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Features of critical resource trade networks of lithium-ion batteries

Abstract: Critical resources are key for low carbon development. International trade in critical resources is commonplace. It is important to clarify country roles within this trade network so that resource supply risk can be mitigated and low carbon industries can be supported. This study investigates global trade of typical ores and chemical compounds for lithium-ion batteries—lithium carbonate, cobalt oxide, nickel sulfate, manganese sulfate, nickel ore and manganese ore. The period 2010-2018 is selected to explore different country roles using network analysis. A competition trade model is developed to identify relationships between countries. A critical resource influence model is developed using bootstrap percolation theory to simulate impacts arising from dominant countries—those countries with rich resource endowments or mature markets. Results show that dominant countries tend to maintain close trade relationships. Trade scale is a key factor influencing each country's trade competitiveness and influence. Several policy recommendations are proposed to promote sustainable resource trade and use.

Keywords: Critical resources; network analysis; trade; low carbon development; Lithium-ion batteries; governance

Introduction

Many countries are paying attention to enhance electric vehicle (EV) markets in order to decrease negative environmental and energy impact of the transport sector (Hao et al., 2017; Watari et al., 2019). Yet, this technological investment for a low-carbon energy transition will increase some mineral production by 350%-700% to meet global transportation sector requirements by 2050 (Watari et al., 2019). This increased demand is especially true for lithium-ion batteries (LIBs)—the major EV electric power source (Harvey, 2018; Dominish et al., 2019; Huang et al., 2020).

LIBs are used in modern plug-in EVs because of their high specific energy and power densities when compared to alternative battery choices (Perner and Vetter, 2015). These characteristics are connected to the critical and unique qualities of the LIB materials[1]. These materials include lithium, manganese, cobalt, and nickel (Ketterer et al., 2009).

~~EV sales are expected to increase from 5 million units sold annually in 2015 to about 180 million in 2045 (Li et al., 2017). Cobalt and lithium demand are likely to increase 37-fold and 18-fold by 2030, respectively, when compared to 2015 baseline levels (Jones et al., 2020). These increases in demand and usage make it imperative for us to~~

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[1] No standard definition of critical minerals and metals currently exists. Typical definitions can be found in (NRCNA, 2008; EC, 2010; Graedel et al., 2012; Coulomb et al., 2015). Typically, critical minerals and metals play key roles in economic systems. They are characterized by high supply and environmental risks; which results in high vulnerability to supply restriction.

~~explore critical resource concerns and limitations for low-carbon technology so that sustainable low-carbon energy transition in the transport sector can be achieved.~~

Previous studies have mainly identified critical resource issues in LIBs and EVs along two dimensions—recycling potential and supply constraints.

(1) Evaluation of the recycling potential of critical resources.

Ortego et al.~~,~~ (2018) identified end-of-life vehicle material compositions and evaluated the thermodynamic rarity of critical metals using exergy measures. Their results show that molybdenum, cobalt, niobium, and nickel accounted for less than 1% of the car's metal content, but these materials' contribution to the car's rarity was larger than 7%. Rarity increases with electrification due to greater critical metal quantities used.

Nguyen et al.~~,~~ (2020) evaluated two types of vehicles and critical materials content. They show that key scarce metals such as stannum, niobium, terbium, neodymium, and cobalt are most concentrated in the vehicular magnetic components.

Researchers have studied the recycling potential of critical resources from multiple perspectives. For instance, Gao et al.~~,~~ (2018) and Zhang et al.~~,~~ (2018), proposed that the valid recycling strategy of critical resources for all components from obsolete LIBs is important. Chen et al.~~,~~ (2019) conducted a systematic review of recycling LIBs and suggested that integrated efforts from academia, industry, and governments would help improve the recycling activities.

(2) Evaluation of supply risks. To reduce supply chain disruption risks, Ziemann et al.~~,~~ (2013), introduced a global manganese cycle model using material flow analysis to identify LIB manganese demand. Critical resource reserves and demands for LIBs in Europe were examined by Simon et al.~~,~~ (2015). Their results show for future traction battery cell production, a supply shortage of lithium and nickel can occur by 2025. Another finding from this study is that cobalt and manganese demand are far greater than available reserves.

Sun et al.~~,~~ (2018) developed a global lithium material flow analysis model to identify the supply risks and evaluate lithium resource efficiency. Their results show that the LIBs industry is the largest consumer of lithium and will continue to increase with rapid EV development. EVs accounted for 44% of the total lithium consumption in 2015. They also found that countries importing lithium may face a high risk of lithium shortage.

Sun et al.~~,~~ (2019)—using a material flow analysis—show that LIBs utilized the highest amount of cobalt in 2003, accounting for 27% of the total cobalt production. From 1995 to 2015, the amount of cobalt used in LIBs grew by 17%. These results indicate that the most significant driving factor in global cobalt consumption was the rapid growth of the LIBs industry.

Habib et al.~~,~~ (2020) sought to identify future resources constraints based on EV demand in 2050. Their results show that the geological reserves of cobalt, lithium and nickel have quickly reduced due to increasing EV sector demands. They also proposed that recycling these metals and innovative technological development may mitigate the vulnerability to EV production. Sun et al.~~,~~ (2020) constructed a basic trade-linked manganese material flow analysis model and found that although the current supply chain is relatively stable, several supply risks exist in the manganese industrial chain. This risk will likely lead to an urgent need for establishing an integrated manganese recovery system, particularly from LIB usage.

From consumption perspective, EV sales are expected to increase from 5 million units sold annually in 2015 to about 180 million in 2045 (Li et al., 2017). Cobalt and lithium demand are likely to increase 37-fold and 18-fold by 2030, respectively, when compared to 2015 baseline levels (Jones et al., 2020). From production perspective, the critical resources of LIBs are mainly concentrated in few countries in the world, such as The Republic of Congo (58% for global LIBs production with its cobalt resource in 2017) and Australia (45% for global LIBs production with its lithium resource in 2017), and other countries heavily depend on these concentrated sourcing countries (USGS, 2018). For instance, China heavily depends on import lithium resources, for instance, consumption of lithium in China is 50% of the global share, while its production is only 7% (Hao et al., 2017); 96% cobalt related sources from Russia is satisfied with the demand of EU's LIBs manufacturing (EC, 2020). Besides, in terms of the recycling economically of these critical resource, production of these resources will mainly depend on resources in the ground in the short-run (Kushnir and Sandén, 2012). Under such circumstances, international trade plays a key role in transferring different types of critical resources across the global supply chain (Sun et al., 2018; Sun et al., 2019; Habib et al., 2020).

~~These increases in demand and usage make it imperative for us to explore critical resource concerns and limitations for low carbon technology so that sustainable low-carbon energy transition in the transport sector can be achieved.~~

~~Due to rapid globalization and the uneven distribution of critical resources, international trade plays a key role in transferring different types of critical resources across the global supply chain (Sun et al., 2018; Sun et al., 2019; Habib et al., 2020).~~ A complex trade network is formed based on demand and supply of critical resources between countries (Klimek et al., 2015). ~~Many factors will influence this complex global supply network including political, natural disaster, and environmental regulatory factors (Hadri et al., 2018; Li et al., 2015; Sturla-Zerene et al., 2020).~~

Several international trade studies have used complex network analysis. Commodities such as fossil fuels (Chen et al., 2018; Gao et al., 2015; Guan et al., 2016; Hao et al., 2016; Jia et al., 2017), copper (Dong et al., 2018), virtual carbon (Dong et al., 2017), timber products (Long et al., 2019; Lovrić et al., 2018; Pizzol and Scotti, 2016), agricultural commodities (Cai and Song, 2016), virtual water (Suweis et al., 2011), seafood (Gephart and Pace, 2015), rare earths (Wang et al., 2016), and lithium (Chen et al., 2020), have been investigated. However, few international trade studies have been performed to investigate LIB resources. Fully understand of complex trade of these resources would make it imperative for us to explore critical resource concerns and limitations for low carbon technology. In addition, many factors will influence this complex global supply network including political, natural disaster, and environmental regulatory factors (Hadri et al., 2018; Li et al., 2015; Sturla-Zerene et al., 2020), and the supply risks are existing in critical resources of LIBs across their supply chains (Sun et al., 2019), it is necessary to identify the impacts of supply risks in the network so that sustainable low-carbon energy transition in the transport sector can be achieved.

This study aims to bridge and build on this research by evaluating LIB relevant mineral and chemical compounds. These compounds include nickel-cobalt-manganese lithium-ion cathode material, including minerals (nickel ore, manganese ore) and chemical compounds (lithium carbonate, cobalt oxide, nickel sulfate, manganese sulfate)[2]. This investigation will consider these flows along a complex global trade network from 2010 to 2018. Each country's role in this trade network will be evaluated using complex network indicators. Also, a trade competition model will be developed to identify the complex relationships among trade countries. In addition, a trade risk model will be developed using the bootstrap percolation process to assess each country's impact and contingency capability.

In summary, this study tries to address the following issues: (1) What is the network feature of each critical resource across its global supply chain? (2) What is the key feature of each involved country in the critical resource trade network? (3) What are the competitive relationships between different countries? (4) What impact does each country have in the trade network and how to evaluate each country's contingency capability to cope with global supply risk?

The remainder of the paper is organized as below. After this introduction section, section 2 details research methods and data sources; section 3 presents research results and section 4 shows the discussions and policy implications; Finally, section 5 draws research conclusions.

2 Methods and data sources

Complex network analysis is an effective method to help uncover hidden relationships between different countries in their global trade networks. It helps policymakers

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[2] Nickel-Cobalt-Manganese (NCM) battery as one type of Lithium-ion batteries represents the largest cathode market share in electric vehicles globally, accounting for 57% of vehicles sold in 2017 (Ballinger et al., 2019). Due to the data availability Cobalt ore and Lithium ore are excluded.

identify critical nodes along trade networks (Fan et al., 2014). In this section, firstly the construction of the non-competitive critical resource flow network is presented in 2.1; secondly, the construction of the competitive networks is shown in 2.2; Simulation model for each country's influence within one network is introduced in 2.3; finally, data sources are shown in 2.4.

~~Complex network analysis includes competitive and non-competitive networks.~~

2.1 Construction of the critical resource flow network

~~Complex network analysis is an effective method to help uncover hidden relationships between different countries in their global trade networks. It helps policymakers identify critical nodes along trade networks (Fan et al., 2014). Complex network analysis includes competitive and non-competitive networks.~~

For a critical resources *non-competitive* network, each node refers to a country and the width of each edge refers to the mass trade volume of a given commodity. The direction of each edge corresponds to the direction of the export and import of each commodity flow.

