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# Characteristics of the Global Copper Raw Materials and Scrap Trade Systems and the Policy Impacts of China's Import Ban

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**Abstract**

Copper raw materials (CRM) and copper waste and scrap (CWS) are the two main sources of copper manufactured products. Due to the uneven geographical distribution of copper production and consumption, international CRM and CWS trade developed. However, no study has explored the complicated interdependencies between CRM trade and CWS trade or investigated the characteristics of this multiplex trade system. This study uses trade records from 1988 to 2017 to construct multiplex trade networks: a global CRM trade network and a global CWS trade network. The evolution of copper trade in the last three decades is reviewed, and the intricate relationships in the multiplex trade network are identified. It is found that CWS trade has a highly positive correlation with CRM trade, but there are obvious differences between CWS trade and CRM trade in the multilateral trade structure. Multilateral trade structures driven by core exporting countries and core importing countries are prominent in CRM trade and CWS trade, respectively. In addition, the impacts of China's restrictive policies on the multiplex trade system are analyzed. The results provide policy implications for countries regarding copper resource security strategies and safeguarding the multiplex trading system.

**Keywords:** Copper raw materials; Copper waste and scrap; Multiplex trade network; Evolution and correlation; Policy impacts; China's import ban

## 1. Introduction

Copper manufactured products are widely used in every field of industrial production and daily life, and play a crucial role in economic growth (Graedel et al., 2002; Sverdrup et al., 2014). For centuries, copper ores were mined and processed to provide copper raw materials (CRM), including copper pipes, copper sheets, copper tubes, copper plates, copper bars, copper sheets, and copper coils, for manufacturing (Tong and Lifset, 2007). However, due to exponential growth in the amount of copper-manufactured products, copper is considered a scarce mineral with only 60 years of expected availability at current production levels (Harmsen et al., 2013; Sverdrup et al., 2017). Recycling copper is one of the best ways to alleviate a resource shortage. Copper waste and scrap (CWS) is recycled and replaces virgin copper from ore for manufacturing copper products.

Due to the uneven geographical distribution of copper production and consumption (Northey et al., 2013), international trade of CRM and CWS formed and has become a multiplex trade system. However, no studies have explored the interdependencies between CRM trade and CWS trade or investigated the characteristics of this multiplex trade system. As is well known, due to economic globalization, countries are vulnerable to trade disruption, such as those caused by natural disasters and geopolitical restrictions (Liu and Müller, 2013). In particular, China, the largest CWS importer, has proposed a series of restrictive policies to stop waste imports since 2010 (Wang et al., 2020). China's policies will shape the copper-related multiplex trade system. However, in the existing literature, there is no study investigating the policy impacts of China's import ban on global copper raw materials and scrap trade (CRM&WS) systems until now.

Therefore, this study obtained trade records for CRM and CWS from 1988 to 2017 to construct a global CRM&WS trade network called the multiplex copper trade network (MCTN). The MCTN includes two layers, i.e., a global CRM trade network and a global CWS trade network. Complex network theory is used to identify the relationship between CRM trade and CWS trade and to understand the impact of China's import ban on the MCTN. The contributions of this study are summarized as follows: (1) The dynamic evolution of the MCTN from 1988 to 2017 is reviewed, and the core countries are revealed. The intricate relationship between CRM trade and CWS trade is explored from various perspectives, including the participating countries, trade relationships and multilateral trade structures. This study conducts a comprehensive analysis of the MCTN. (2) A multiple shock model is proposed, and the impacts of China's restrictive policies on the MCTN are evaluated. The results provide some policy implications for governments seeking to maintain the security and adequacy of copper materials.

The remainder of this paper is organized as follows. Section 2 reviews the related literature on the international trade of CRM and CWS. Section 3 describes the data and methods. Section 4 describes the evolution of the MCTN over the past three decades. Section 5 discusses the intricate relationship between CRM trade and CWS trade. Section 6 analyzes the impacts of China's restrictive policies on the MCTN. Section 7 discusses the results and policy implications. Section 8 reports the conclusions and future work directions.

## 2. Literature review

Copper is one of the most significant basic substances for social and economic development because of its high electroconductibility, thermal conductivity and chemical stability (Figge et al., 2017; Li et al., 2017; Pothen and Reaños, 2018; Sverdrup et al., 2014). Copper has been extensively used in many fields; for example, in China, more than 90% of modern industrial enterprises require copper (Chang et al., 2013). Thus, copper has been the second most strategic raw material following petroleum (Wang, 2014). However, mineral resources are nonrenewable natural resources, and copper ore will be exhausted within a few decades under the current mining level based on predictions in previous studies (Harmsen et al., 2013; Sverdrup et al., 2017). In this context, circular economy is proposed to understand how resources can be used more efficiently (Figge et al., 2018; Korhonen et al., 2018). Recycled copper from waste and scrap is increasingly crucial to relieve the pressure from the scarcity of copper ore. In 2014, 30% of the copper supply came from scrap and discarded products (ICSG, 2017). Moreover, recycling copper reduces risks to the environment. In particular, the energy consumption for copper production from secondary sources is approximately 85% of that from primary sources (Fu et al., 2017; Rankin, 2011). Therefore, CRM and CWS have strategic importance for national development, and international trade plays a crucial role in resource allocation; therefore, studying the CRM trade and CWS trade has practical significance.

Numerous studies have examined the international copper or copper scrap trade. Espinoza and Soulier (2016) analyzed international trade flows of copper and revealed the positions of six different regions in copper-relevant value chains. Chen et al. (2016) and Goonan (2016) explored the trade patterns of copper metal and scrap in the USA and revealed that the USA has been supplying increasingly more scrap to the world, and that China is the main importer. Wang and Badman (2016) analyzed the copper trade in Peru based on the gravity model and identified the main factors affecting the copper trade. Dong et al. (2017) analyzed the embodied carbon emissions network of the international copper trade and revealed core countries. Li et al. (2017) revealed the high external dependency of copper resources in China and investigated China's copper trade flows. Dong et al. (2018) combined resource dependence and network theory to explore factors affecting the community formation of the international copper trade among 20 countries from 2007 to 2015. Soulier et al. (2018) proposed a dynamic model to model the copper stock and the copper trade flows for the European Union (EU28) and explored the different dynamic patterns between different countries.

The studies mentioned above reveal the close connections among countries in the international copper trade. At the same time, intimate relationships in markets have been increasingly acknowledged to cause an adverse effect on the stability of the trade system (Klimek et al., 2015). Due to the interconnectedness of a system, a local shock will lead to the collapse of a large fraction of the system, which is defined as a systemic trade risk (Klimek et al., 2015). To understand the systemic risk in international trade and enhance trade security, many researchers have conducted related studies. An approach to assess the systemic risk of trade networks was suggested by Klimek et al. (2015), and their results showed that the centrality of a trade network can capture regional price volatility and the supply risk. Furthermore, many studies have explored the trade risk from the perspectives of various influential factors in the process of trade. Korniyenko et al. (2017) identified inherent vulnerabilities from the composition of a country's import basket. Different from the perspective of imports, Gephart et al. (2016) considered shocks from reductions of exports to explore the supply risk in the seafood trade. Gemechu et al. (2016) integrated the geopolitical aspect of resource criticality into the life cycle sustainability assessment framework to calculate the geopolitical supply risk. In addition, the effects of infectious diseases among livestock (Lebl et al., 2016) and climate variability on food production (Dolfing et al., 2019) are discussed in the trade systemic risk.

Although existing studies provide insights on the CRM and CWS trade patterns, the findings are limited to specific countries or regions. A systemic analysis of the international CRM and CWS trade has not yet been conducted, and trade relations between these two commodities have not been investigated. Therefore, systemic trade risks in the MCTN under the shock of import and export policies will be underestimated.

To understand the complex relationships between CRM trade and CWS trade and to estimate systemic trade risks, this study analyzes the global CRM and CWS trade by constructing a multiplex network. Boccaletti et al. (2014) defined multiplex networks as a set of nodes linked by more than two kinds of relationships; thus, the MCTN is constructed by designating countries as nodes and CRM and CWS trade relationships as two types of edges. Complex network theory provides effective perspectives to investigate multiplex networks and can be used to consider correlations between different layers (Boccaletti et al., 2014), resilience and percolation (Baxter et al., 2012; Parshani et al., 2011a) and cooperation (Gómez-Gardenes et al., 2012). The theory has been applied in different real-world contexts and focuses on three main topics (Boccaletti et al., 2014): social networks (Lewis et al., 2012; Szell and Thurner, 2010), technological networks (Cardillo et al., 2013; Parshani et al., 2011b) and economic networks (Barigozzi et al., 2010; Boss et al., 2004; Hu et al., 2020). These previous studies have set a solid foundation for an analysis of the MCTN.

## 3. Data and methods

### 3.1 Data description

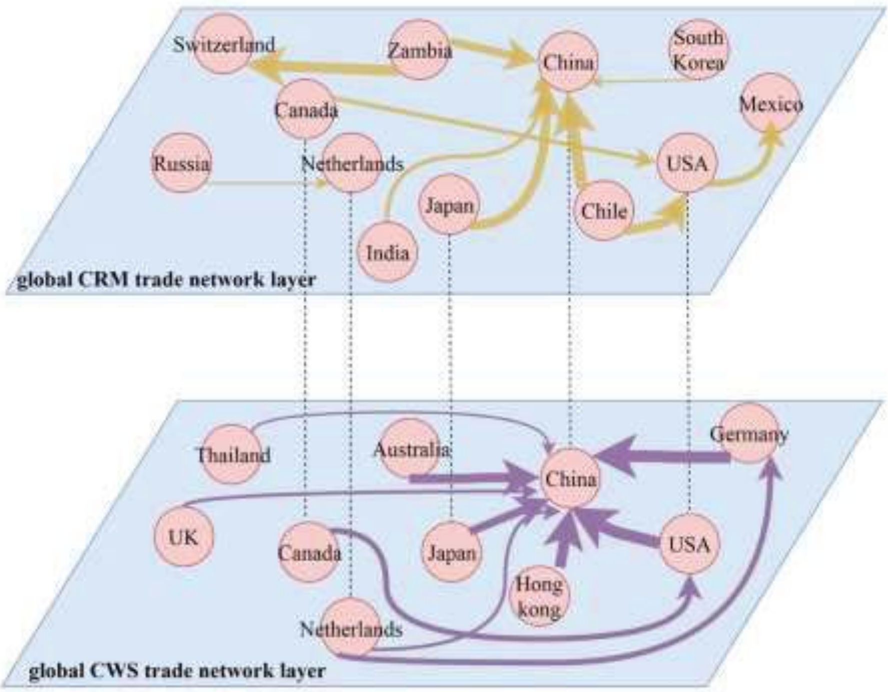
International trade data were obtained from the United Nations Commodity Trade Statistics Database (UN Comtrade, https://comtrade.un.org/). This database contains bilateral import and export data on approximately 200 countries/territories (countries hereafter) from 1962 to the most recent year. Each record contains detailed information on the periods, trade flows, trade countries and the unique code of commodities (called HS code from the interpretation of the Harmonized System). The volume of trade is measured in weight (kg) and value (US dollar). This study obtained all trade records of 19 categories of copper and articles thereof, including 7401 (Copper mattes; cement copper), 7402 (Copper; unrefined, copper anodes for electrolytic refining); 7403 (Copper; refined and copper alloys, unwrought); and 7404 (Copper; waste and scrap). For a detailed list of the categories and data preprocessing details, please see Appendix A. The data include records from 1988 to 2017, and the unit of measurement is value (ten million US dollars). Note that the Hong Kong Special Administrative Region of China (Hong Kong) and Mainland China (China) are considered separately.

