is crucial for policy-makers and industrial practitioners to understand the characteristics and evolution patterns of the global scrap metal trade network.

Therefore, this study applies complex network theory to investigate the topological characteristics and community evolution patterns of the global scrap metal trade by constructing a weighted and directed GSMTN from 1988 to 2017. Specifically, the process of globalization of the international scrap metal trade is reviewed, and our results show the scale-free and hierarchical structural characteristics of trade networks. In addition, the countries at the central position in the GSMTN are measured by different indicators and the variation of the core countries are revealed. Furthermore, we detect the communities in the GSMTN and find a tripartite configuration in 2017: the European community led by Germany and the UK; the East Asia-America-Oceania community led by China, the USA and Australia; and the South Asia-Middle East community led by India and the UAE. By reviewing the split and merger process of these communities, it is clear that geopolitics and economic turbulences are important elements in community fragmentation and integration. The findings in this study provide implications to support authorities in developing policies and avoiding the risks involved in the scrap metal trade.

In the future, we will build a two-layer global metal trade network, including the metal ore trade layer and the scrap metal trade layer. Then, we will discuss the relations between the two layers, explore the correlation of dynamic evolution in each layer, and investigate the influences of political turmoil in the core countries on this two-layer global trade network.

Acknowledgments

Financial support was provided in part by National Natural Science Foundation of China (61603011 and 61773029), Beijing Social Science Foundation (16JDGLC005), and International Postdoctoral Exchange Fellowship Program (20170016). We gratefully acknowledge the discussions with and the support of Professor H. Eugene Stanley from Boston University.

References:

An, H., Zhong, W., Chen, Y., Li, H., Gao, X., 2014. Features and evolution of international crude oil trade relationships: A trading-based network analysis. Energy 74(5), 254-259.

Barabási, A.-L., 2016. Network science. Cambridge university press.

Baskaran, T., Blöchl, F., Brück, T., Theis, F.J., 2011. The Heckscher–Ohlin model and the network structure of international trade. International Review of Economics & Finance 20(2), 135-145.

Batagelj, V., Zaversnik, M., 2003. An O (m) algorithm for cores decomposition of networks. arXiv preprint cs/0310049.

Borgatti, S.P., 2005. Centrality and network flow. Social networks 27(1), 55-71.

Borgatti, S.P., Everett, M.G., 2006. A graph-theoretic perspective on centrality. Social networks 28(4), 466-484.

Bosworth, B., Collins, S.M., 2008. United States-China trade: where are the exports? Journal of Chinese Economic and Business Studies 6(1), 1-21.

Brandes, U., 2001. A faster algorithm for betweenness centrality. Journal of mathematical sociology 25(2), 163-177.

Dong, D., An, H., Huang, S., 2017. The transfer of embodied carbon in copper international trade: An industry chain perspective. Resources Policy 52, 173-180.

Estrada, E., 2010. Quantifying network heterogeneity. Physical Review E 82(6), 066102.

Fagiolo, G., Reyes, J., Schiavo, S., 2008. On the topological properties of the world trade web: A weighted network analysis. Physica A: Statistical Mechanics and its Applications 387(15), 3868-3873.

Fagiolo, G., Reyes, J., Schiavo, S., 2010. The evolution of the world trade web: a weighted-network analysis. Journal of Evolutionary Economics 20(4), 479-514.

Fan, Y., Ren, S., Cai, H., Cui, X., 2014. The state's role and position in international trade: A complex network perspective. Economic Modelling 39, 71-81.

Fischer, C.S., Shavit, Y., 1995. National differences in network density: Israel and the United States. Social Networks 17(2), 129-145.

Fortunato, S., 2010. Community detection in graphs. Physics reports 486(3-5), 75-174.

Freeman, L.C., 1977. A set of measures of centrality based on betweenness. Sociometry, 35-41.

Freeman, L.C., 1978. Centrality in social networks conceptual clarification. Social networks 1(3), 215-239.

Garlaschelli, D., Loffredo, M.I., 2004. Fitness-dependent topological properties of the world trade web. Physical Review Letters 93(18), 188701.

Garlaschelli, D., Loffredo, M.I., 2005. Structure and evolution of the world trade network. Physica A: Statistical Mechanics and its Applications 355(1), 138-144.

Garlaschelli, D., Matteo, T.D., Aste, T., Caldarelli, G., Loffredo, M.I., 2007. Interplay between topology and dynamics in the World Trade Web. European Physical Journal B 57(2), 159-164.

Geng, J.B., Ji, Q., Fan, Y., 2014. A dynamic analysis on global natural gas trade network. Applied Energy 132(1), 23-33.

Ghadimi, P., Wang, C., Lim, M.K., 2019. Sustainable supply chain modeling and analysis: Past debate, present problems and future challenges. Resources, Conservation and Recycling 140, 72-84.