Within this network, if country a exports one commodity to country b in the year t, then a link from a to b is drawn and $p_{ab}(t) = 1$. Otherwise, no link is drawn and $p_{ab}(t) = 0$. If there is a link between a and b, this commodity flow from country a to country b is denoted as w_{ab}.

Five complex network indicators are selected to summarize the features of this critical resource network. The indicators include network density, cluster analysis, stability, betweenness centrality, and eigenvector centrality. The definitions for each of these five indicators are provided below.

(1) Network density

Network density measures the relationship tightness with other countries in a network (Marsden, 1993). It provides an overall network feature. Larger values indicate closer relationships among different countries. Network density can be calculated using equation (1):

$$\text{Density} = M/N(N-1) \tag{1}$$

Where M is the number of actual relationships within one network. $N(N-1)$ is the theoretical maximum number of possible relationships.

(2) Cluster analysis

Cluster analysis is used to identify the hidden trade relationships between countries within the global network. Countries within the same cluster have denser or greater numbers of links than with countries outside this cluster. A two phased cluster analysis based on undirected networks to separate the whole network into different clusters is applied for this study (Blondel et al., 2008).

Before the cluster analysis we identify the partition threshold of each single cluster based on a value of modularity. Modularity is an indicator to measure the extent of partition. A higher modularity value means that the partition of the whole network is clearer.

The modularity of partition (C) is calculated using Equation (2).

$$\mathrm{C} = \frac{1}{2m}\sum_i\sum_j\left(m_{ij} - \frac{m_i m_j}{2m}\right)\partial\left(G_i, G_j\right) \tag{2}$$

Where the weight of the edge between i and j is given by m_{ij}; m_i and m_j are node strengths of i and j respectively; $m_i = \sum_i m_{ij}$ and $m_j = \sum_j m_{ij}$ are the sum of the weights of the edges of the studied country. Country i is located in cluster G_i, and country j is located in cluster G_j. The ∂-function $\partial(a,b)$ is a variable which is used for identifying whether country i and country j belong to the same cluster. The ∂-function $\partial(a,b)$ is 1 if a = b. Otherwise, the ∂-function $\partial(a,b)$ is 0, and $2n = \sum_i\sum_j m_{ij}$. If country i and country j are located in the same cluster, the modularity of partition (C) would change, the result can be calculated by Equation (2).

Now we apply the two-phased iterative clustering approach using the evolution of a grouped cluster. In the first phase, the location of one node mainly depends on the feature of the change of modularity ΔC, calculated using equation (3). ΔC measures how close a node is to a cluster. For example, if the value of ΔC is positive, then node i is placed in the new cluster; if not, node i stays in its original cluster. In the second phase, a new network is made based on the results from the first phase. The two phases are iterated until there are no more changes and the maximum modularity is achieved.

The change of modularity is calculated via equation (3):

$$\Delta C = \left[\frac{\sum_{ig} + s_{i,ig}}{2q} - \left(\frac{\sum_{tot} + s_i}{2q}\right)^2\right] - \left[\frac{\sum_{ig}}{2q} - \left(\frac{\sum_{tot}}{2q}\right)^2 - \left(\frac{s_i}{2q}\right)^2\right] \tag{3}$$

Where $\sum_{ig}$ is the sum of the weights of the links within cluster (*G*), $\sum_{tot}$ is the sum of the weights of the links at cluster nodes, s_i shows the sum of the weights of node *i*, $s_{i,ig}$ shows the sum of the weights from *i* to nodes in cluster (*G*), and *q* represents the sum of the weights of all the links within the network.

(3) Stability of a cluster

The stability of a cluster is used to identify the status of one country's trade relationship in the network. It helps identify the potential risks for one country's trade. The stability of a cluster can be measured by the Normalized Mutual Information Index (NMI). This indicator quantifies the statistical information shared between two distributions. According to Fred and Jain (2003), the calculation of NMI depends on the confusion matrix. Given two cluster partitions Z_t and Z_{t+1}, the confusion matrix *M* is defined as a matrix whose M_{ij}-*th* element is the number of nodes in the cluster *i* of the partition Z_t that appear in the cluster *j* of the partition Z_{t+1}. Equation (4) is used to calculate this indicator.

$$NMI(Z_t, Z_{t+1}) = \frac{-2\sum_{i=1}^{X_A}\sum_{j=1}^{X_B} M_{ij} log\left(\frac{M_{ij}M}{M_i M_j}\right)}{\sum_{i=1}^{X_A} M_i log\left(\frac{M_i}{M}\right) + \sum_{j=1}^{X_B} M_j log\left(\frac{M_j}{M}\right)} \cdots \tag{4}$$

Where X_A and X_B refers to the number of clusters in Z_t and Z_{t+1}, respectively; $M_i = \sum_i M_{ij}$, $M_j = \sum_j M_{ij}$, and $M = \sum_i \sum_j M_{ij}$, respectively. If Z_t and Z_{t+1} are identical, then the NMI index is equal to 1. If the two partitions are independent, then the NMI index is 0.

(4) Betweenness centrality

Betweenness centrality (Bc) represents the number of weighted shortest paths through the nodes. It reflects one country's control of resources. It also represents the connectivity status of one network and the importance of the node as a bridge in the network (Freeman, 1977). A larger value of Bc implies greater resources control by a country.

The value of Bc of the node *i* can be calculated by equation (5).

$$Bc = \sum_{a \neq b \neq c} \frac{l_{ac}^{b}}{d_{ac}} \tag{5}$$

Where, d_{ac} refers to the number of paths from node *a* to node *c*; l_{ac}^{b} refers to the number of the shortest paths from node *a* to node *c* and through the node *b*.

(5) Eigenvector centrality

Eigenvector centrality (Ec) can measure the importance of one node. It is not only dependent on the number of its neighbor nodes, but also on the importance of its neighbor nodes (Bonacich and Lloyd, 2001). This indicator reflects the importance of the given country via the contribution of the importance of its partners. Equation (6) shows how to calculate the value of this indicator.

$$Eci = \lambda^{-1} \sum_{j=1}^{N} A_{ij}\, h_j \tag{6}$$

Where λ and h_j are the largest eigenvalues of the adjacent matrix and its eigenvector. A_{ij} is the adjacent matrix of the network. If *i* and *j* have an edge, then A_{ij}= 1, otherwise, A_{ij}= 0. *N* represents the total number of nodes within one network.

2.2 The competitiveness of countries in a complex trade network

Global critical resource competitive relationships can be taken as two types of networks. One is import-oriented, which is described by the set *A* = (*N, M*), where commodity importers *N* = $(n_1, n_2, \dots, n_n)$ are denoted as network nodes, and competitive relationships *M* = $\{m_{ij}\}$ are represented as network links. Competition occurs if there is the same country import source for commodity importers n_i and n_j, m_{ij} = 1. Otherwise, m_{ij} = 0.

The other one is export-oriented, which is described by the set *B* = (*E, F*), where commodity exporters *E* = $(e_1, e_2, \dots, e_n)$ are denoted as network nodes, and competitive relationships *F* = $\{f_{ij}\}$ are represented as network links. If exporters e_i and e_j export commodity to the same country, f_{ij} = 1. Otherwise, f_{ij} = 0.

In order to construct the weighted import-oriented network and weighted export-oriented network, we applied the indicator proposed by Glick and Rose (1999) to measure the competitive intensity. The competitive intensity is taken as the link weight.

The indicator of competitive intensity of import ($S_I(ij)$) is defined as follows:

$$S_I(ij) = \sum_c \left\{ \left(\frac{T_{ca} + T_{cb}}{T_g} \right) \times \left[1 - \frac{|(T_{ca}/T_a) - (T_{cb}/T_b)|}{(T_{ca}/T_a) + (T_{cb}/T_b)} \right] \right\} \times 100 \tag{7}$$

Where *c* represents the country that exports commodity to countries n_a and n_b, T_{ca} (T_{cb}) represents the total mass trade volume that country n_a (n_b) imports commodity from country n_c, T_g represents global total mass import volume and $T_a(T_b)$ represents gross import mass volume for country $n_a(n_b)$.

The competitive intensity indicator of an export ($S_E(ij)$) is defined as follows:

$$S_E(ij) = \sum_d \left\{ \left(\frac{T_{da} + T_{db}}{T_g} \right) \times \left[1 - \frac{|(T_{da}/T_a) - (T_{db}/T_b)|}{(T_{da}/T_a) + (T_{db}/T_b)} \right] \right\} \times 100 \tag{8}$$

Where *d* represents the country that imports a commodity from countries n_a and n_b, T_{da} (T_{db}) represents the total mass trade volume that country n_a (n_b) exports a commodity to country n_d, T_g represents global total mass export volume and $T_a(T_b)$ represents gross mass export volume for a country $n_a(n_b)$.

2.3 Simulation for each country's influence within one network

Greater globalization has increased international trade connections between countries. Each country plays a role in the global supply chain based upon its resource endowments and comparative advantages. Although international trade connections are integral to the global economy, a single country's ability to mitigate its risks in a global supply chain is weak. For instance, the rapid spread of COVID-19 had dramatic impact on global financial markets (Zhang et al., 2020).

In a given international trade network, it is expected that some countries have much stronger influences. If they suffer from a critical disruption, they may transmit such a crisis to other countries within this trade network. This study identifies these critical countries based on the bootstrap percolation process under different trade crisis scenarios and uncovers the response capacities of different countries coping with a global crisis.

By referring to Fan et al.~~,~~ (2014), several assumptions are necessary for this simulation analysis. The bootstrap percolation process supports the idea that each node has two possible states, namely, 'active' and 'inactive'. There is a critical threshold of nodes in the network. All the nodes in the network present an 'inactive' state originally. If the disturbance effect of one inactive node is higher than the critical threshold, then this node becomes an 'active' state and transmits the disturbance to its neighboring nodes. Its neighbor nodes will repeat this disturbance process again until all the nodes become active in the network. The whole bootstrap percolation process presents the node's influence in the network (Candellero and Fountoulakis, 2016; Chalupa et al., 1979; Saberi, 2015).