### 3.2 Network construction

Annual MCTNs are built for the time period of 1988 to 2017. As shown in Figure 1, the MCTN consists of two layers, namely, the global CRM trade network and the global CWS trade network. The global CRM trade network is constructed as $G_d^{[t,T_1]} = (V_d^{[t,T_1]}, E_d^{[t,T_1]}, \mathbf{W}_d^{[t,T_1]})$ by using nodes to denote countries and edges to represent the bilateral trade relationships. $t$ represents a particular year ranging from 1988 to 2017, and $T_1$ is the CRM trade layer. The set of the involved countries in $G_d^{[t,T_1]}$ is denoted as $V_d^{[t,T_1]} = \{v_1, v_2, \cdots, v_{N^{[t,T_1]}}\}$, and $N^{[t,T_1]}$ represents the number of countries. In addition, the set of trade relationships is defined as $E_d^{[t,T_1]} = \{e_{ij,d}^{[t,T_1]} : i, j \in V_d^{[t,T_1]}\}$, where $e_{ij,d}^{[t,T_1]}$ indicates that in year $t$, country $i$ exported CRM to country $j$ and $m_d^{[t,T_1]}$ is the number of edges. The matrix of trade values is represented by $\mathbf{W}_d^{[t,T_1]} = \{w_{ij,d}^{[t,T_1]}\}$, where $w_{ij,d}^{[t,T_1]}$ is the aggregate export trade value of 18 kinds of copper commodities from country $i$ to country $j$ in year $t$. In addition, a signal adjacency matrix of $G_d^{[t,T_1]}$ is defined as $\mathbf{A}_d^{[t,T_1]} = \{a_{ij,d}^{[t,T_1]}\}$, in which we have $a_{ij,t}^{[t,T_1]} = 1$ if $e_{ij,d}^{[t,T_1]} \in E_d^{[t,T_1]}$; otherwise, $a_{ij,t}^{[t,T_1]} = 0$. Similarly, the global CWS trade network is constructed as $G_d^{[t,T_2]} = (V_d^{[t,T_2]}, E_d^{[t,T_2]}, \mathbf{W}_d^{[t,T_2]})$, where the element of the weight matrix $\mathbf{W}_d^{[t,T_2]}$ is $w_{ij,d}^{[t,T_2]}$, denoting the export trade value of CWS, and $T_2$ is the CWS trade layer.

Based on the definitions for the two single-layer networks, the MCTN is denoted as $G_d^{[t,M]} = (\mathbf{V}_d^{[t,M]}, \mathbf{E}_d^{[t,M]}, \mathbf{W}_d^{[t,M]})$, where $\mathbf{V}_d^{[t,M]} = [V_d^{[t,T_1]}, V_d^{[t,T_2]}]$, $\mathbf{E}_d^{[t,M]} = [E_d^{[t,T_1]}, E_d^{[t,T_2]}]$ and

$\mathbf{W}_d^{[t,M]} = [\mathbf{W}_d^{[t,T_1]}, \mathbf{W}_d^{[t,T_2]}]$. It is noted that some nodes only exist in a single layer. For unification, we add these nodes as isolated nodes in the corresponding layers; that is, $a_{ij,d}^{[t,T_1]} = 0$ for each node $j \in V_d^{[t,T_1]}$ if $i \notin V_d^{[t,T_1]}$. Furthermore, we construct weighted and undirected multiplex trade networks $G_u^{[t,T_1]} = (V_u^{[t,T_1]}, E_u^{[t,T_1]}, \mathbf{W}_u^{[t,T_1]})$ , $G_u^{[t,T_2]} = (V_u^{[t,T_2]}, E_u^{[t,T_2]}, \mathbf{W}_u^{[t,T_2]})$ and $G_u^{[t,M]} = (\mathbf{V}_u^{[t,M]}, \mathbf{E}_u^{[t,M]}, \mathbf{W}_u^{[t,M]})$ based on the extension of the definition of $G_d^{[t,T_1]}$, $G_d^{[t,T_2]}$ and $G_d^{[t,M]}$. Specifically, $w_{ij,u}^{[t,l]} = w_{ij,d}^{[t,l]} + w_{ji,d}^{[t,l]}$ and $w_{ij,u}^{[t,l]} = w_{ji,u}^{[t,l]}$ for $l \in [T_1, T_2]$.




Notes: The first layer indicates the global CRM trade network, and the second layer embodies the global CWS trade network. Only the top ten trade relationships in 2017 sorted by trade value in each layer are shown as yellow and purple edges, respectively. The width of lines denotes the trade value between countries, and the nodes common to both networks are linked by dashed lines.

Figure 1. Schematic example of the MCTN.

### 3.3 Measures of the MCTN's structure

To understand the characteristics of the MCTN, this study proposes three measures, including centrality and tightness, community structure, and topological correlation. Then, a multiple shock model is built to evaluate the policy impacts of China's import ban.

#### 3.3.1 Centrality and tightness

(1) Centrality

In complex network theory, centrality is used to evaluate the importance of nodes (Borgatti and Everett, 2006). The degree of a node is the simplest measure of the importance of a node and is defined as the number of links connected to the vertex (Freeman, 1978). To distinguish the direction of the links, we use two indicators for the in-degree $k_i^{[t,l]}(in)$ and out-degree $k_i^{[t,l]}(out)$ of node $i$ in network $G_d^{[t,l]}$, $l \in [T_1,T_2]$,

$$k_i^{[t,l]}(in)=\sum\nolimits_{j\in V_d^{[t,l]}} a_{ji,d}^{[t,l]},\ k_i^{[t,l]}(out)=\sum\nolimits_{j\in V_d^{[t,l]}} a_{ij,d}^{[t,l]}\ . \tag{1}$$

For the undirected network $G_u^{[t,l]}$, the node degree is defined as the sum of the in-degree and out-degree; that is, $k_i^{[t,l]}=k_i^{[t,l]}(in)+k_i^{[t,l]}(out)$. In the MCTN, a country with a higher in-degree/out-degree has more trade partners of imports/exports and its import-export policies impact more countries than those with a lower a higher in-degree/out-degree.

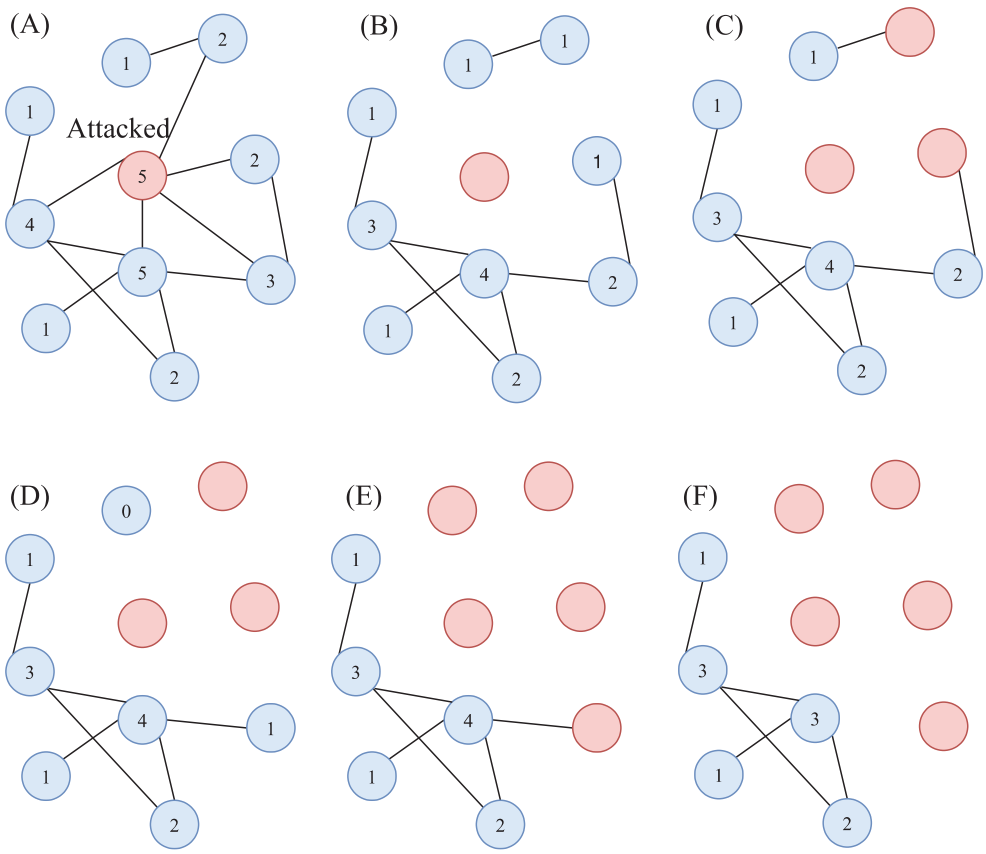
Different from the degree, the strength of the node quantifies the importance of the node by considering the weight of the links. The specific definitions of the in-strength $s_i^{[t,l]}(in)$ and out-strength $s_i^{[t,l]}(out)$ of node $i$ in network $G_d^{[t,l]}$, $l \in [T_1,T_2]$ are proposed as follows,

$$s_i^{[t,l]}(in)=\sum\nolimits_{j\in V_d^{[t,l]}} w_{ji,d}^{[t,l]},\ s_i^{[t,l]}(out)=\sum\nolimits_{j\in V_d^{[t,l]}} w_{ij,d}^{[t,l]}\ . \tag{2}$$

The strength of node $i$ is the aggregate import and export trade value, namely, $s_i^{[t,l]}=s_i^{[t,l]}(in)+s_i^{[t,l]}(out)$. A high in-strength/out-strength of a country in the MCTN indicates that that country has a high import/export trade value.

Compared to the above static indicators that mainly measure the direct influence of the nodes, the avalanche size of node $as_i^{[t,l]}$ is a key metric for measuring the scale of the direct and indirect influences of a targeted country when it collapses (Lee and Goh, 2016; Lee et al., 2011). The computational process can be described as follows. First, the seed node $i$ collapses and is removed from the network. Second, all the links connected to the failure node $i$ are also removed from the network, and the strength of the nodes in the network is updated. Then, the status of each non-collapsed node is changed to failure when the decrement in strength exceeds a certain percentage of its total strength. Next, the dynamic procedures described in the previous steps are restarted in parallel. Finally, the cascade of failure led by the seed node

$i$ is terminated when no more new nodes collapse. Thus, the total number of failure nodes in the entire procession is called the avalanche size, and this indicator assesses the potential impact of a country that is central to the global CRM&WS trade. We find that the different values of the threshold lead to different specific rankings, but the major results remain unchanged. Therefore, for simplicity, we set the threshold of the percentage to 0.5. An illustration is provided in Figure 2 to show the computational process for avalanche size.




Notes: To provide a clear explanation of avalanche size, we simplified the network by setting all weights of edges to 1, and the threshold is 0.5. (A) One node labeled by red color collapses under an attack. (B) All links connected to the collapsed node are removed, and the strength of all nodes is updated. (C) Two nodes' strengths change from 2 to 1, and the change ratio reaches the threshold of 0.5. Therefore, these two nodes collapse and are labeled by red color. (D) Then, the links connected to the new collapsed nodes are removed, and the strength of the nodes is updated. (E) A new node has a strength change from 3 to 1. Thus, this node collapses and is labeled by red color. (F) After removing all connections of the collapsed node in the previous steps, no new nodes collapse and the iteration is therefore terminated. In this example, the avalanche size of the attacked red node in (A) is 4.

Figure 2. Schematic diagram of the calculation process for avalanche size.

(2) Tightness

The tightness of the MCTN is used to evaluate the trade relationships between countries, and a trade network with high tightness indicates that the countries have considerable influence on each other. This study introduces three specific metrics to quantify the tightness of the MCTN.

The percentage of edges compared to the maximal number of possible edges is called density (Fischer and Shavit, 1995), which is used to evaluate the tightness of the trade relationships between countries. The definition of this indicator satisfies the following equation:

$$d^{[t,l]} = \frac{m_d^{[t,l]}}{N_d^{[t,l]}(N_d^{[t,l]}-1)}, \tag{3}$$

where $m_d^{[t,l]}$ is the total number of edges in network $G_d^{[t,l]}$ and $N_d^{[t,l]}$ is the number of nodes, $l \lfloor [T_1,T_2]$.