Ghisellini, P., Cialani, C., Ulgiati, S., 2016. A review on circular economy: the expected transition to a balanced interplay of environmental and economic systems. Journal of Cleaner Production 114(1), 11-32.

Giorgio, F., Javier, R., Stefano, S., 2009. World-trade web: topological properties, dynamics, and evolution. Physical Review E Statistical Nonlinear & Soft Matter Physics 79(2), 036115.

Girvan, M., Newman, M.E., 2002. Community structure in social and biological networks. Proceedings of the national academy of sciences 99(12), 7821-7826.

Giurco, D., Littleboy, A., Boyle, T., Fyfe, J., White, S., 2014. Circular economy: Questions for

responsible minerals, additive manufacturing and recycling of metals. Resources 3(2), 432-453.
Golev, A., Corder, G., 2016. Modelling metal flows in the Australian economy. Journal of Cleaner Production 112, 4296-4303.
Graedel, T.E., Harper, E.M., Nassar, N.T., Reck, B.K., 2015. On the materials basis of modern society. Proceedings of the National Academy of Sciences 112(20), 6295-6300.
Klimek, P., Obersteiner, M., Thurner, S., 2015. Systemic trade risk of critical resources. Science advances 1(10), e1500522.
Landherr, A., Friedl, B., Heidemann, J., 2010. A critical review of centrality measures in social networks. Business & Information Systems Engineering 2(6), 371-385.
Lee, H., Sohn, I., 2015. Global scrap trading outlook analysis for steel sustainability. Journal of Sustainable Metallurgy 1(1), 39-52.
Li, X., Chen, G., 2003. A local-world evolving network model. Physica A: Statistical Mechanics and its Applications 328(1-2), 274-286.
Li, X., Jin, Y.Y., Chen, G., 2003. Complexity and synchronization of the world trade web. Physica A: Statistical Mechanics and its Applications 328(1-2), 287-296.
Liu, Y., Farnsworth, M., Tiwari, A., 2017. A review of optimisation techniques used in the composite recycling area: State-of-the-art and steps towards a research agenda. Journal of cleaner production 140, 1775-1781.
Lothar, 2013. Process engineering in circular economy. Particuology 11(2), 119-133.
Page, L., Brin, S., Motwani, R., Winograd, T., 1999. The PageRank citation ranking: Bringing order to the web. Stanford InfoLab.
Reck, B.K., Graedel, T.E., 2012. Challenges in Metal Recycling. Science 337(6095), 690.
Rosvall, M., Bergstrom, C.T., 2008. Maps of random walks on complex networks reveal community structure. Proceedings of the National Academy of Sciences 105(4), 1118-1123.
Saramäki, J., Kivelä, M., Onnela, J.-P., Kaski, K., Kertesz, J., 2007. Generalizations of the clustering coefficient to weighted complex networks. Physical Review E 75(2), 027105.
Serrano, M.A., Boguná, M., 2003. Topology of the world trade web. Physical Review E 68(1), 015101.
Spatari, S., Bertram, M., Gordon, R.B., Henderson, K., Graedel, T., 2005. Twentieth century copper stocks and flows in North America: A dynamic analysis. Ecological Economics 54(1), 37-51.
Sverdrup, H.U., Ragnarsdottir, K.V., Koca, D., 2017. An assessment of metal supply sustainability as an input to policy: security of supply extraction rates, stocks-in-use, recycling, and risk of scarcity. Journal of Cleaner Production 140, 359-372.
Terao, T., 2005. The rise and fall of ‘mixed metal scrap’recovery industry in Taiwan: international trade of scraps and transboundary relocation of the business. International trade of recyclable resources in Asia, 63-84.
Wang, C., Zhang, X., Wang, M., Lim, M.K., Ghadimi, P., 2019. Predictive analytics of the copper spot price by utilizing complex network and artificial neural network techniques. Resources Policy 63, 101414.
Wang, H., Yan, G., Xiao, Y., 2009. Symmetry in world trade network. Journal of Systems Science and Complexity 22(2), 280-290.

Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of ‘small-world’networks. Nature 393(6684), 440.

Yang, Y., Poon, J.P.H., Liu, Y., Bagchi-Sen, S., 2015. Small and flat worlds: A complex network analysis of international trade in crude oil. Energy 93(93), 534-543.

Zeng, X., Wang, F., Li, J., Gong, R., 2017. A simplified method to evaluate the recycling potential of e-waste. Journal of cleaner production 168, 1518-1524.

Zhang, L., Xu, Z., 2018. A critical review of material flow, recycling technologies, challenges and future strategy for scattered metals from minerals to wastes. Journal of cleaner production.