2.3.1 Assumptions of the bootstrap percolation process

(1) In the original trade network, all countries present a normal state as inactive nodes. There is a critical node threshold. When a country suffers from a crisis and the disturbance effect is higher than the critical threshold of the node, then this node becomes active. We assume that such a disturbance will influence this country's import or export volumes. In this study, we do not identify a specific crisis in which only one country suffers.

(2) The crisis transmission is processed in a short time—it is assumed that there are no effective means available to countries to prevent the crisis. Thus, it is ensured that the country which becomes an active node will not become inactive in a short time.

2.3.2 The disturbance procedure

In this study, we simulate the export and import disturbance processes in each selected critical resource trade network. We set up four types of crisis levels—low, middle, high, and extreme levels. A low level means that if the original country has suffered from this crisis, its import (or export) volume from (to) its trade partner would decrease by 20%. For middle, high and extreme levels, the relevant import (or export) volume would decrease by 50%, 80%, and 100%, respectively. We take exports in a low-level crisis as an illustrative example to show the transmission steps. All other levels can be processed in the same way.

Step 1:

Country S is the original crisis country. A_1 is country S's trade partner. Due to S's crisis, S reaches an active state, the export volume from S to A_1 decreases by 20%, and then the trade volume of A_1 which imports from S would be equal to $T_{SA1} = T_{SA} \times (1\text{-}20\%)$. Where, T_{SA} presents the original import of A_1 from S.

Step 2:

For country A_1, its import sources are defined by N_1, N_2, ……N_i. The total import volume of A_1 is T_{A1}, $T_{A1} = T_{SA} + T_{NA}$. If $(T_{SA1} + T_{NA})/T_{A1} \geq$ critical threshold value, A_1 maintains its inactive state; else, A_1 will have an active state and then transmit the crisis. Critical threshold values indicate the sensitivity of a country's trade and represents a country's ability to tackle a trade crisis. It is a randomly generated value ranging from 0 to 1, and it is different by resources.

Step 3:

If country A_1 becomes the next source of crisis transmission, the export volume of A_1 to its trade partner would decrease by 20% as well. Then the whole process would repeat step 1 and step 2 until there is no active node in the network.

Step 4:

Calculate the influence of country S. This influence is equal to the proportion of active nodes to the original total nodes.

2.4 Data sources

Two critical minerals (Manganese ore, HS code 2602 and Nickel ore, HS code 2604) and four chemical compounds (Lithium Carbonate, HS code 283691, Cobalt Oxide, HS code 282200, Nickel Sulfate, HS code 283324, Manganese Sulfate, HS code 283321) are selected to build up the relevant international trade networks. The export and import flows (mass trade volumes) of these commodities are obtained from the UN Commodity Trade Database[3]. Data for years 2000-2018 are used in this study due to data availability limitations.

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[3] http://comtrade.un.org/

3 Results

3.1 The features of critical resource networks and the roles of different countries

Table A1 in the supporting information (SI) lists all the indicators during the study period, while F~~f~~igure 1-6 illustrates the key features of critical resource networks.

(1) Lithium Carbonate

Figure 1 shows the features of lithium carbonate. For the whole lithium carbonate network, the density was unstable from 2010 to 2018. The whole network can be divided into 2-3 clusters during the study period, but cluster membership was relatively unstable.

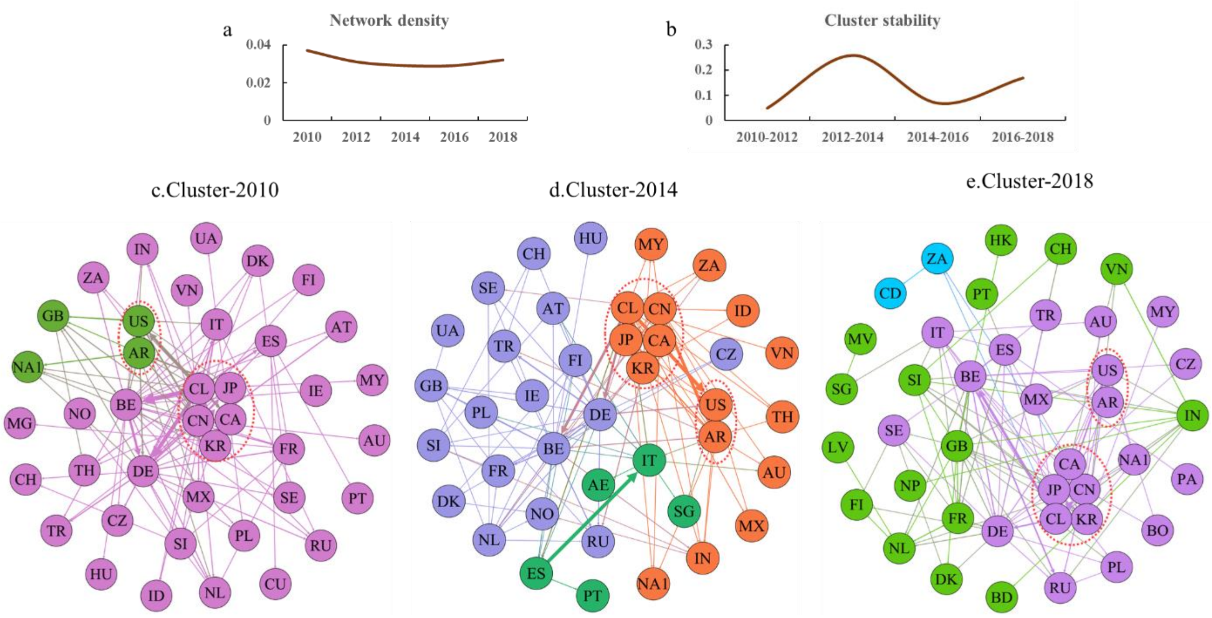
In general, EU countries—such as Germany and Belgium, China, and the US have more trade partners than other countries.

Due to high demand from batteries production (Jaskula, 2016; Pillot, 2016; Chung et al., 2016), Asian countries (such as Korea, Japan, and China), the USA and EU countries (such as Germany and Belgium) are major top import countries.

In terms of high resource richness almost 60% of lithium reserves were found in South America, especially in Chile and Argentina (Jaskula, 2016). This resource richness allows Chile and Argentina to be top export countries. Belgium and Germany are important lithium transit countries in the EU, both their export and import trade volumes are higher (Belgian Foreign Trade Agency, 2014; Eurostat, 2000-2018; Heinrich et al., 2019; Meersman and Nazemzadeh, 2017).

Countries such as China and Germany have high betweenness centrality values and play key bridge roles in this network. In addition, their eigenvector centrality values are high, indicating that they are powerful in this network due to their high impacts on trade partners. Take China as an example. China's top trade partners included Korea, Japan, and Australia in 2018. Korea and Japan are major global lithium buyers, and Australia is a major lithium exporter.

China, Japan, and Korea belong to the same cluster during the study period, and they stay in the same cluster with lithium reserve rich countries such as Chile and Canada. The USA stays in the same cluster with lithium reserve rich countries such as Argentina and Australia. All the EU countries remained in the same cluster. In addition, another key finding is that countries with high betweenness centrality and eigenvector centrality values tend to stay in the same cluster.



Note: Figure-a shows the network density indicator during the period; Figure-a shows the cluster stability indicator; Figure-c,d,e show the changes of clusters in 2010, 2014 and 2018. For these clusters, different colors present different clusters. Each circle presents each country or economy. Countries of the same color located in the same cluster. The straight lines behind the circle present the mass trade volume between countries. All numbers and countries' full name in detail is shown in the SI. The key feature of the countries' cluster is highlighted via the red box. Countries' full name in the red box are shown below: US(USA), AR(Argentina), AU(Australia), CN(China), JP(Japan), KR(Korea), CL(Chile), CA(Canada).

Figure 1 The features of lithium carbonate

(2) Cobalt Oxide

Figure 2 shows the features of cobalt oxide. The density of the cobalt oxide network increased from 0.031 in 2010 to 0.035 in 2018, indicating that different economies connected closely. There are 3-4 clusters during the study period although the clusters are unstable.

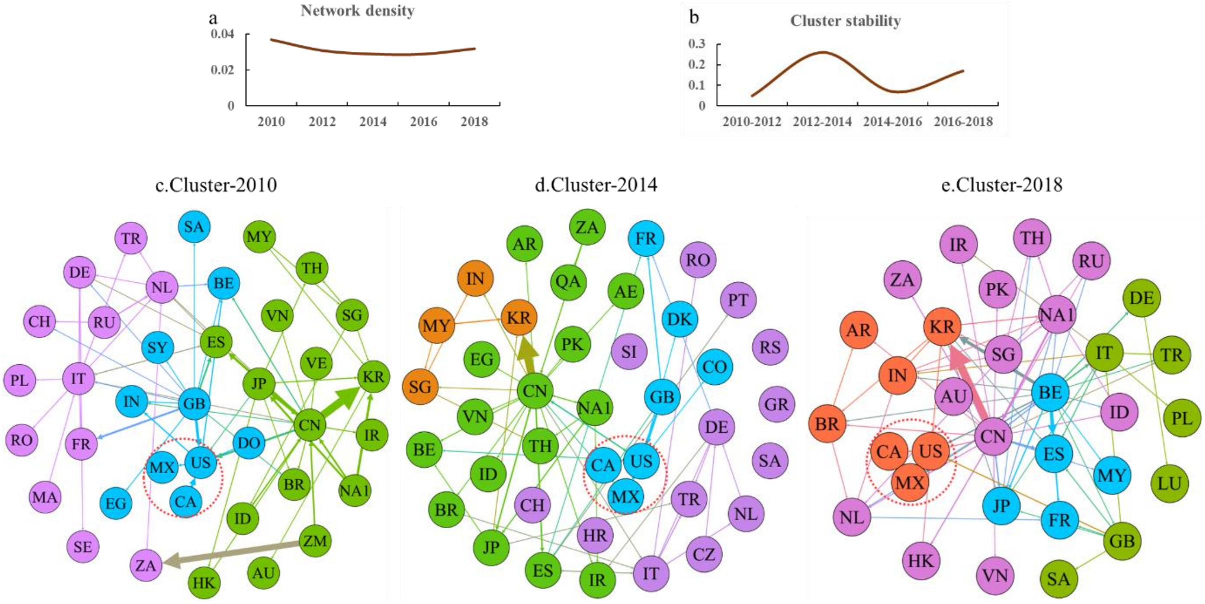
During the study period, Germany, China, Belgium, and USA have more import partners. China, Germany, and the United Kingdom have more export partners.