Considering the weight of the links, the weighted clustering coefficient $wcc_i^{[t,l]}$ of the node $i$ is proposed to quantify if its neighbors are in a clique. The average of the weighted clustering coefficient of all nodes $\overline{wcc^{[t,l]}}$ quantifies the overall level of clustering and is calculated as (Saramäki et al., 2007),

$$\overline{wcc^{[t,l]}} = \frac{1}{N_u^{[t,l]}} \sum\nolimits_{i \in V_u^{[t,l]}} wcc_i^{[t,l]}, \; wcc_i^{[t,l]} = \frac{1}{k_i^{[t,l]}(k_i^{[t,l]}-1)} \sum\nolimits_{i,j,k \in V_u^{[t,l]}} (\hat{w}_{ij,u}^{[t,l]} \hat{w}_{ik,u}^{[t,l]} \hat{w}_{jk,u}^{[t,l]})^{1/3}, \tag{4}$$

where $k_i^{[t,l]}$ is obtained using Equation (1), $\hat{w}_{ij}^{[t,l]}$ is the normalized weight of the edge $(i,j)$ and is calculated as $\hat{w}_{ij}^{[t,l]} = w_{ij}^{[t,l]} / \max(w^{[t,l]})$, in which $\max(w^{[t,l]})$ is the maximal element in the weight matrix $\mathbf{W}_u^{[t,l]}$.

In addition, the core number (Batagelj and Zaversnik, 2003) is introduced to quantify the tightness of a network, and this indicator is used to calculate the depth of the entire network. The maximal component containing nodes with degree *k* or more is called the *k*-core, and the core number of a node is defined as the maximal value *k* of the *k*-core including that node. Consequently, the core number of a network is the *k* with the largest value of all nodes. A network with a high core number indicates that the network has a deep hierarchical structure, and the nodes are far apart from each other.

### 3.3.2 Community structure

A community structure is characterized by an uneven distribution of links among nodes. The connections within a community are tighter than those between different communities (Fortunato, 2010; Girvan and Newman, 2002). To understand the community structure, we use the *Infomap* algorithm (Rosvall and Bergstrom, 2008). This approach regards community detection as an optimization problem. For network $G_u^{[t,l]}$, the optimization objective is described as

$$L(M^{[t,l]}) = q^{[t,l]} H(\theta^{[t,l]}) + \sum_{i=1}^{|M^{[t,l]}|} \rho_i^{[t,l]} H(\varsigma_i^{[t,l]}) . \tag{5}$$

$q^{[t,l]} H(\theta^{[t,l]})$ is the entropy of the intercommunity movements, and $\sum_{i=1}^{|M^{[t,l]}|} \rho_i^{[t,l]} H(\zeta_i^{[t,l]})$ is the entropy of the intracommunity movements. $q^{[t,l]}$ is the probability of a random walk between two communities, and $H(\theta^{[t,l]})$ is the entropy function of the community names. $\rho_i^{[t,l]}$ denotes the percentage of walks within community $i$ and walks leaving community $i$. $H(\varsigma_i^{[t,l]})$ represents the entropy function of random walks within community $i$, $M^{[t,l]}$ stands for the community partition, and $|M^{[t,l]}|$ is the number of communities.

Due to the dynamic evolution of the network, some members leave their origin communities and join new communities. To evaluate changes in the members of community $i$ in network $G_u^{[t_1,l]}$ and community $j$ in network $G_u^{[t_2,l]}$, member stability is defined as the percentage of the same nodes to all nodes in two communities,

$$ms_{ij}^{[t_1,t_2,l]} = \frac{|c_i^{[t_1,l]} \cap c_j^{[t_2,l]}|}{|c_i^{[t_1,l]} \cup c_j^{[t_2,l]}|}, \tag{6}$$

where $c_i^{[t_1,l]}$ and $c_j^{[t_2,l]}$ are the sets of nodes in community $i$ and community $j$, respectively. When $ms_{ij}^{[t_1,t_2,l]} = \max(ms_{ik}^{[t_1,t_2,l]})$ for $k \in [1988, 2017]$ and $k \neq i$, community $i$ corresponds to community $j$ from time $t_1$ to time $t_2$.

### 3.3.3 Topological correlation

A multiplex network provides more information than a single-layer network due to the intricate relationships between different layers. The topological correlation between the two layers in the MCTN reveals the relation between CRM trade and CWS trade. The topological correlation in the MCTN is investigated by considering nodes, edges and network motifs.

The simplest metric used to distinguish the correlation between two layers is the total overlap of nodes/edges, which refers to the percentage of the number of common nodes/edges between two layers. The specific definitions of the overlap of nodes and edges are shown as

$$on^{[t]} = \frac{|V_d^{[t,T_1]} \cap V_d^{[t,T_2]}|}{|V_d^{[t,T_1]} \cup V_d^{[t,T_2]}|}, \quad oe_d^{[t]} = \frac{|E_d^{[t,T_1]} \cap E_d^{[t,T_2]}|}{|E_d^{[t,T_1]} \cup E_d^{[t,T_2]}|}, \tag{7}$$

where $V_d^{[t,T_1]}$ and $E_d^{[t,T_1]}$ denote the set of nodes and edges, respectively, in the directed network $G_d^{[t,T_1]}$. Similarly, the overlap of edges in the undirected network $G_u^{[t,T_1]}$ is defined as $oe_u^{[t]}$. The range of the overlap of nodes/edges is from 0 to 1, and a value close to 1 indicates a strong correlation between two single-layer networks.

Furthermore, the distribution of node degree, node strength and link weight in different layers must be evaluated. A node with a high node degree in CRM also has a high node degree in CWS and vice versa. To understand this relation, an indicator is proposed to evaluate the positions of nodes/links in the CWS trade network given a node/link in the CRM trade network from the perspectives of node degree, node strength and link weight. Considering the differences in the trade network in different years, the indicator is processed under dimensionless treatment. In particular, the indicator based on node degree is defined as

$$f(nr(k_i^{[t,T_1]}),t) = \frac{k_i^{[t,T_2]}}{\max(k^{[t,T_2]})}, nr(k_i^{[t,T_2]}) = \frac{r(k_i^{[t,T_1]}, G_u^{[t,T_1]})}{N_u^{[t,T_1]}}, \tag{8}$$

where $r(k_i^{[t,T_1]}, G_u^{[t,T_1]})$ is the ranking of node $i$ in the CRM trade network $G_u^{[t,T_1]}$ sorted by node degree, and $N_u^{[t,T_1]}$ is the number of nodes in $G_u^{[t,T_1]}$. Thus, $nr(k_i^{[t,T_1]})$ is the normalized rank of node $i$ in $G_u^{[t,T_1]}$ sorted by node degree. $k_i^{[t,T_1]}$ and $k_i^{[t,T_2]}$ are the node degrees of node $i$ in $G_u^{[t,T_1]}$ and $G_u^{[t,T_2]}$, respectively. $\max(k^{[t,T_2]})$ represents the maximum value of node degree in $G_u^{[t,T_2]}$. For node strength, the indicator is calculated as

$$f(nr(s_i^{[t,T_1]}),t)=\frac{s_i^{[t,T_2]}}{\max(s^{[t,T_2]})},nr(s_i^{[t,T_2]})=\frac{r(s_i^{[t,T_1]},G_u^{[t,T_1]})}{N_u^{[t,T_1]}}, \tag{9}$$

where $nr(s_i^{[t,T_1]})$ is the normalized rank of node $i$ in $G_u^{[t,T_1]}$ sorted by node strength. Similarly, the indicator from the perspective of link weight is defined as

$$f(nr(w_{ij,u}^{[t,T_1]}),t)=\frac{w_{ij,u}^{[t,T_2]}}{\max(w_u^{[t,T_2]})},nr(w_{ij,u}^{[t,T_2]})=\frac{r(w_{ij,u}^{[t,T_1]},G_u^{[t,T_1]})}{m_u^{[t,T_1]}}, \tag{10}$$

where $nr(w_{ij,u}^{[t,T_1]})$ is the normalized rank of the edge $(i,j)$ in $G_u^{[t,T_1]}$ sorted by edge weight, and $m_u^{[t,T_1]}$ is the number of edges in $G_u^{[t,T_1]}$. In addition, the cumulative normalized weight in the CWS trade network can be obtained by $\sum_{nr(w_{ij,u}^{[t,T_1]})<=a} f(nr(w_{ij,u}^{[t,T_1]}),t)$, where $a \in [0,1]$.

Network motifs are introduced to evaluate the correlation of the trade patterns in the MCTN. Network motifs are the patterns of the interconnections among nodes (Milo et al., 2002), and 13 types of three-node connected components are shown in Figure 3. The distribution of the network motifs in the MCTN reflects the patterns of trade relationships among three countries. To evaluate the main multilateral trade patterns, we calculate the probability that network motif $ms_u$ exists in network $G_d^{[t,l]}$ as

$$p^{[t,l]}(ms_u)=\frac{\sum_{i,j,k\in V_d^{[t,l]}} I^{[t,l]}(i,j,k,ms_u)}{\sum_{i,j,k\in V_d^{[t,l]}}\sum_{ms_u\in S} I^{[t,l]}(i,j,k,ms_u)}, \tag{11}$$

where the set of 13 network motifs is $S=\{S1,S2,\cdots,S13\}$ and $ms_u \in S$. The characteristic function $I^{[t,l]}(i,j,k,ms_u)=1$ when the three nodes $i$, $j$ and $k$ are connected as the pattern $ms_u$ in the network $G_d^{[t,l]}$; $I^{[t,l]}(i,j,k,ms_u)=0$, otherwise.

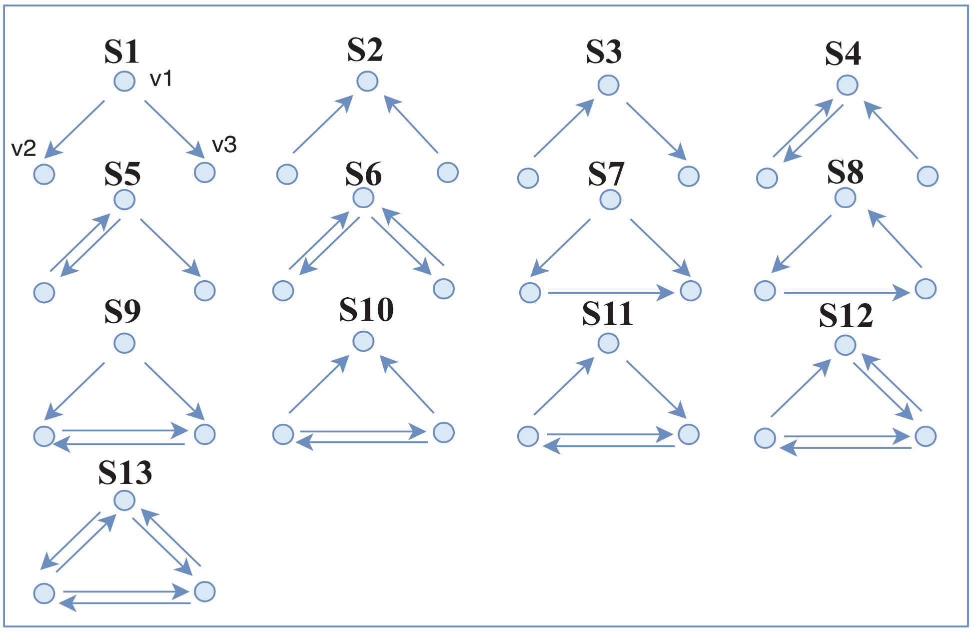



Figure 3. Schematic of 13 types of network motifs.

A sophisticated metric is the conditional probability that one type of subgraph exists in the MCTN given the presence of the other network motif among the same nodes $i$, $j$ and $k$ in the MCTN. The specific definition is shown as follows:

$$p^{[t]}(ms_u \mid ms_v) = \frac{\sum_{i,j,k \in V_d^{[t,M]}} I^{[t,T_1]}(i,j,k,ms_v) I^{[t,T_2]}(i,j,k,ms_u)}{\sum_{i,j,k \in V_d^{[t,M]}} \sum_{ms_u \in S} I^{[t,T_1]}(i,j,k,ms_v) I^{[t,T_2]}(i,j,k,ms_u)} . \quad (12)$$

### 3.3.4 The multiplex shock model

A multiplex shock model is proposed to simulate the shock from the restrictive policies on CWS imports enacted in China, which is denoted as country $i$. In terms of direct impacts, the shock leads to a reduction in CWS imports to China in the global CWS trade network layer. In terms of indirect impacts, China increases its CRM imports from its trade partners in the global CRM trade network to fill the gap in the total demand for copper materials.

(1) The direct impacts on the global CWS trade

In the simulation, we assume that two scenarios can illustrate how the shock spreads to the global CWS trade network layer, i.e., trade weight preference and trade country preference.

In the scenario of trade weight preference, we assume that the shock is spread to exporters equally, but the reduction in CWS imports is proportional to the trade weight between China and the exporter. For China, the reduction in CWS exports from trade partner $j$ is calculated by

$$r_j^{[T_2]}(i,\gamma)=\frac{\gamma s_i^{[t,T_2]}(in)w_{ji}^{[t,T_2]}}{\sum_{(j,i)\in E_d^{[t,T_2]}} w_{ji}^{[t,T_2]}}, \tag{13}$$

where $s_i^{[t,T_2]}(in)$ is the total trade value of CWS in China and $w_{ji}^{[t,T_2]}$ is the trade value of CWS imports from country $j$ to China. $t$ is set at 2017 to estimate the future impact. $\gamma$ represents the degree of the shock, which is the proportion of the reduction in CWS imports from China. The simulation is conducted in the range of [5%, 100%] with increments of 5% for $\gamma$.

In the scenario of trade country preference, we assume that China prefers to maintain trade connections with large exporters when China stops importing CWS. In other words, the shock damages the trade relationships starting with the exporters with the lowest trade value. The spread process can be described as follows. First, the existing CWS exporters to China are ranked by $w_{ji}^{[t,T_2]}$ in ascending order. Second, the shock breaks the trade relationship between China and the trade partner with the lowest trade value $w_{ji}^{[t,T_2]}$. The process is repeated until the accumulative reduction of trade value reaches $\gamma s_i^{[t,T_2]}(in)$.

(2) The indirect impacts on the global CRM trade

The reduction in CWS imports caused by the shock will stimulate an increase in China's CRM imports to meet the copper demand. The increment in the CRM demand from importers is proportional to the trade weight between China and the exporter, which is calculated by

$$r_j^{[T_1]}(i,\gamma)=\frac{\gamma s_i^{[t,T_2]}(in)w_{ji}^{[t,T_1]}}{\sum_{(j,i)\in E_d^{[t,T_1]}} w_{ji}^{[t,T_1]}}, \tag{14}$$

where $s_i^{[t,T_2]}(in)$ is the total trade value of CWS imports in China and $w_{ji}^{[t,T_1]}$ is the import value of CRM from country $j$ to China.

(3) Relative impacts on the CWS and CRM trade

To evaluate the influence of the shock on individual countries, two indicators are introduced: absolute value and relative value. A change in the export/import value indicates the absolute influence of the shock on the trade partners, which are defined as $r_j^{[T_1]}(i,\gamma)$ and $r_j^{[T_2]}(i,\gamma)$. The ratio of the export reduction/import increment $r_j^{[l]}(i,\gamma)$ to the total export/import value for country $j$ is used to evaluate the relative influence of China on trade partner $j$ in layer $l$ and is defined as:

$$e_j^{[l]}(i,\gamma) = \frac{r_j^{[l]}(i,\gamma)}{\sum_{(j,k)\in E_d^{[t,l]}} w_{jk}^{[t,l]}}, \tag{15}$$

where $l \in [T_1, T_2]$ and $j \in \{j:(j,i) \in E_d^{[t,l]}\}$. $e_j^{[l]}(i,\gamma)$ evaluates the relative influence of the shock on trade partner $j$.

To evaluate the full relative influences on layer $l$, the probability of countries with an export reduction of $e^{[l]}$ is calculated to embody the whole situation of the affected countries as follows:

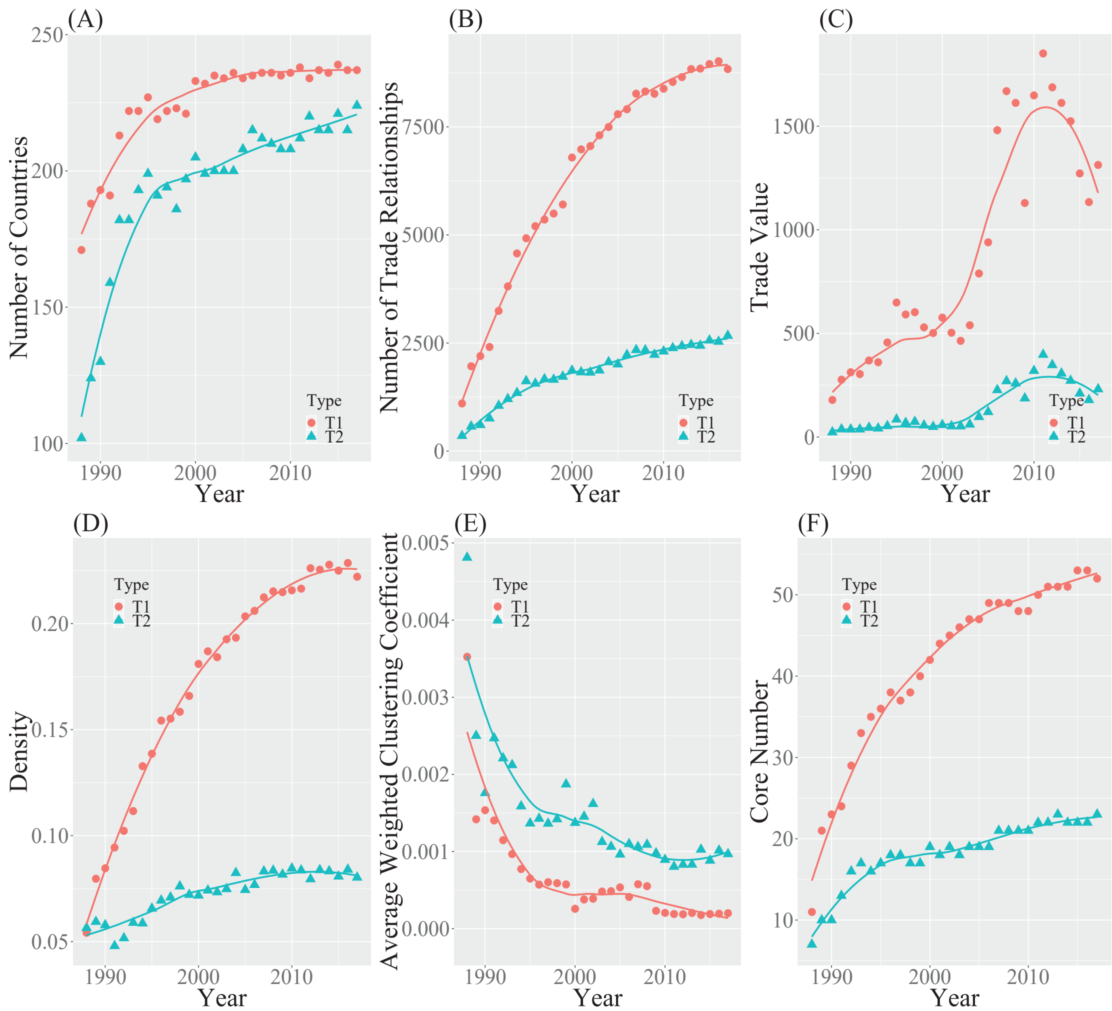
$$p(e^{[l]}) = \frac{n(e^{[l]})}{k_i^{[t,l]}(in)}, \tag{16}$$

where $n(e^{[l]})$ denotes the number of China's exporters with $e_j^{[l]}(i,\gamma)$ equaling $e^{[l]}$. When the value of $p(e^{[l]})$ increases by $e^{[l]}$, then a considerable number of China's trade partners are seriously affected. The cumulative probability is defined as $p(e_j^{[l]}(i,\gamma) \le e^{[l]})$ and $j \in \{j:(j,i) \in E_d^{[t,l]}\}$.

## 4. Dynamic evolution of the MCTN

### 4.1 Structural characteristics of the MCTN

To evaluate the development of global CRM and CWS trade, this study reviews the evolution of the MCTN from 1988 to 2017. It is obvious that global CRM and CWS trade developed rapidly in the last 30 years. As shown in Figure 4(A), the number of participating countries in the MCTN grew dramatically from 1988 to 1995 and reached a peak in 2017, with 236 countries in the global CRM trade and 224 countries in the global CWS trade. However, in contrast to the number of participating countries, the number of trade relations in the MCTN shows a very large gap, as shown in Figure 4(B), indicating that the degree of globalization of the CWS trade is lower than that of the CRM trade. Figure 4(C) depicts the changes in the trade value in the MCTN. The trade values of the CRM and CWS climbed sharply since 2000 and reached their highest levels in 2011. After 2011, both trade values showed a downward trend. In terms of the tightness of the trade relationships among countries, Figure 4(D) shows that the density of CRM trade and CWS trade increased gradually over the last 30 years. The countries in the global CRM trade network are closer than those in the global CWS trade network. Furthermore, we introduce the average weighted clustering coefficient to evaluate the tightness of the trade relations by considering the number and weight of the links. Notably, the tendency of the change in the average weighted clustering coefficient demonstrated in Figure 4(E) is significantly different from that of the density, indicating that the tightness of the two single-layer trade networks gradually decreased. The distinct changes in these two metrics indicate that trade ties are increasingly established; however, the distribution of the trade values of different countries is heterogeneous. Increasing heterogeneity has led to a decline in the average weighted clustering coefficient. In addition, Figure 4(F) shows the upward trend of the core number, indicating that the global CRM trade network and the global CWS trade network have increasingly deeper hierarchical structures. The CRM trade network has a larger core number than the CWS trade network, indicating that, in terms of the organizational structure, countries in the CRM trade network have looser connections with each other than they do in the CWS trade network.




Notes: CRM trade networks and CWS trade networks are represented as T1 and T2 , respectively. In addition, the unit of trade value is ten million US dollars.

Figure 4. Trend of the MCTN in the last 30 years.

### 4.2 Core countries in the MCTN

In this subsection, we use different criteria to identify core countries and review changes in the central countries in the MCTN. Due to space limitations, the results are tabulated in Appendix B.

Table B1 lists the top 10 countries in the global CRM network in 1988 and 2017 based on the indicators in-degree $k_i^{[t,T_1]}(in)$, in-strength $s_i^{[t,T_1]}(in)$, out-degree $k_i^{[t,T_1]}(out)$, out-strength $s_i^{[t,T_1]}(out)$, strength $s_i^{[t,T_1]}$ and avalanche size $as_i^{[t,T_1]}$. Core countries with high in-degree/out-degree have already established diverse import/export trade relationships with many countries. In both 1988 and 2017, these core countries are mainly geographically distributed in Europe and Asia. Countries with high in-strength/out-strength play crucial roles in manufacturing copper products. China exhibits its predominance in CRM imports, followed distantly by the USA and Germany. Regarding avalanche size, the USA and China have the largest direct and indirect impacts on CRM trade, and their collapses led to 26 and 13 countries collapsing in 2017, respectively. Therefore, countries trading CRM with China and the USA should closely review the policy guidance of these two countries.