From a trade volume point of view, Asian countries such as Korea, China, and Japan are top import countries—this list also includes Spain and the US. Unlike other investigated products, cobalt is used to produce cobalt compounds-cobalt (mixed) oxides, that are eventually used for battery production. The high demand for cobalt is one reason for the skepticism toward the widespread use of lithium-ion batteries in electric mobility (Bertau et al., 2016). Therefore, countries with high lithium-ion batteries production capacities have large import volumes.

China, United Kingdom, Belgium, Japan, and Zambia are major export countries during the study period. Cobalt refineries, however, are rarely located near the cobalt mine sites. Instead, these companies purchase cobalt concentrate from various mines and deliver them to their own local locations. Interestingly, some of these top export countries are because they refine cobalt in large refinery companies such as China and the UK (Terence, 2019). Other countries, such as Zambia have mixed refineries capacity and major natural cobalt resources and export ores to the refining locations in other countries.

In terms of high trade linkages as mediator between countries, countries such as China, Germany, the United Kingdom, and the US play the key transit roles between different countries.

The major feature of this network is that the US, Canada, and Mexico remain in the same cluster, the only stable cluster during the study period.



Note: Figure-a shows the network density indicator during the period; Figure-a shows the cluster stability indicator; Figure-c,d,e show the changes of clusters in 2010, 2014 and 2018. For these clusters, different colors present different clusters. Each circle presents each country or economy. Countries of the same color located in the same cluster. The straight lines behind the circle present the mass trade volume between countries. All numbers and countries' full name in detail is shown in the SI. The key feature of the countries' cluster is highlighted via the red box. Countries' full name in the red box are shown below: US(USA), CA(Canada), MX(Mexico).

Figure 2 The features of cobalt oxide

(3) Nickel Sulfate

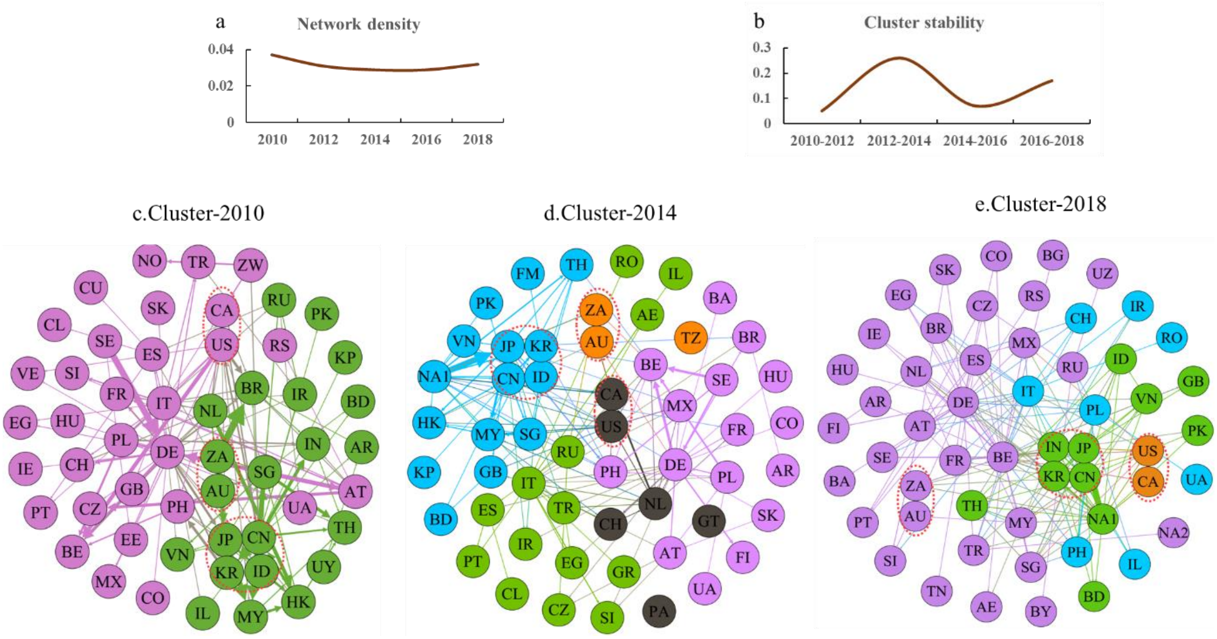
Figure 3 shows the features of nickel sulfate. The density of this network decreased first and then increased, reaching 0.038 in 2018. The whole network is composed of 2-5 clusters during the study period. The stability of clusters decreased from 0.24 in 2010 to 0.10 in 2018, indicating that the hidden trade relationship between different countries has changed.

In general, the order of import market is unstable during the study period. Countries with large nickel demand and consumption, such as Japan, Korea, China, and Belgium, have large import volumes. Japan, South Africa, Germany, and the US are the top export countries.

In the study period, Germany, China, India, Japan play important roles in connecting different countries. The Netherlands and Singapore also have high betweenness centrality values because they established storage facilities approved by London Metal Exchange and became important global distribution centers for refined nickel logistics (LME, access to 2020.5).

In terms of the powerful roles of their trade partners, EU countries like Germany and Italy, Asian countries like China and India, and the US, have high eigenvector centrality values.

The feature of this product network includes: (1) Canada and the US stay in the same cluster all the time; (2) South Africa and Australia stay in the same cluster except for the year 2012; (3) Asian countries maintain tight relationships, especially China, Japan, Korea, Indonesia, and India; (4) European countries maintain tight relationships. Thus, in this network it seems that geography, culture, and political alliances play important roles.



Note: Figure-a shows the network density indicator during the period; Figure-a shows the cluster stability indicator; Figure-c,d,e show the changes of clusters in 2010, 2014 and 2018. For these clusters, different colors present different clusters. Each circle presents each country or economy. Countries of the same color located in the same cluster. The straight lines behind the circle present the mass trade volume between countries. All numbers and countries' full name in detail is shown in the SI. The key feature of the countries' cluster is highlighted via the red box. Countries' full name in the red box are shown below: US(USA), ZA(South Africa), AU(Australia), CN(China), JP(Japan), KR(Korea), IN(India), CA(Canada), ID(Indonesia).

Figure 3 The features of nickel sulfate

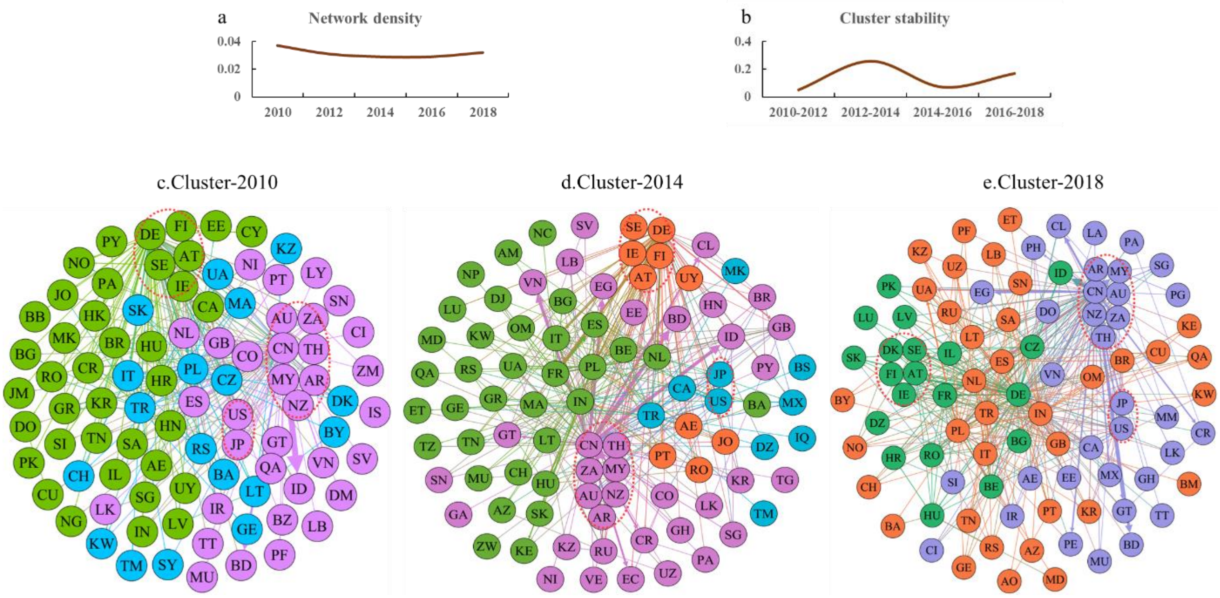
(4) Manganese Sulfate

Figure 4 shows the features of manganese sulfate. The density of the whole network increased from 0.027 in 2010 to 0.038 in 2018. There are 3-4 clusters during the study period. The stability of these clusters decreased from 0.19 in 2010 to 0.04 in 2018.

China, Germany, India, Poland, and France are major export countries, while Asian countries such as Malaysia, Indonesia, Bangladesh, and Thailand are major import countries.

Germany and China play key roles in connecting different countries in this network. Germany, China, India, Belgium, and Netherlands have high impacts due to their trade partners' power.

The tight and stable relationships among different countries include: (1) The US and Japan; (2) China, Australia, South Africa, Malaysia, Thailand, New Zealand, Argentina; (3) EU countries such as Germany, Sweden, Finland, Ireland, Austria.



Note: Figure-a shows the network density indicator during the period; Figure-a shows the cluster stability indicator; Figure-c,d,e show the changes of clusters in 2010, 2014 and 2018. For these clusters, different colors present different clusters. Each circle presents each country or economy. Countries of the same color located in the same cluster. The straight lines behind the circle present the mass trade volume between countries. All numbers and countries' full name in detail is shown in the SI. The key feature of the countries' cluster is highlighted via the red box. Countries' full name in the red box are shown below: US(USA), ZA(South Africa), AU(Australia), CN(China), JP(Japan), MY(Malaysia), TH(Thailand), NZ(New Zealand), AR(Argentina), DE(Germany), SE(Sweden), FI(Finland), IE(Ireland), AT(Austria).

Figure 4 The features of manganese sulfate

(5) Nickel ore

Figure 5 shows the features of nickel ore. The whole density of this network is unstable during the study period, but with a decreasing trend. Three or four clusters existed during the study period.