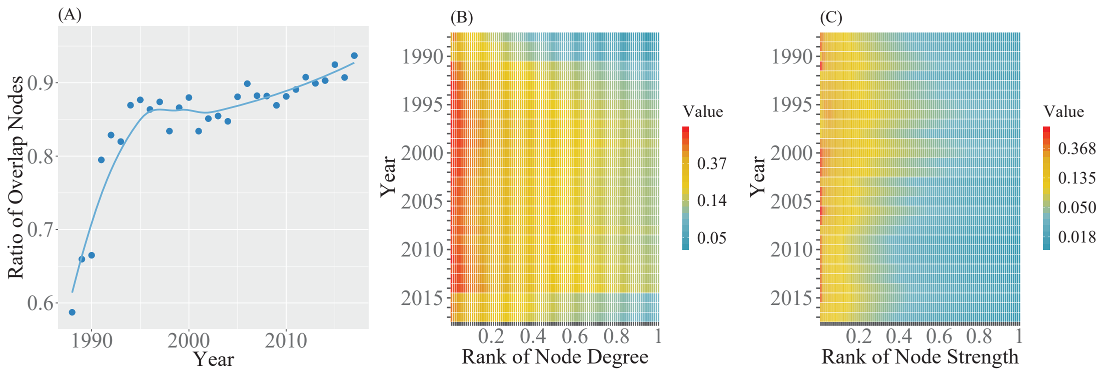
The core countries in the global CWS trade network are shown in Table B2. Some countries such as Germany, Switzerland, the Netherlands and other developed countries in Europe have a high in-degree/out-degree, indicating that these countries have obvious advantages in terms of the number of trade channels. The other countries with a high in-degree/out-degree are mainly located in Asia, including India, South Korea, China, Hong Kong and United Arab Emirates (UAE). Notably, the gap between the largest importing country and the second largest importing country in the CWS trade network is larger than that in the CRM trade network, and China imports approximately four-times as many CRM as Germany. In addition, core exporting countries in the CWS trade network are mainly long-industrialized countries, including the USA, Germany, the Netherlands and Australia. The avalanche size of China is 124 and is approximately 7 times that of the Netherlands, the second largest influential country in the CWS trade network in 2017. Therefore, for both direct and indirect influence, China occupies an irreplaceable position in the global CWS trade network.

## 5. Relationship between the global CRM trade and global CWS trade

### 5.1 Relationship in terms of nodes and edges

Figure 5 demonstrates the correlation between the CRM layer and the CWS layer in terms of the participating countries (nodes). As shown in Figure 5(A), the number of overlapping countries in both layers showed an upward trend in the last 30 years; specifically, the number experienced dramatic growth from 1988 to 1995 and then increased slightly to reach a peak of 0.94 in 2017. This result indicates that most countries participating in CRM trade were also actively participating in CWS trade in 2017 and that the correlation between the two trade networks is steadily increasing. Figure 5(B) shows the change in the node degree in the global CWS trade network given the nodes ranked by the node degree in the global CRM trade network in descending order. It can be seen that a country tends to establish more trade relationships in the CWS trade network when it has more trade channels in the CRM trade network. Similarly, the CWS trade value of a country will increase with the growth in its CRM trade value, as illustrated in Figure 5(C). Both Figure 5(B) and Figure 5(C) show a clear color change from 2015, indicating that a large gap exists between countries in terms of the number of trade relationships and the trade value in the global CWS trade network. Thus, the distribution of the global CWS trade has become increasingly imbalanced in recent years.

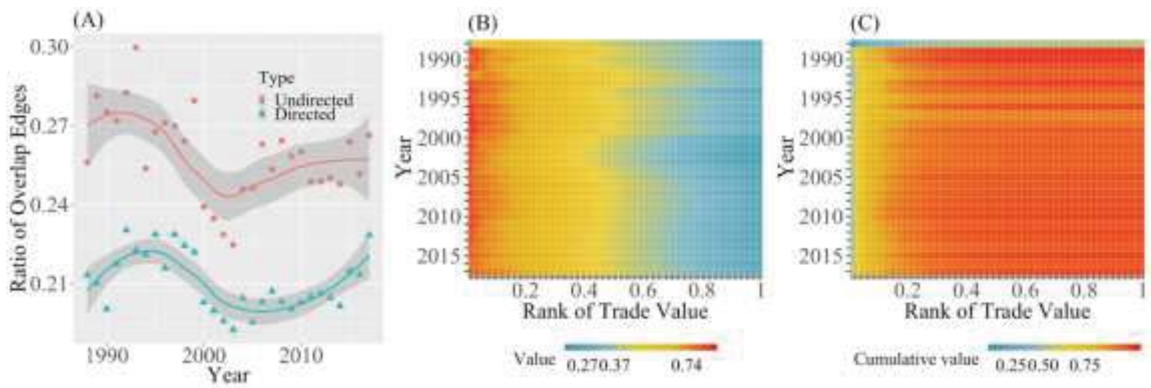
Moreover, to provide a fine-grained correlation measurement, the Pearson, the Spearman and the Kendall's correlation coefficients are introduced to quantify the association of countries' sequences in terms of the in-degree, out-degree, degree, in-strength, out-strength and strength between the global CRM trade network and the global CWS trade network. The results are shown in Appendix C. These results confirm our findings that the CWS trade is highly associated with the CRM trade in each country regardless of the number of import/export/all-trade relationships or the trade value.




Notes: (A) Changes in the ratio of overlapping nodes in the global CRM trade network and the global CWS trade network. (B)(C) Changes in the normalized node degree/strength in the CWS trade network given that the node existed in the CRM trade network. For each year, the nodes in the CRM trade network are sorted by node degree/strength in reverse order, and in each row, we report the values of the normalized node degree/strength in the CWS trade network $f(nr(k_i^{[t,T_1]}),t)$ / $f(nr(s_i^{[t,T_1]}),t)$, which are defined in Equations (8-9) for the corresponding nodes. The color of each grid represents the values of node degree/strength, and a dark red color indicates a high value.

Figure 5. The correlation between the two layers in terms of nodes.

Next, we investigate the correlation in terms of country pairs (edges). Figure 6(A) illustrates the change in the number of overlapping trade relationships between the global CRM trade network and the global CWS trade network during the past 30 years. In contrast to the ratio of the overlapping participating countries in Figure 5(A), the ratio of the overlapping trade relationships between the two layers is remarkably low. The reason for the low value of the link overlap is the large gap between the number of trade connections in the CWS and CRM trade networks, as shown in Figure 4(B). Therefore, from the perspective of link overlap, the differences in trade connections between the CRM and CWS trade networks are obvious. Figure 6(B) shows that the volume of CWS exchanged between two countries is higher when a higher trade value for CRM exists between the same two countries. In addition, Figure 6(C) shows that a few countries with higher values of CRM trade account for the vast majority of the trade value of CWS.




Notes: (A) Changes in the ratio of the overlapping trade relationships between the global CRM trade network and the global CWS trade network. (B) Changes in the trade value of the global CWS trade network given that the same trade relationship existed in the global CRM trade network. The trade value in the CWS layer is normalized by the maximum trade value to avoid scale effects in different years. For each year, edges in the CRM trade network are ranked by weight in reverse order, and in each row, we report the normalized edge weight in the CWS trade network defined as $f(nr(w_{ij,u}^{[t,T_1]}),t)$ in Equation (10) for the corresponding nodes. (C) Changes in the cumulative trade value in the global CWS trade network given that the same set of trade relationships existed in the global CRM trade network. The cumulative trade value in the CWS layer is normalized by the total trade value to eliminate dimensional effects calculated by $\sum_{nr(w_{ij,u}^{[t,T_1]})<=a} f(nr(w_{ij,u}^{[t,T_1]}),t)$, where $a$ is the normalized rank. In (B) and (C), the country pairs in the CRM layer are ranked according to the trade value in descending order. The color of each grid denotes the trade value in (B) and the cumulative trade value in (C); a dark red color represents a high value.

Figure 6. The correlation between the two layers in terms of edges.

### 5.2 Relationship in terms of network motifs

Network motifs define the universal classes of networks and are used to uncover the basic block of networks (Milo et al., 2002). In trade networks, network motifs reveal the basic structure of multilateral trade among three countries. Figure 7 demonstrates the distribution of network motifs in the global CRM and CWS trade networks. The distribution remained stable over the past 30 years, with a slight change in the two layers. Notably, there are obvious differences in the distribution of the network motifs of the two layers.

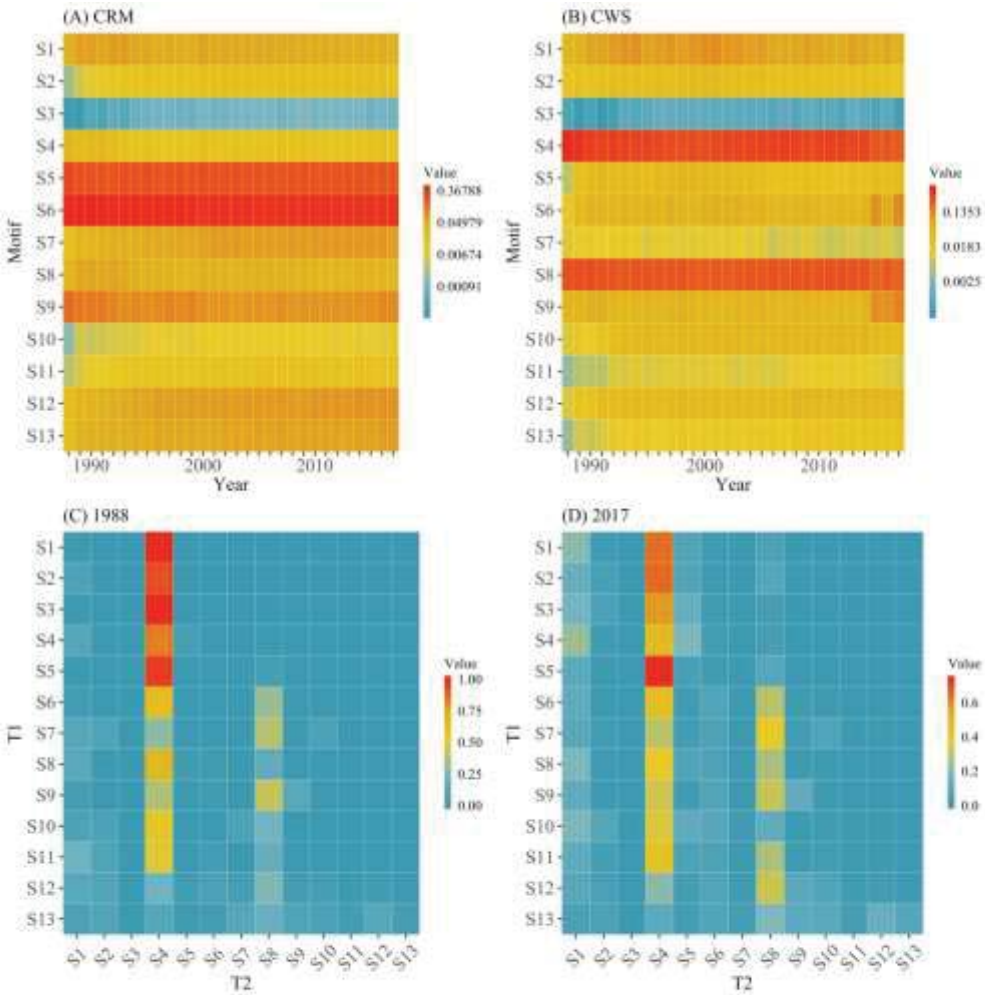
Figure 7(A) shows that the major motifs in the CRM trade network are $\mathrm{S6}$ and $\mathrm{S5}$, as shown in Figure 3. Considering the structure of the network motifs and the context of trade relationships, we assume that $\mathrm{S6}:\{(v_1,v_2),(v_1,v_3),(v_2,v_1),(v_3,v_1)\}$ reflects the trade pattern of bidirectional interaction driven by the core country. Although this highlights the significance of the core countries in terms of forming multilateral trade relationships in CRM trade, the bidirectional trade relations in $\mathrm{S6}$ show the fully commercial interaction between the core countries and other countries. $\mathrm{S5}:\{(v_1,v_2),(v_1,v_3),(v_2,v_1)\}$, as the second major network motif in the global CRM trade network, shows the multilateral trade relationships driven by the core exporting country.

The major network motifs in the global CWS trade network are $\mathrm{S4}$ and $\mathrm{S8}$, as shown in Figure 7. The multilateral trade pattern shown by $\mathrm{S4}:\{(v_1,v_2),(v_2,v_1),(v_3,v_1)\}$ is driven by the core importing country, which underscores the central positions of importing countries in promoting CWS trade. The other major network motif in the global CWS trade network is $\mathrm{S8}:\{(v_1,v_2),(v_2,v_3),(v_3,v_1)\}$, which has a trade pattern that is unidirectional cyclic, revealing industrial specialization among countries in the global CWS trade network.