In general, China, Germany, Canada, Japan, and Korea had more import partners, while the USA had the most export partners.

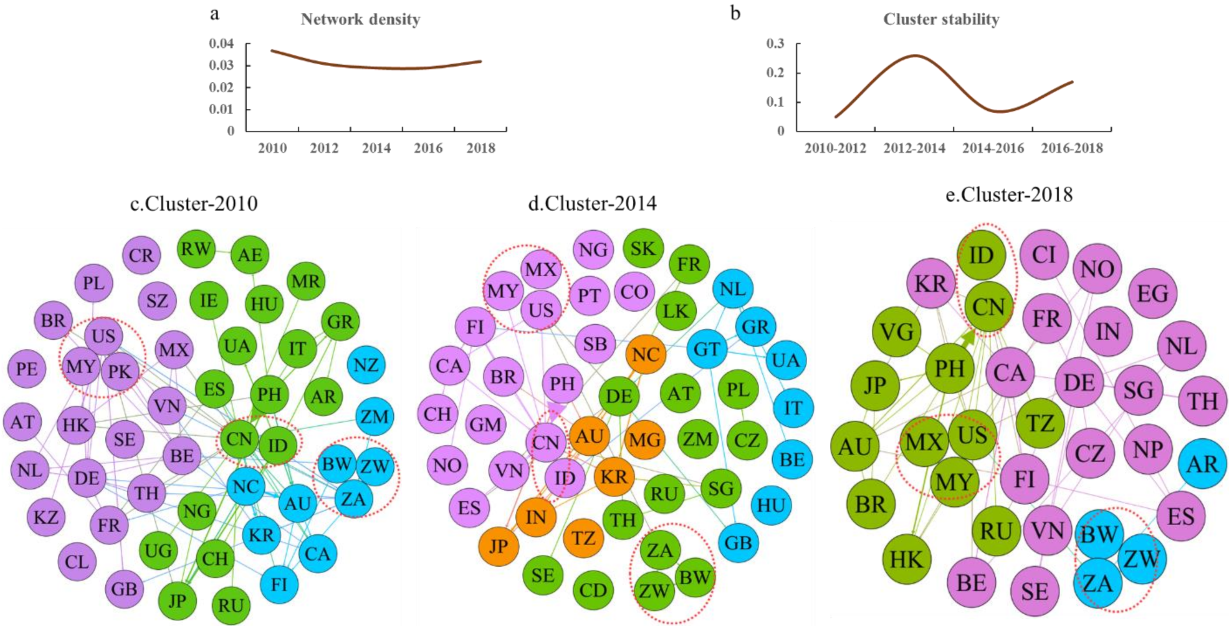
China had the highest import volume during the study period because nickel used in stainless steel accounted for two thirds of primary nickel use at the global level. China is the world's leading stainless-steel producer. In 2014 China produced 16.7 million tons of austenitic stainless steel (Survey, 2011-2019). In addition, major steel production countries like Japan, Korea, and Ukraine have large import volumes as well.

The export volume of each country is determined by the resource endowments of this country. For instance, countries like the Philippines, Indonesia, Guatemala, New

Caledonia, Australia, and Russia have large export volumes.

The US, Germany, South Africa, Canada, and China play important roles in connecting different countries in this network. China, the US, and Germany have high eigenvector centrality values due to the power of their trade partners.

Resources-oriented countries such as Botswana, South Africa, and Zimbabwe stay in the same cluster during the study period. Similarly, China and Indonesia stay in the same cluster, and the US, Malaysia, and Mexico remain in the same cluster. In general, the economies with high betweenness centrality and eigenvector centrality values always remained in the same cluster.



Note: Figure-a shows the network density indicator during the period; Figure-a shows the cluster stability indicator; Figure-c,d,e show the changes of clusters in 2010, 2014 and 2018. For these clusters, different colors present different clusters. Each circle presents each country or economy. Countries of the same color located in the same cluster. The straight lines behind the circle present the mass trade volume between countries. All numbers and countries' full name in detail is shown in the SI. The key feature of the countries' cluster is highlighted via the red box. Countries' full name in the red box are shown below: US(USA), ZA(South Africa), CN(China), MY(Malaysia), BW(Botswana), ZW(Zimbabwe), ID(Indonesia), MX(Mexico).

Figure 5 The features of nickel ore

(6) Manganese ore

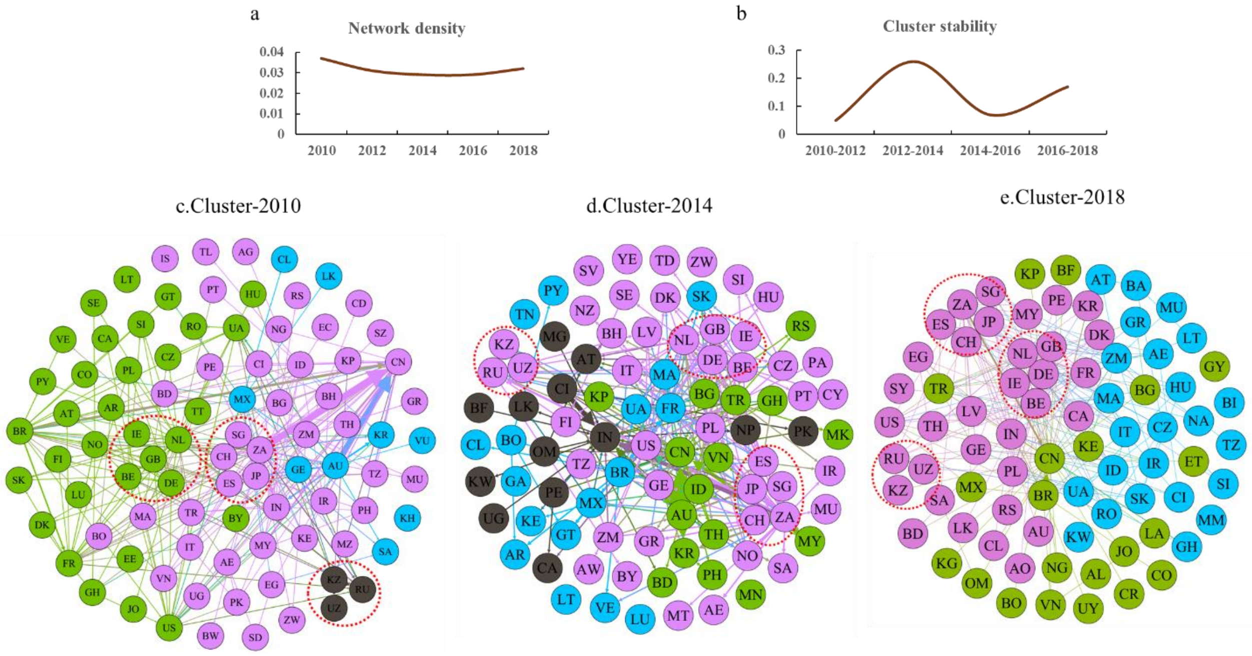
Figure 6 shows the features of manganese ore. The density of this network is unstable, with a decreasing trend from 0.037 in 2010 to 0.032 in 2018. The whole network includes 3-4 clusters during the study period. But these clusters were unstable, indicating that the trade relationships were also unstable.

Manganese ore is normally used for steel production. Major steel production countries such as China, India, Ukraine, Japan, Korea, and Russia are major import countries.

Countries with rich manganese ore such as South Africa, Australia, Brazil, Malaysia, Kazakhstan, and Ghana are major export countries. Brazil and Ghana experienced rapid export growth of this ore.

During the study period, China, Germany, and South Africa play key roles in connecting different countries. South Africa, the Netherlands, China, and Germany have high eigenvector centrality values due to the power of their trade partners.

The tight and stable relationships among different countries include: (1) Russia, Uzbekistan, and Kazakhstan; (2) Japan, Spain, Switzerland, Singapore, and South Africa; (3) Mexico and Brazil (since 2012); (3) several key EU countries such as Germany, UK, Belgium, Ireland, and the Netherlands.



Note: Figure-a shows the network density indicator during the period; Figure-a shows the cluster stability indicator; Figure-c,d,e show the changes of clusters in 2010, 2014 and 2018. For these clusters, different colors present different clusters. Each circle presents each country or economy. Countries of the same color located in the same cluster. The straight lines behind the circle present the mass trade volume between countries. All numbers and countries' full name in detail is shown in the SI. The key feature of the countries' cluster is highlighted via the red box. Countries' full name in the red box are shown below: RU(Russia), UZ(Uzbekistan), KZ(Kazakhstan), JP(Japan), ES(Spain), CH(Switzerland), SG(Singapore), ZA(South Africa), MX(Mexico), BR(Brazil), DE(Germany), GB(UK), BE(Belgium), IE(Ireland), NL(Netherlands).

Figure 6 The features of manganese ore

3.2 Competition relationships within these networks

The competitive trade networks reflect competitive relationships between countries. Import and export competitive networks of selected resources are constructed based on the method in section 2.2.

The density values of selected competitive networks appear in the supplementary information as Table A2. Network density indicates how close relationships are between countries based on connecting edges. Higher density represents a greater number of linkages between countries. As an example, for the import trade network, its high-density value indicates that two or more countries import resources from the same export country. These additional links reflect greater competition for resources from importing countries.

The market for cathode materials of lithium-ion batteries remains very dynamic and is currently seeing "deconcentrating" as more companies enter the market and provide a share of the global supply (Pillot, 2015, 2016). Country competition is fierce for the chemical critical resources of lithium carbonate, cobalt oxide, nickel sulfate and manganese sulfate. For instance, in 2018, the import competitive network density of cobalt oxide is 5.8 times higher than its export competitive network density. For the ore networks such as nickel ore and manganese ore, no significant gap exists between export competitive network and import competitive network densities.

Competitive intensity can be used for measuring competitive relationships amongst countries. Table A2 in the supplementary information lists the top five competitive countries. Table 1 lists the most competitive relationships of the six study commodities during this study period.

There are several general observations we can make for the import and export network competitions results. For import chemical compounds networks a “strong-weak” relationship between countries is prevalent. The competitive relationships between high trade volume countries and low trade volume countries are especially competitive.