Next, the conditional probability $p^{[t]}(ms_u \mid ms_v)$ defined in Subsection 3.3.3 is applied to investigate the relationship between the formation of the trade patterns in the CRM trade network and CWS trade network. Figure 7(C) and (D) show that the distribution of this metric remained stable over the past 30 years. In 2017, the three main motif pairs in the MCTN are $P(\mathrm{S4}^{[T_2]} \mid \mathrm{S5}^{[T_1]})$, $P(\mathrm{S4}^{[T_2]} \mid \mathrm{S1}^{[T_1]})$ and $P(\mathrm{S4}^{[T_2]} \mid \mathrm{S2}^{[T_1]})$. These three motif pairs reflect two typical aspects of the relationship between CRM trade and CWS trade.

- The first two motif pairs, $[\mathrm{S5}^{[T_1]}:\{(v_1,v_2),(v_1,v_3),(v_2,v_1)\} \to \mathrm{S4}^{[T_2]}:\{(v_1,v_2),(v_2,v_1),(v_3,v_1)\}]$ and $[\mathrm{S1}^{[T_1]}:\{(v_1,v_2),(v_1,v_3)\} \to \mathrm{S4}^{[T_2]}:\{(v_1,v_2),(v_2,v_1),(v_3,v_1)\}]$, belong to one group. This cross-layer relationship is driven by the core exporting countries in the CRM trade network. In other words, the exporting countries in the global CRM trade network tend to become importers in CWS trade with their trading partners. We assume that the exporting countries in the CRM trade network, as major CRM producers, import CWS to produce CRM and further promote CRM exports.

- The second pattern is $[\mathrm{S2}^{[T_1]}:\{(v_2,v_1),(v_3,v_1)\}\rightarrow \mathrm{S4}^{[T_2]}:\{(v_1,v_2),(v_2,v_1),(v_3,v_1)\}]$. This cross-layer relationship is driven by the core importing countries in the CRM trade network; that is, the CRM-importing countries tend to become exporting countries in the CWS trade network. We suppose that this pattern is mainly embodied in some CRM-importing countries, especially highly industrialized countries. These countries produce a large amount of copper-containing electronic goods and have vast consumer markets. Large quantities of copper scrap are retrieved from infrastructure construction renewal and discarded consumption goods. Additionally, due to the complete waste classification system and high labor costs, these countries become CWS exporters to their trade partners.



Notes: (A) Distribution of the network motifs in the global CRM trade network. (B) Distribution of the network motifs in the global CWS trade network. (C) and (D) Probability that the network motifs exist in the CWS trade networks given the network motifs in the CRM trade network in 1988 and 2017. A dark red color indicates a high probability.

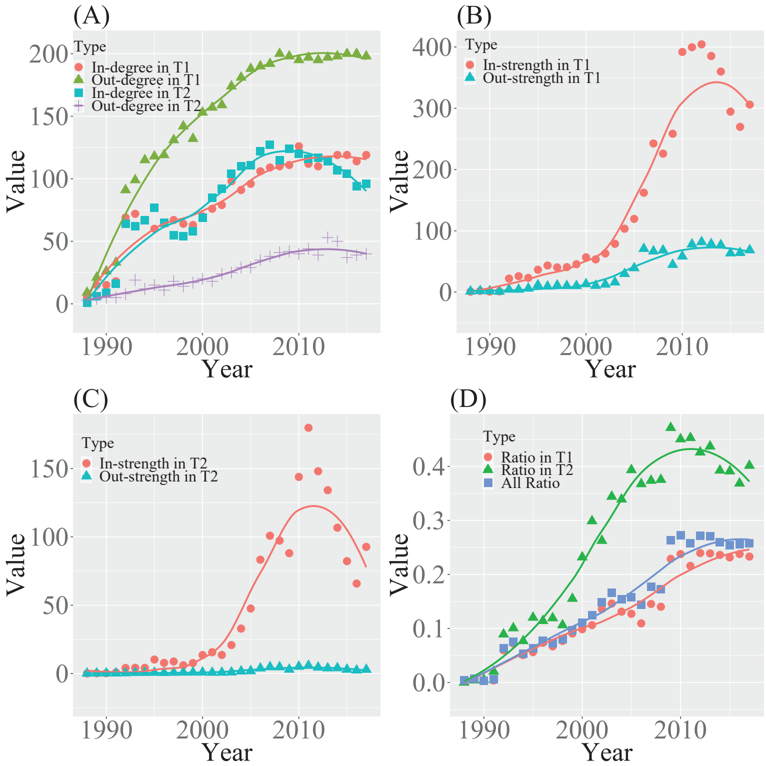
Figure 7. Network motifs in the MCTN.

## 6. Policy impacts of China's import ban on the MCTN

### 6.1 Overview of China's CRM trade and CWS trade

Figure 8 illustrates China's development in the global CRM and CWS trade between 1988 and 2017. Figure 8(A) shows that the trade relationships, especially import trade relations, have been increasingly established since 1988. Notably, there has been a slight decline in the number of import trade channels since 2010. Similarly, the import trade value in the global CRM and CWS trade grew from 1988 until 2010, as shown in Figure 8(B) and (C). To eliminate the impact of the downward tendency of the global trade value and to evaluate China's share of the global CRM and CWS trade, the ratio of China's import trade value to the world's trade value is introduced. Figure 8(D) shows that China's share of the global CWS trade clearly decreased in 2010 in contrast to its relatively stable share in the global CRM trade.

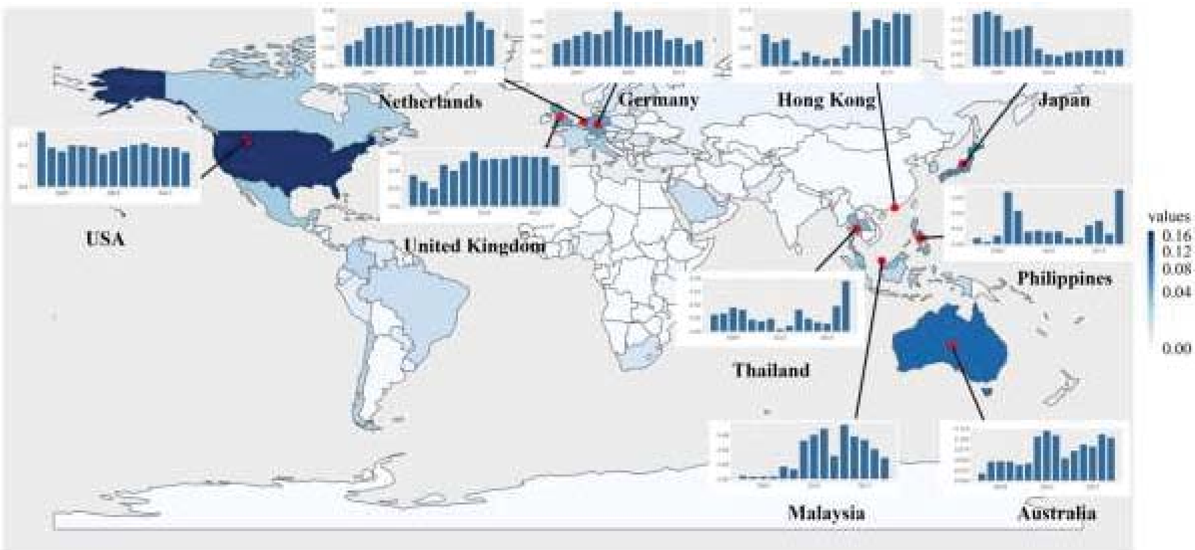
The obvious downward tendency of China's trade value in CWS trade in 2010 reflects the effects of a series of CWS import restrictions. In 2010, China initiated urban mining to address China's mineral resource shortage and excessive dependence on foreign mineral resources (Wen et al., 2015). China also began reclaiming secondary resources from urban waste and obsolete materials. In addition, some restrictive policies on scrap imports were launched. For example, the Green Fence Operation was enacted in 2013 by China Customs to strengthen the supervision of solid waste imports. In 2018, China imposed a ban on the import of certain kinds of solid waste. The stricter regulations regarding solid waste implemented by China are expected to further reduce CWS imports.




Note: (A) Changes in the import and export relationships during the past three decades. (B) and (C) Changes in the import-export trade values in the CRM trade and CWS trade networks from 1988 to 2017. (D) Changes in the proportion of China's imports to the global trade value. The global CRM trade network is labeled T1, and the global CWS trade network is denoted as T2.

Figure 8. Trend of China's CRM trade and CWS trade compared to that of global CRM trade and CWS trade.

China, as the largest importer in the CWS trade network, has had a huge direct impact on CWS-exporting countries due to its CWS import restrictions. Due to the unavailability of trade records in 2018 from the UN Comtrade, this study compares changes in China's CWS trade in 2010 and 2017. As shown in Table D1 of Appendix D, the top five CWS exporters to China in 2010 were the USA, Australia, Spain, Germany, and Malaysia. By comparing the top 10 CWS exporters to China in 2010 and 2017, we find that some Southeast Asian countries, including Thailand and the Philippines, are increasingly important. Particularly, Figure 9 shows the geographical distribution of the main exporters to China in 2017, and Table D2 of Appendix D provides detailed information on the major exporters with the greatest increases and decreases in export shares to China. Two different patterns are identified for exporters under the influence of China's restrictive policies. One pattern is that the export shares of some countries, such as Germany, Australia and the USA, to China decreased from 2010 to 2017. The other type is represented by Hong Kong, Thailand and the Philippines, which had a growth in their export share to China. These two distinct patterns indicate that the CWS export share to China is shifting from Europe and the Americas to Asia to a certain degree. This shift is occurring because China's restrictive policies limit the import of low-quality CWS, which is exported to some Southeast Asian countries that have lower labor costs and laxer environmental regulations. Countries in Southeast Asia seem to serve as hubs for the off-shore purification business, and then the purified CWS is shipped to China. Therefore, emerging CWS-importing countries should seize opportunities to develop their CWS cleaning and processing industry. However, these countries must also pay attention to the risk of environmental pollution caused by CWS recycling.




Note: The color of each country reflects the proportion of China's CWS imports in 2017. A dark blue color indicates that China imported a large proportion of CWS from this country in 2017. The top 10 countries are marked by red points, and the proportion of China's CWS imports from these countries in the past fifteen years is shown as bar charts.

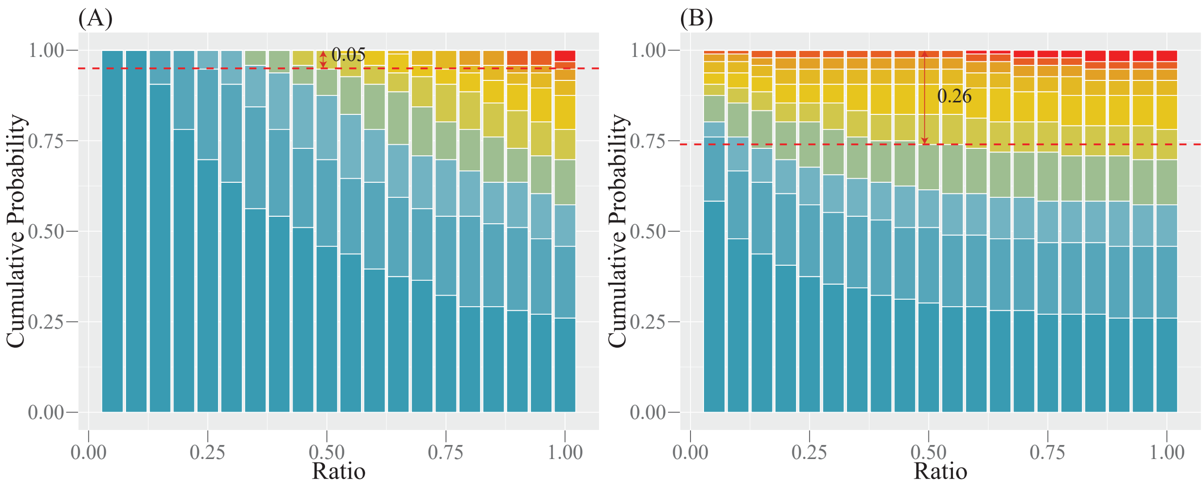
Figure 9. Major CWS exporters to China.

### 6.2 Simulation of China's restrictive policies

The multiplex shocks model is applied to simulate the shock of CWS import restrictions in China. This subsection discusses three types of impacts on the MCTN: direct impacts from a reduction in CWS exports, indirect impacts from an increase in CRM imports, and overall impacts on the MCTN.

#### 6.2.1 The direct impacts on global CWS trade

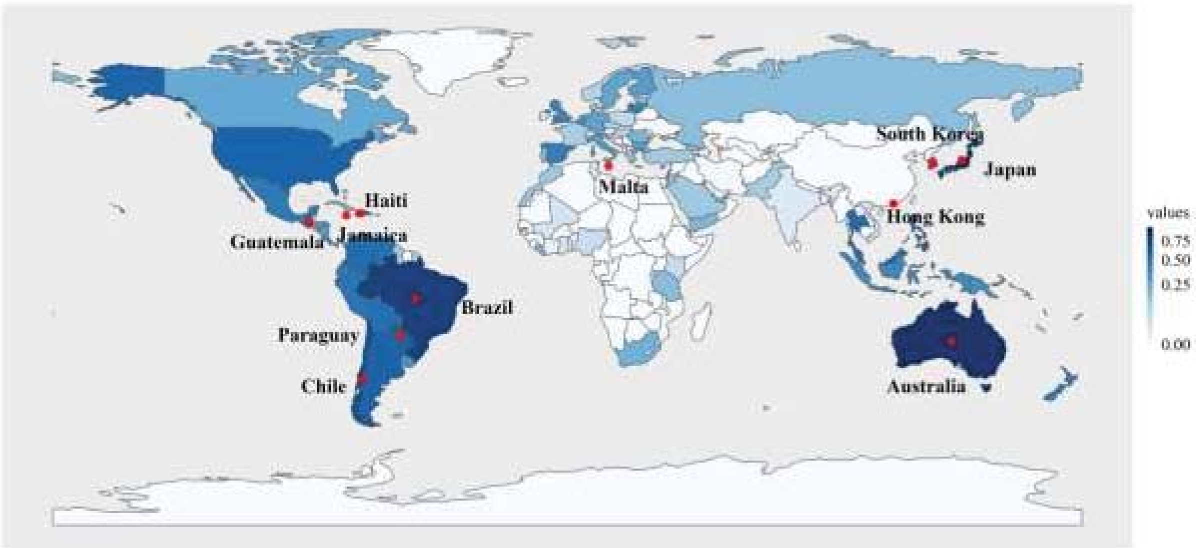
As discussed in Subsection 3.3.4, two scenarios, i.e., trade weight preference and trade country preference, are simulated to spread the shock to the global CWS trade network layer. These scenarios are shown in Figure 10. Generally, more exporters are seriously affected by the increasing shock degree ( $\gamma$ ) created by the policies enacted in China. Notably, two different shock spread scenarios lead to different probability distributions of each countries' relative reduction. Specifically, the effect of the trade weight preference scenario on CWS exporters, which is shown in Figure 10(A), is lower than that of the trade country preference scenario, which is shown in Figure 10(B). In fact, the effect of the real policy should be between the effects of the trade weight preference scenario and the trade country preference scenario. When decreasing CWS imports, countries will prioritize maintaining good trade connections with their major trade partners but will be less extreme compared to those under the trade country preference scenario. Therefore, the comparison of results in Figure 10(A) and (B) provides an estimated range of the real policy impact. For instance, when China's CWS imports are reduced by half, the countries with a greater than 40% reduction account for 5%-26% of all exporters to China.




Note: (A) The shock is propagated in proportion. (B) The shock is propagated starting with the exporters with the lowest trade value. The horizontal axis in the two subfigures shows the scale of the shock, which is defined as $\gamma$ . The affected countries with a reduction in $e^{[l]}$ from 0.1 to 1 and an increase of 0.1 are labeled by different colors. Warmer colors indicate that these countries are more seriously affected. The heights of the color blocks show the probability of countries with a corresponding exporting reduction, which is defined as $p(e^{[l]})$ in Equation (16). The vertical axis is the cumulative probability of countries with a reduction of more than $e^{[l]}$ .

Figure 10. Reduction in the number of China's CWS exporters.

To clearly observe the consequences of the policy shocks, we discuss the extreme case in which all CWS imports are prohibited in China. Figure 11 geographically illustrates the policy impacts on China's CWS exporters. In contrast to Figure 9, Figure 11 indicates that most countries sustain a massive hit. Specifically, exports from Australia, Asia and Latin America suffer greater than those from Europe. The 90.8% and 90.3% export values of CWS in Australia and Japan are influenced by China's import ban.




Note: Countries exporting scrap copper to China are colored based on their reduction in $e_j^{[T_2]}(i,\gamma)$, where the shock scale $\gamma$ is set as 1 and $i$ represents China. The dark blue color indicates that the country is severely influenced by the shock. The top 10 countries are labeled by red solid circles.

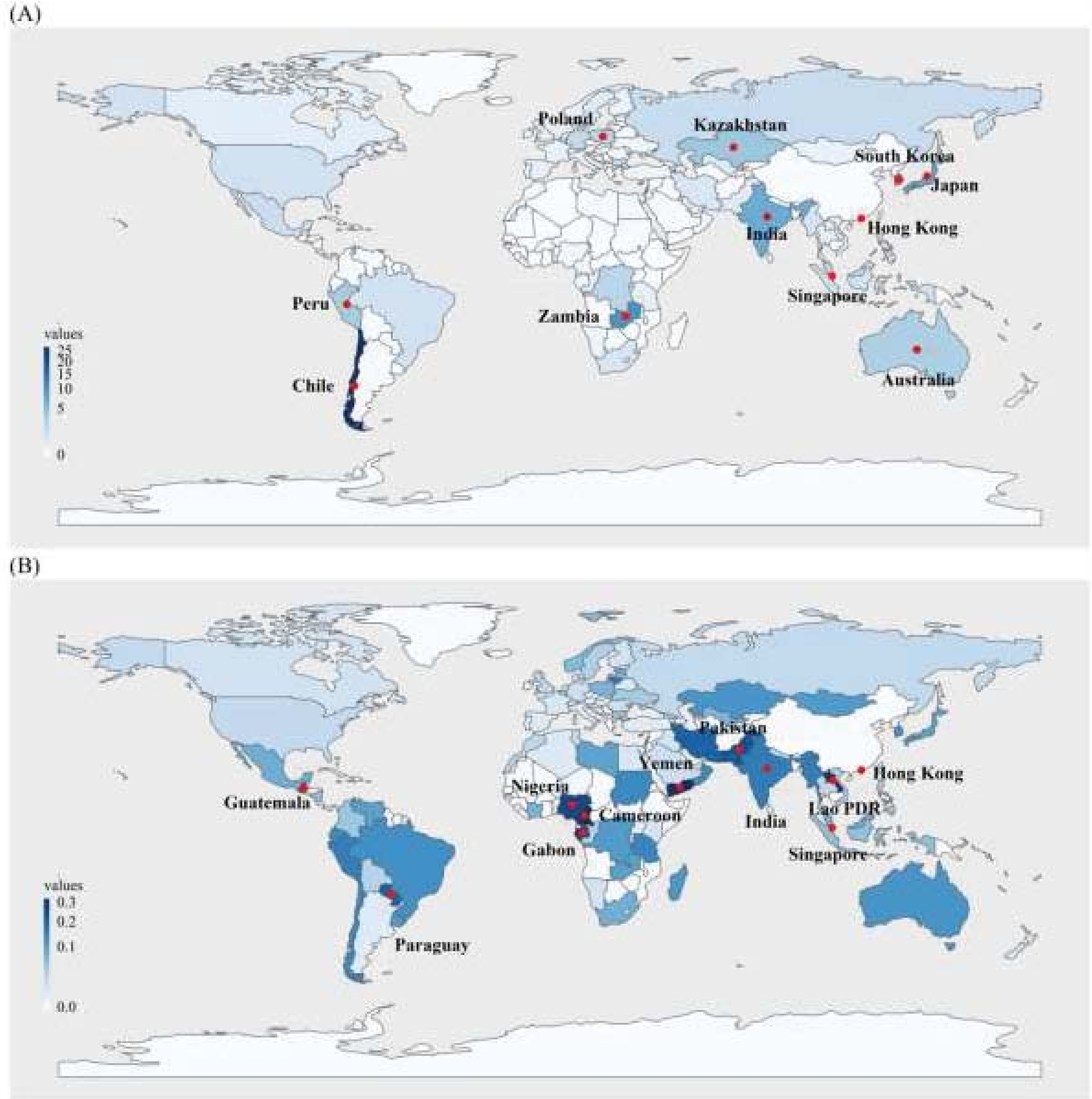
Figure 11. Geographical distribution of the reduction in CWS exports.

### 6.2.2 The indirect impacts on global CRM trade

Because of the reduction in CWS imports, China must expand CRM imports to meet the copper demand. Figure 12 shows that China's increased demand for CRM is mainly supplied by South America and Asian countries, such as Chile, Peru, Japan and India. Copper ore resource-rich counties, including Chile, Zambia, Peru, Poland, occupy a central position in Figure 12(A). The largest expected import increment in Chile embodies the high dependence of China's CRM on Chile.

Figure 12(B) reflects the geographical distribution of exporting countries, and the color reflects the indicator $e_j^{[T_1]}(i,\gamma)$, which measures the relative influence. Notably, countries in

Africa and Southeast Asia will greatly increase exports from their original export levels. Therefore, China's restrictive policy on CWS will promote CRM imports from Nigeria, Gabon, the Lao PDR, etc.




Notes: (A) Countries are colored based on their proportions of CRM exports. (B) Countries are colored based on the ratio of exporting increment to the total value of the original exports. The dark blue color indicates a high value. The top 10 countries are labeled by red solid circles.

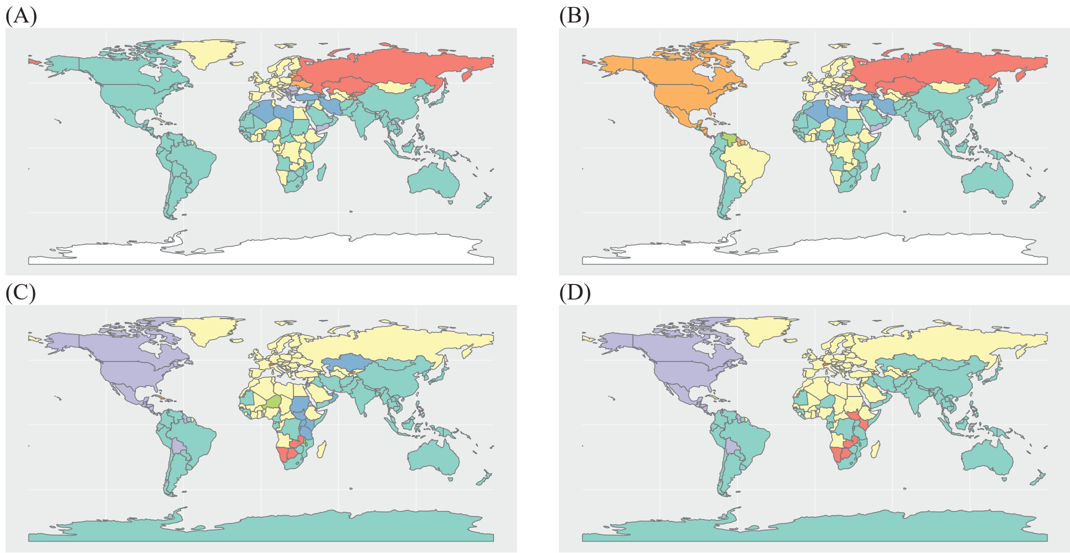
Figure 12. Geographical distribution of copper production export increments.

### 6.2.3 The impacts on the community structures of the MCTN

China's restrictive policies will change the trade connections among countries by resulting in the splitting and merging of trading communities in the MCTN. The results of the *Infomap* algorithm (Rosvall and Bergstrom, 2008) identify the trade communities, as shown in Figure 13.