Take the competitive relationship between Korea (strong) and Uzbekistan (weak) in 2016 in the cobalt oxide trade network as one example. Both Korea and Uzbekistan import from China in amounts of 8.21E+06 kg and 2000 kg, respectively. Both Korea and Uzbekistan import 99% of their total international cobalt oxide imports from China. This situation indicates that Korea and Uzbekistan are each heavily dependent and compete for China’s resources. Uzbekistan with its very much smaller import quantities when compared with Korea is at a major competitive disadvantage in trade of cobalt oxide with China. In this situation high import scale and high market share represent competitive advantages for countries.

For import ore network competitiveness there exists a preponderance of “strong-strong” relationships. The 2016 nickel ore competitive relationship between Japan and China exemplifies this situation. China has a total of 18 import partners and Japan has a total of 5 import partners—import partners are countries who export their materials to China and Japan. Four of these import trade partners overlap between the two countries. These four overlapping import partners represent high overall import market shares for both China (98%) and Japan (99%). The reason for this is that nickel ore demand in both China and Japan are high due to high steel production, therefore, a fierce competitive relationship between China and Japan exists.

The same “strong-weak” and “strong-strong” results exist for exports between countries. High country resource endowment plays an important role in the “strong-strong” trade competition results.

Table 1 The fiercest competitive relationships over time (the value is competitive intensity)

	2010	2012	2014	2016	2018
lithium carbonate					
Export	Argentina vs Canada (12)	Chile vs Japan (16)	Argentina vs Chile (7)	Chile vs Thailand (12)	Chile vs China (5)
Import	Czechia vs Germany (2)	China vs Korea (14)	Italy vs Portugal (8)	Korea vs South Africa (16)	Korea vs Egypt (6)
Cobalt oxide					
Export	Canada vs United Kingdom (3)	Canada vs United Kingdom (6)	Canada vs United Kingdom (6)	Canada vs United Kingdom (3)	Belgium vs Netherlands (2)
Import	Korea vs Uzbekistan (14)	Korea vs Kyrgyzstan (34)	Korea vs Uzbekistan (46)	Korea vs Uzbekistan (60)	Korea vs Russia (34)
Nickel ore					
Export	Canada vs Indonesia (37)	Indonesia vs Russia (49)	Philippines vs China, Hong Kong (70)	Philippines vs Turkey (68)	Indonesia vs Russia (92)
Import	China vs Ukraine (28)	China vs Ukraine (43)	Australia vs China (33)	China vs Japan (77)	China vs Ukraine (94)
Nickel Sulfate					
Export	Sweden vs Austria (3)	Sweden vs Austria (7)	Philippines vs Sweden (4)	Korea vs Poland (3)	Netherlands vs South Africa (4)
Import	Canada vs Belgium (3)	Brazil vs China (9)	Japan vs Thailand (10)	Japan vs Pakistan (21)	Japan vs Pakistan (31)
Manganese ore					
Export	Australia vs Bulgaria (18)	Australia vs Bulgaria (25)	Australia vs India (21)	South Africa vs Malaysia (32)	Brazil vs Ghana (47)
Import	China vs New Zealand (20)	China vs Saudi Arabia (19)	China vs Korea (26)	China vs Russia (37)	China vs Uruguay (30)
Manganese sulfate					
Export	Australia vs China (6)	Germany vs Luxembourg	China vs Viet Nam (3)	China vs Italy (2)	China vs Singapore (2)

		(2)			
Import	Indonesia vs Papua New Guinea (18)	Indonesia vs Papua New Guinea (12)	Malaysia vs Papua New Guinea (8)	Malaysia vs Honduras (9)	Malaysia vs Honduras (11)

3.3 Country influence from resource trade disruptions

The country influence results show how a trade crisis in one country diffuses to other countries in its trade network. Using results from sections 3.1 and 3.2, a summary of countries who play significant export roles in the resource trade network is established and presented. The crisis transmission is simulated to arrive at these trade disruption influence—and diffusion—results.

Using the method from 2.3 section, we simulate various levels of export and import trade crises at 20%, 50%, 80% and 100% levels. For example, the 20% level represents a simulation with a country losing 20% of its resource trade capacity.

Table A3 in the supplementary information summarizes influence results of different commodities during the study period. In this main text we provide some exemplary key simulation results—specifically at a 100% disruption level using 2018 data.

In general, there are several features summarized in the trade networks: (1) more countries are affected as the crisis level increases. Take Korea—from Table A3—in 2018 lithium carbonate network as an example. If Korea's imports decrease by 20%, 50%, 80%, and 100%, then 11, 15, 32 and 32 countries are affected at some levels, respectively.

(2) A country needs to have high critical threshold value in order to prevent a trade crisis. Take the same example in Korea, if Korea's imports decrease by 20%, 50%, 80%, and 100%, the critical threshold values required by trading partners increase by 12%, 30%, 48% and 60%, respectively. Requiring those countries to build up greater resilience so the disruptions do not cause them harm.

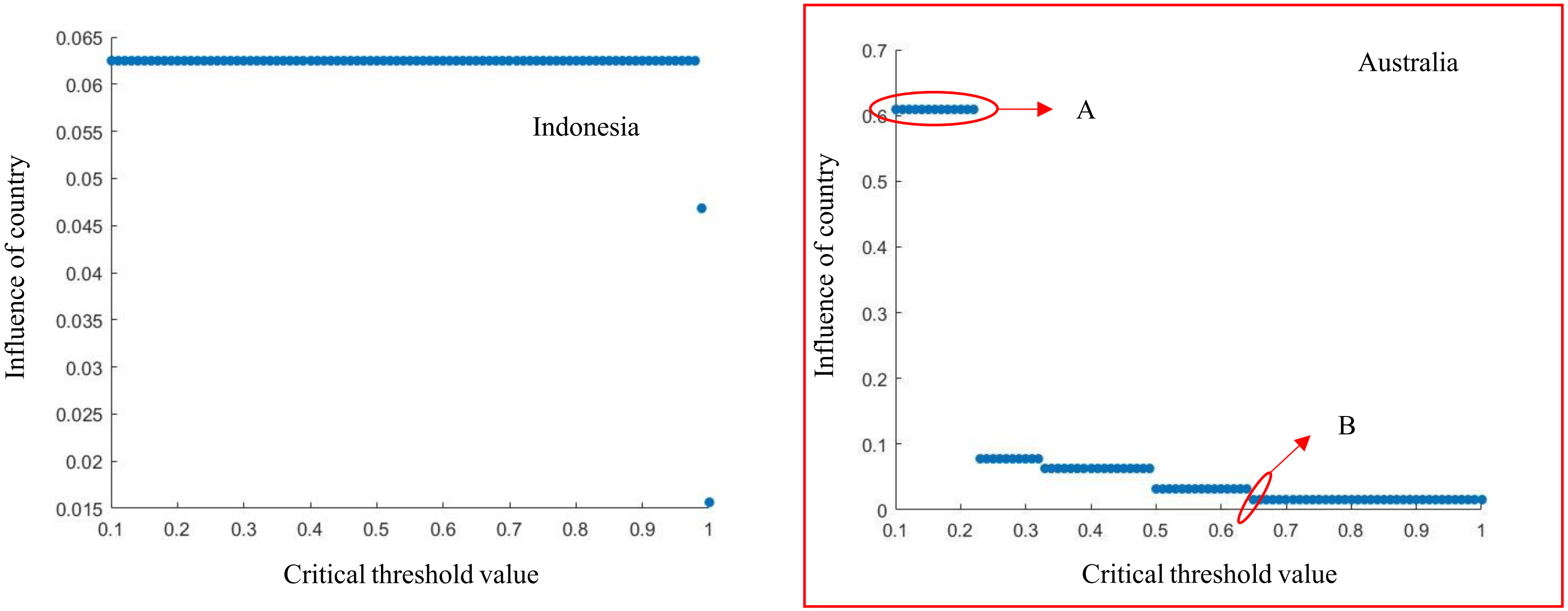
(3) The trade crises are likely to be more pronounced transmitted along export networks. Take China in 2018 cobalt oxide export network as an example, when China suffers a trade crisis at 100% level, it affects 37 countries in the import trade network and 100 countries in the export trade network.

Figure ~~2~~ 7 provides illustrations of key countries across different resources. To explain the graphics, we will initially consider nickel ore resources in Australia's export trade network –Figure ~~2a~~ 7a on the right-hand side. In this case the X-axis represents the critical threshold value in a trade network with each blue dot representing an export trading partner for the country facing the disruption. Critical threshold values represent the sensitivity of a partner country's trade and this country's ability to handle a trade crisis—larger threshold values mean that these partner countries are relatively resilient to disruptions—with each blue dot represents a trade partner country whose value has been simulated many times. The range of this threshold value ranges from 0.1 to 1. Y-axis presents the influence of a country, it is equal to the proportion of active nodes to the original total nodes.

The Y-axis shows how many partner countries are affected by a trade crisis at the given critical threshold value level. For instance, in Figure ~~2a~~ 7a for Australia and nickel-ore exports, we see in the circle represented by “A” that 61% of Australia’s direct and indirect trade partners are affected—become ‘active nodes’—when average critical threshold values for the Australia’s trade network ranges from 10% to 22% (along the X-axis). The “B” in Figure ~~2a~~ 7a for Australia represents the maximum critical threshold value. This value meaning is the point where no nodes become active when Australia has 100% disruption. After this point no nodes are disrupted—they remain inactive.

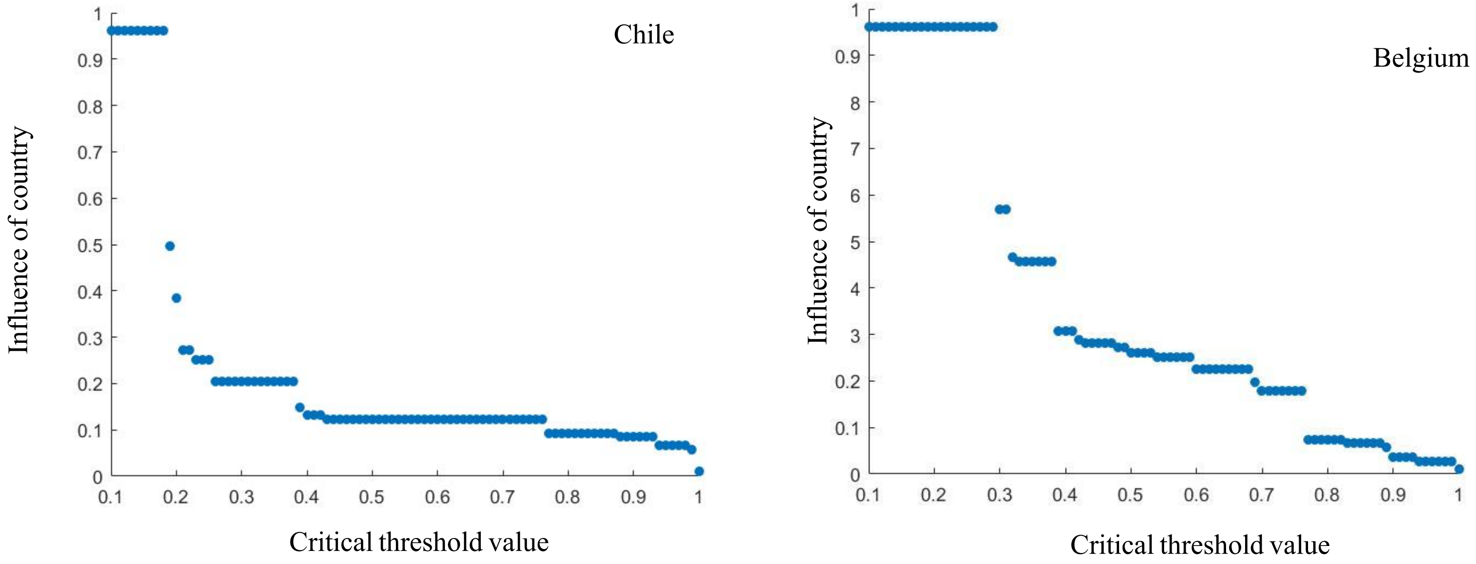
Two general shapes can be observed in Figure ~~2~~7. Take nickel sulfate export as an example (Figure ~~2~~7-c). On the righthand side for Germany there are a number of threshold breakpoints that cause variations in percentage of active nodes in the network. There are cascading breakpoints as the range goes from 0.5 to 1 in threshold value. The other distinct shape is represented by fewer break points amongst trade partners—which is representative of the South Africa trade network on the left-hand side of Figure ~~2~~7-c. These differences are likely attributable to the trade relationships including the material dispersion across countries and the quantities and amounts of country trade partners. For instance, South Africa has 9 major direct export trade partners in their network, among these partners Belgium, Japan and China are the top three trade partners. The top three trade partners account for 72% of South Africa’s total export trade volume. If South Africa suffers a trade crisis (100% disruption), the number of direct and substantive influences is limited. Germany has 47 direct export trade partners, the trade relationship between Germany and its trade partners is more complex—given the variations in critical threshold values—than that of South Africa. This cascading shape is represented with a multitude of influence values especially given Germany’s positioning in the global value chain of not being a direct source of the material but has processed it.

a. Nickel Ore-export



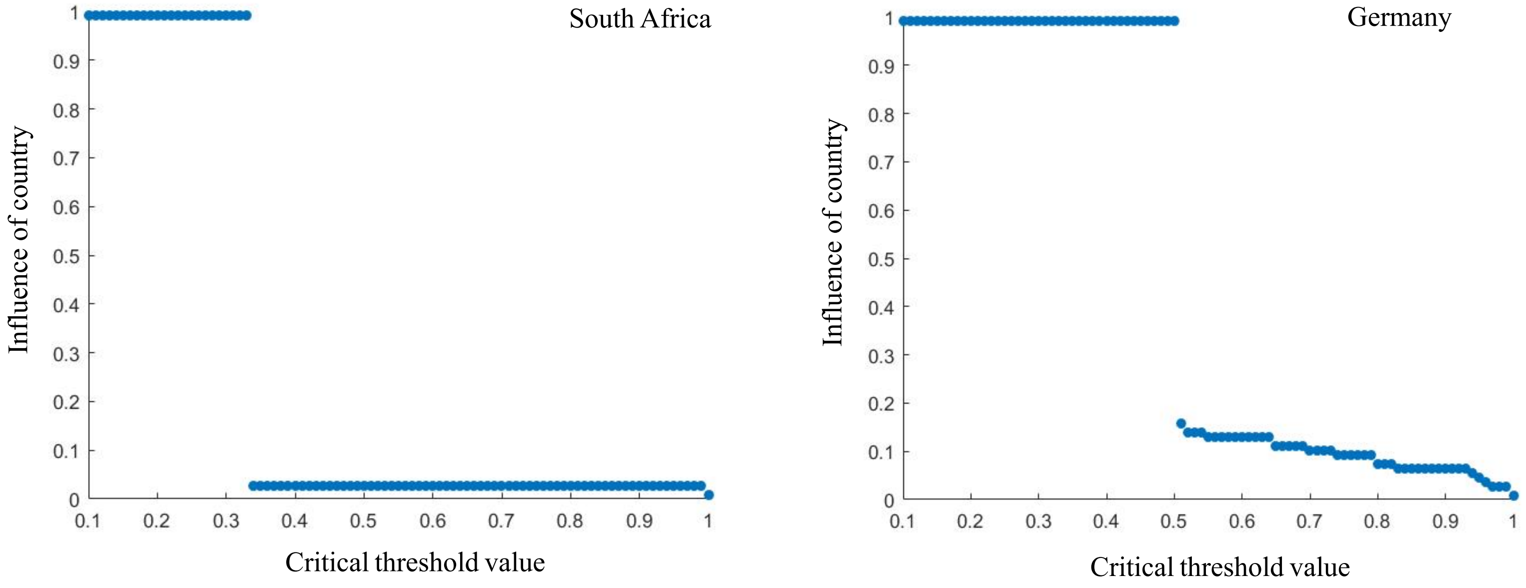
Note: ~~The influence of a country is equal to the proportion of active nodes to the original total nodes.~~Figure 7-a shows the trade crisis transmission from Indonesia and Australia in nickel ore export network, respectively. The influence of a country is equal to the proportion of active nodes to the original total nodes. Critical threshold values represent the sensitivity of a partner country's trade and this country's ability to handle a trade crisis. The illustrations of trade crisis transmission are in results 3.3.

b. Lithium Carbonate-export



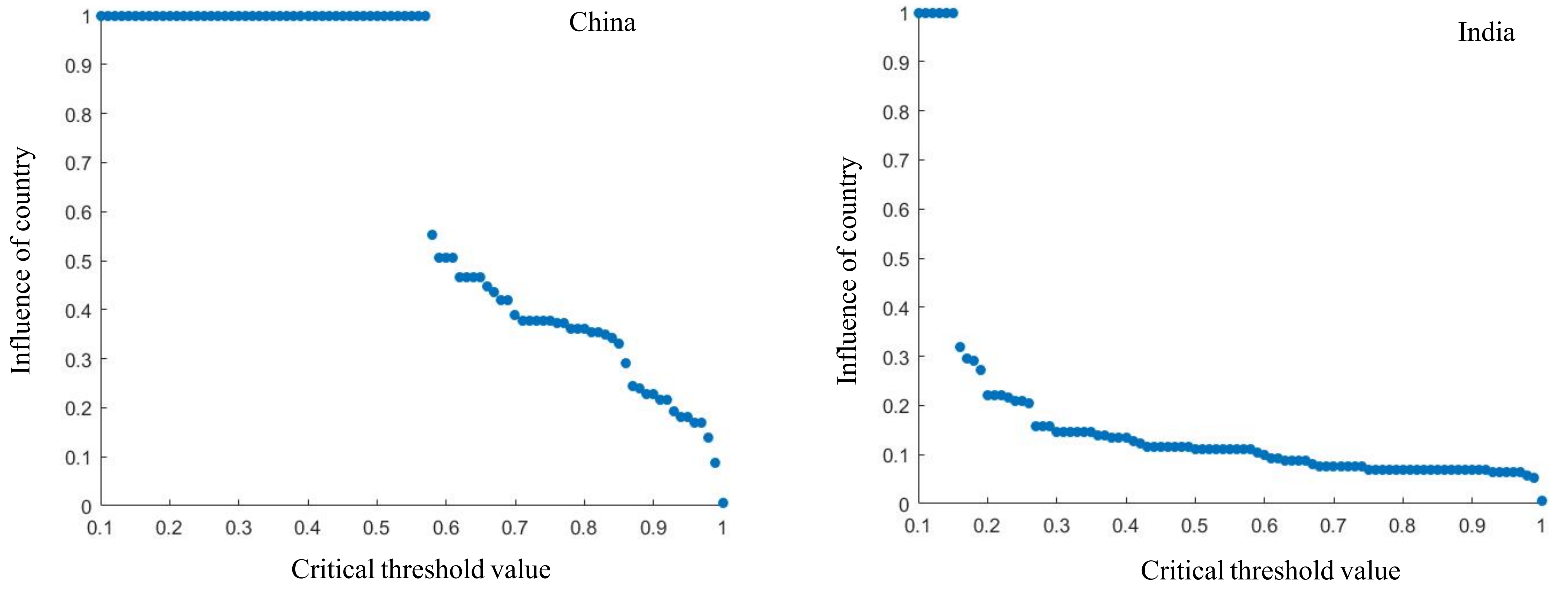
Note: Figure 7-b shows the trade crisis transmission from Chile and Belgium in lithium carbonate export network, respectively. The influence of a country is equal to the proportion of active nodes to the original total nodes. Critical threshold values represent the sensitivity of a partner country's trade and this country's ability to handle a trade crisis. ~~The influence of a country is equal to the proportion of active nodes to the original total nodes.~~