In the global CWS trade network, the participating countries are divided into seven groups, and two of these communities have overwhelming positions, namely, the Asia-America-Australia community and the Europe community, which are labeled by green and yellow, respectively, in Figure 13(A). The largest community (Asia-Americas-Australia) involves 121 countries led by core countries, including China, the USA and Japan. The second largest community, with 75 members, is mostly composed of European countries. The results verify that geopolitics is an important factor in the formation of trading communities. Interestingly, the countries in Africa mainly belong to two different communities rather than form a close trade group; this occurs because most countries in the continent are poor and import considerable amounts of CWS from richer countries outside the continent (Lupu and Traag, 2013). Figure 13(B) shows that the biggest Asia-America-Australia community is split, and a new community with countries in North America is formed. The countries in South America merge with the community in Asia and Europe. Therefore, China's restriction on copper scrap imports will break the close trade links and decrease the level of globalization in CWS trade.

In the global CRM trade network, there are three major communities, as shown in Figure 13(C), namely, the Europe-North Africa community, the Asia-South America community and the North America community, with 102, 80 and 34 members, respectively. As the shock of China's policy spreads from CWS trade to CRM trade, the community structure of the global CRM trade network will change slightly in several Asian and African countries, although the major communities will remain stable, as shown in Figure 13(D). Specifically, some Asian countries, such as Omen and Kazakhstan, will join the community dominated by Asian countries. In addition, more African countries, including Sudan and Niger, will merge with European countries to form the largest community. Due to the large gap in the total trade value between CRM trade and CWS trade, the shock from China's CWS imports has a limited impact on the community structure of the global CRM trade network. However, the shock is remarkably able to strengthen the relations between some developing countries in the Asian and African countries and the two major communities.




Notes: (A) and (B) Communities in the global CWS trade network under the respective scale of China's policy shock $\gamma$ set as 0 and 1. (C) and (D) Communities in the global CRM trade network under the respective scale of China's policy shock $\gamma$ set as 0 and 1. Countries in the same communities are labeled by the same color in each subfigure. The similarity of communities in subfigures (A) and (B) is calculated using the ratio of the same countries defined as member stability $ms$ in Subsection 3.3.2. The communities with the greatest similarity in subfigures (A) and (B) are labeled by the same color. The relationships between the communities in (C) and (D) are similarly labeled.

Figure 13. Changes in communities in the global CRM and CWS trade network.

## 7. Discussions and policy implications

### 7.1 Spatial-temporal evolution of the MCTN

In Subsections 4.1 and 4.2, we review the spatial-temporal evolution of the MCTN during the period of 1988 to 2017. The results show that the global CRM and CWS trade networks have grown rapidly in the past three decades, and both trade networks have obvious hierarchical structures driven by some core countries. However, some differences exist between the global CRM and CWS trade networks. The global CRM trade network has more dense trade ties among countries, although the number of participating countries is similar to that of the CWS trade network, indicating that the degree of globalization in CRM trade is higher than that in CWS trade. In contrast to the mature market of the global CRM trade, the emerging global CWS trade is promising. Analysis of the core countries in the global CRM trade reveals a resource-driven exporting pattern because the major exporters are mineral resource-rich countries. In contrast, the global CWS trade shows an industrial production-driven exporting pattern because the core exporters are highly industrialized nations.

Although a certain amount of disparity exists between the trade values of CWS and CRM, CWS trade is playing an increasingly prominent role in alleviating the shortage of CRM. As mentioned in previous studies, the current copper ore reserves will be depleted in approximately 60 years (Harmsen et al., 2013; Sverdrup et al., 2017). Therefore, the development of a CWS recycling system by participating countries is an urgent task. Specifically, highly CRM import-dependent countries, such as China, the USA, and Germany, must promote infrastructure investment in scrap metal collection and recycling, encourage domestic recyclers to upgrade innovative technologies, and develop close trade relationships with trading countries to ensure the security of copper resources.

### 7.2 Complicated interdependencies between CRM trade and CWS trade

The analytical results in Subsections 5.1 and 5.2 show the complex relationships between CRM trade and CWS trade. First, the close correlation between the CRM trade network and CWS trade network is identified from the perspective of different structural characteristics. In particular, for each country, trade values and the number of trade relationships in the global CRM trade are highly positively correlated with those in the global CWS trade. In other words, if a country builds more trade relations and has more trade value in the global CRM trade network, it also has a plenty of trading partners and considerable trade value in the global CWS trade network. Moreover, if two countries have a close relationship in the global CRM trade network, then they tend to establish a tight trade relationship in the global CWS trade network.

Second, in terms of multilateral trade interactions represented by motifs, the patterns in the global CRM trade network and the global CWS trade network vary. Specifically, as demonstrated in Figure 7, the multilateral trade structure driven by the core exporting countries in $\mathrm{S5}$ is prominent in the CRM trade network, but the structure driven by the core importing countries in $\mathrm{S4}$ is highlighted in the CWS trade network. In addition, the cross-layer relationships show two patterns in multilateral trade structures represented by high conditional probabilities of $P(\mathrm{S4}^{[T_2]}\,|\,\mathrm{S5}^{[T_1]})$ , $P(\mathrm{S4}^{[T_2]}\,|\,\mathrm{S1}^{[T_1]})$ and $P(\mathrm{S4}^{[T_2]}\,|\,\mathrm{S2}^{[T_1]})$. Specifically, the former two probabilities indicate that exporting countries in the global CRM trade network tend to become importers in the CWS trade with their trading partners and further use these CWS items to promote the production of CRM. The last probability indicates that CRM-importing countries with a large copper consumption market tend to produce CWS and are therefore more likely to become CWS-exporting countries.

The above discussion indicates that a high correlation exists between two layers, and the following suggestions are proposed for the involved countries. First, participating countries should direct their attention towards the trade relationships in both layers of the MCTN to mitigate systemic trade risks. When focusing on only one trade network, some trade risks led by the other trade network may be ignored. Second, to better develop CWS trade, countries must identify their positions in the global CWS trade network and utilize their connections in the CWS trade network to establish trade relations in the global CWS trade network. Based on the two patterns of cross-layer relationships, the exporting countries in the global CRM trade network can more easily establish CWS import connections with their trade partners. Importing countries in the global CRM trade are more inclined to export CWS to their trading partners in the CRM trade network.

### 7.3 Policy implications from China's import ban

In Subsection 6.2, the impact of China's import ban on the MCTN is simulated based on the proposed multiplex shock model, and policy implications for different countries are obtained.

(1) Diversify trade connections to reduce dependence on a single country

Based on the simulation results of the proposed multiplex shock model, the countries that heavily rely on China for CWS exports will be seriously influenced by China's CWS import ban. In particular, Australia and countries in Asia and Latin America, which are shown in Figure 11, must face a significant reduction in CWS exports. Therefore, these countries should enhance diversification of their CWS exports to cope with the policy shock from China and properly handle domestic CWS. Meanwhile, domestic CWS recycling infrastructures should also be developed, and the recycling capability should be improved to address external risks.

(2) Develop trade connections across communities

Simply diversifying trade connections is not sufficient; understanding the structures of trade communities and developing trade connections across communities are critical. As demonstrated in Figure 13, the restrictive policies will lead to a split between North American countries and the Asia-America-Australia community in the CWS trade network. In a small trade community, countries are more likely to be affected by policy fluctuations in countries within the same communities. Therefore, strengthening CWS trade relationships with countries in different communities can help countries to reduce trade disruption risks.

(3) Holistic thinking in the MCTN

Although some countries are only involved in a single-layer trade network, all trading countries must develop the copper trade from a holistic point of view. As mentioned in sections 5 and 6, the CRM trade network is highly related with the CWS trade network, and a shock in the CWS trade network will spread to the CRM trade network. Only focusing on a single-layer trade network will cause some countries to underestimate systemic trade risks, and some other countries will miss opportunities to expand trade. Therefore, maintaining holistic thinking in the MCTN can help countries to address copper trade issues. In the context of China's CWS import ban, China's CRM imports will increase to satisfy the copper demand from China's manufacturing industry, rapidly increasing middle-class consumption, and infrastructure construction. This additional CRM demand is mainly expected from countries in South America and Asia, as shown in Figure 12, especially copper ore resource-rich countries, such as Chile and Peru. Additionally, some African and Southeast Asian countries, such as Nigeria, Gabon and Lao PDR, are predicted to have relatively large increases in CRM exports. In addition, some Asian and African countries will have an opportunity to join the Asian community and the European community, which will enhance globalization of the CRM trade in these countries, as shown in Figure 13. Therefore, China's import ban presents an opportunity for these countries to increase CRM exports to China and develop their primary copper industries.

(4) Strengthen trade connections with major trade partners

Due to complicated trade connections among involved countries, changes in import and export policies will cause trade fluctuations or disruption. Therefore, to ensure the security of imports/exports, countries should strengthen trade connections with their major trade partners. For China, maintaining close connections with countries in South America and Asia, including Chile and Peru, is important to ensure the security of its copper supply.

## 8. Conclusions and future work

Copper is widely recognized as one of the most important strategic resources in modern society for economic development. Due to the scarcity of copper ore, CWS is receiving increased attention worldwide because it can be used to alleviate the pressure of the resource shortage. Due to the substitutional relationships in their networks, the global CRM trade and global CWS trade form a multiplex trade system. The import/export policies in certain core countries have very large impacts on the trade system. Identifying complex relationships in the multiplex trade network and understanding the impact of import/export restrictive policies are essential for countries to ensure the security of their copper resources.

This study constructs global CRM and CWS trade networks from 1988 to 2017 as multiplex networks, and the entire system is called the MCTN. The development tendencies of global CRM and CWS trade are reviewed, and the different characteristics of the core countries in the two layers are revealed. In addition, the intricate relationships between the global CRM trade and the global CWS trade are investigated from the perspectives of single countries, country pairs and multilateral trade patterns. Furthermore, a multiplex shock model is developed to analyze the impact of China's CWS import restrictions on the MCTN. Some policy implications are provided for participating countries to ensure national copper resource security, which can be summarized from the macro and micro perspectives. 1) For all the involved countries in the MCTN, developing the CWS recycling industry is an urgent task, which will help countries decrease dependence on CWS exports and provide more sources of copper. To mitigate systemic risks, countries, including those that are involved in only one type of trade, must focus closely on both layers of the MCTN due to the close correlation between CRM trade and CWS trade. In addition, countries are required to have a better understanding of their positions in the MCTN and the two patterns of cross-layer relationships between CRM and CWS trade to efficiently establish trade connections. 2) In response to China's import ban, certain countries such as Australia, Asia and Latin America, which are heavily dependent on China for CWS exports, should improve diversification of exporting connections. North American countries should strengthen their CWS trade links with countries in other communities to reduce trade disruption risks. Meanwhile, countries in South America, Africa and Southeast Asia, including Chile, Peru, Nigeria, and Lao PDR, have the opportunity to expand CRM exports to China, and some Asian and African countries are predicted to further strengthen their connections with the Asian community and European community.

Some limitations related to the UN Comtrade data exist, which may introduce some degree of uncertainty into our analysis. First, countries do not necessarily report their trade statistics every year. The availability of data is dependent on the reporting national statistics authorities. Therefore, the total trade value may be underestimated. However, the trade statistics of large economies are reported yearly, and the impact of the missing data is therefore negligible. Second, some inconsistency exists between the statistics reported by a country and their trade partners. Some factors, such as the difference between importing prices including cost of insurance and freight (CIF) and exporting prices recorded on a "free on board" (FOB) and the timeliness of reporting trade records to the UN Comtrade, may lead to contradictions (Wang et al., 2020). For unification, this study considers the maximum value of the statistics from a reporting country and its partners as the trade value. Therefore, the application of UN Comtrade data will indeed introduce uncertainty into our network analysis, but the uncertainty is not likely to change the main conclusions and trends.

In our future work, we will introduce more factors into the MCTN. For example, the CWS recycling capacity and CRM demand will be incorporated into the multiplex shock model to estimate the impacts of China's import ban. In addition, we will investigate the correlation between the trade network structure and the prices of CRM and CWS and simulate the impacts of import/export policies on price volatility.

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