c. Nickel Sulfate-export



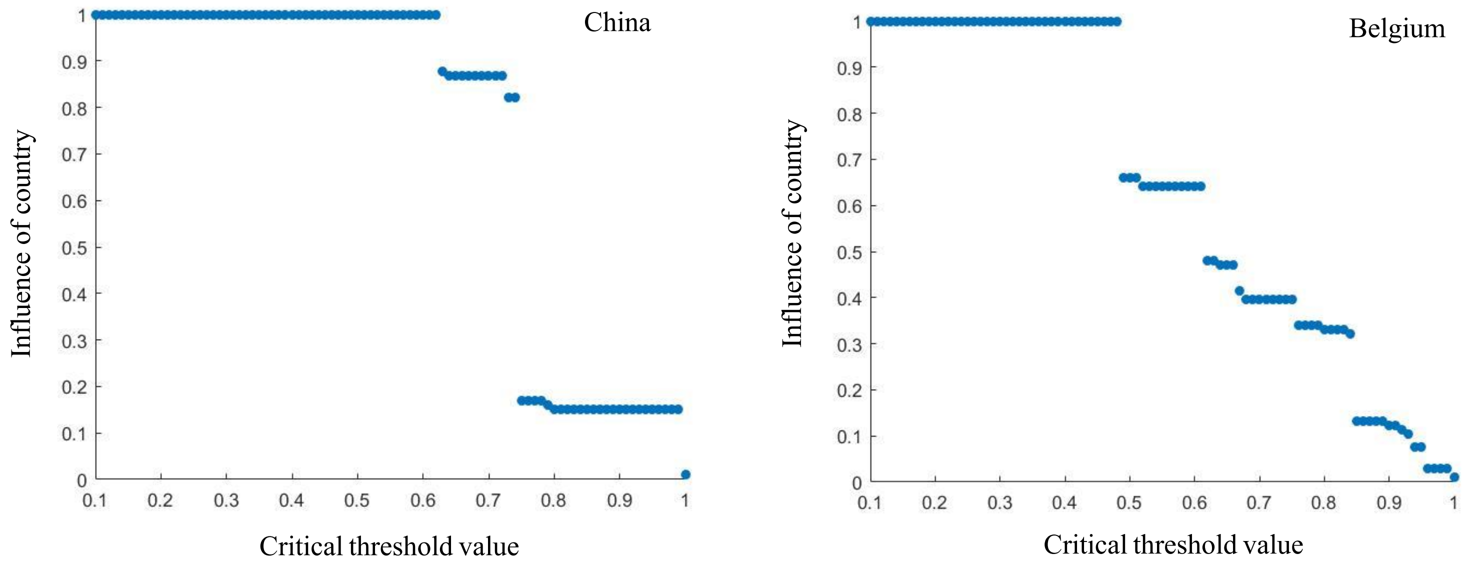
Note: Note: Figure 7-c shows the trade crisis transmission from South Africa and Germany in nickel sulfate export network, respectively. The influence of a country is equal to the proportion of active nodes to the original total nodes. Critical threshold values represent the sensitivity of a partner country's trade and this country's ability to handle a trade crisis. ~~The influence of a country is equal to the proportion of active nodes to the original total nodes.~~

d. Manganese Sulfate-export



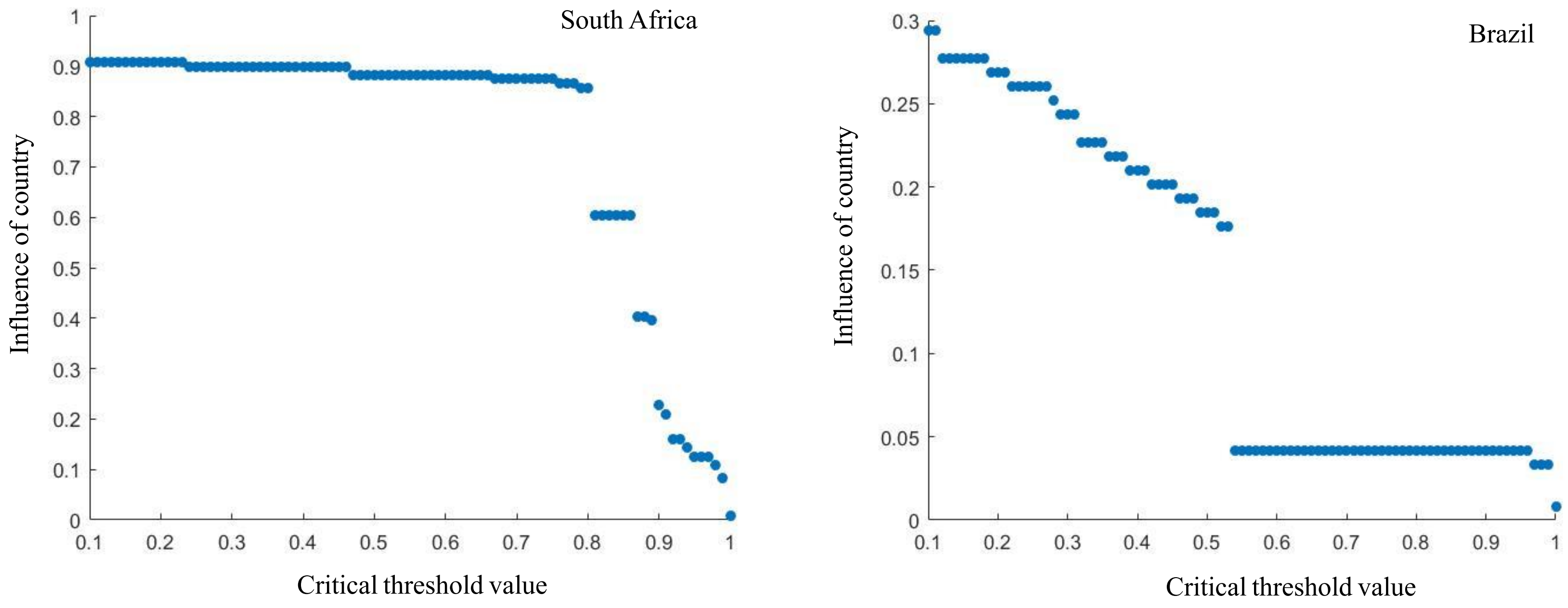
Note: Figure 7-d shows the trade crisis transmission from China and India in manganese sulfate export network, respectively. The influence of a country is equal to the proportion of active nodes to the original total nodes. Critical threshold values represent the sensitivity of a partner country's trade and this country's ability to handle a trade crisis. ~~The influence of a country is equal to the proportion of active nodes to the original total nodes.~~

e. Cobalt Oxide-export



Note: Figure 7-e shows the trade crisis transmission from China and Belgium in cobalt oxide export network, respectively. The influence of a country is equal to the proportion of active nodes to the original total nodes. Critical threshold values represent the sensitivity of a partner country's trade and this country's ability to handle a trade crisis. ~~Note: The influence of a country is equal to the proportion of active nodes to the original total nodes.~~

f. Manganese Ore-export



Note: Figure 7-f shows the trade crisis transmission from South Africa and Brazil in manganese ore export network, respectively. The influence of a country is equal to the proportion of active nodes to the original total nodes. Critical threshold values represent the sensitivity of a partner country's trade and this country's ability to handle a trade crisis. ~~Note: The influence of a country is equal to the proportion of active nodes to the original total nodes.~~

Figure ~~2~~ 7 The key countries influence results of different commodities in 2018 export trade network

4 Discussions and Policy Implications

4.1 The features of resources trade networks

In this study, the features of mineral and chemical compounds trade networks are evaluated. Chemical compounds trade networks are generally increasing density over the study period. This result indicates increasing trade relationships between countries. This situation relates to rapid industrial development from accelerated production globalization and increased resource demands (Hao et al., 2017; Sun et al., 2019; Sun et al., 2020).

Results show that countries with high batteries production demand such as China, Japan and Korea play leading roles across chemical compounds trade networks. Countries with high mineral resource endowments play leading roles in ore trade networks. These countries include Chile, Argentina and South Africa. Countries with strategic geographical locations—such as Belgium and Germany—also play critical trade network roles. This latter finding is consistent with previous study results (Hao et al., 2017; Sun et al., 2019; Sun et al., 2020).

Beside country characteristics, another interesting finding is country trade partners also can influence a country's role in the trade network. This finding is supported by eigenvector centrality values. Eigenvector centrality values provide information for countries to select their trade partners. It measures countries importance while considering the importance of its trade partners. Take China in Lithium Carbonate trade network as an example. China's top trade partners included Korea, Japan, and Australia in 2018. Korea and Japan are major global lithium buyers, and Australia is a major lithium exporter. China has the high values of eigenvector centrality induced by the importance of its trade partners. The implication is that care should be taken in considering trade partner abilities when forming trade partners. This careful relationship development not only helps a country strengthen its global supply chain but also promotes its LIB industrial competitiveness.

We also explored trade network cluster features. A major finding is that cluster stability is low in each trade network. This result means trade relationships between countries are very dynamic. This situation matches the situation in cathode materials of LIB markets which are very dynamic and are currently "deconcentrating" with more companies entering the market and capturing a share of the global supply (Pillot, 2015, 2016).

However, with low cluster stability overall, several stable trade network clusters do exist. Geographically three country groups tend to persist within each of these more stable clusters. One group is composed of EU countries; a second has core Asian countries including China, Japan, and Korea; while a third group is composed of Canada and the US. The major reason is probably related to the transport costs and regionalized trade agreements; these situations appear in other international trade studies (e.g. Tian et al., 2018).

Another cluster feature is that resource-related countries, countries with high connection abilities (betweenness centrality) and high influence (eigenvector centrality) tend to remain in the same cluster. For instance, in the lithium carbonate trade network, the leading country China remains in the same cluster with lithium source countries such as Chile. This situation is likely due to the role of these countries. For example, they are the leading countries in this trade network—China is the top import country with large trade partners and Chile is the top export country. These countries could be considered anchor countries in the cluster. They have greater network trade connections and their trade volumes are high. The exact reason for cluster formation is not always clear due to network and practical complexities—yet these clusters may provide implications for sustainable trade relations and low carbon industrial development. The benefit from the cluster results—the core leading role countries group—is determining the relative security of demand and supply resources can be assured for sustainable LIB industrial development. Another benefit from the clustering—from geographical advantage—is that the cost and transportation-related emissions can be monitored and potentially decreased to help achieve green trade targets.

Besides the above observations concerning network leading countries they can also influence other actions. These countries can help diffuse low carbon technology for production, setting fair prices of their critical resources to sustain markets. These types of efforts can help develop LIB low carbon industrial development—economic, social and environmental outcomes—across partner countries. However, risks and challenges remain. For instance, lack of fair-trade rules can cause these leading countries to form monopoly which can lead to resource trade wars or exploitation. Under such circumstances, international organizations, such as the World Trade Organization (WTO), the Resource Panel of United Nations Environmental Program (UNEP), the World Resource Institute (WRI), could and should carefully monitor the related trade activities so that the potential exploitative trade behaviors of leading countries can be avoided—especially related to exploitation of lower income and less developed nations.

4.2 Improving country trade competitiveness

Country competitiveness along these trade networks were explored. One major finding is trade scale is essential for improving country trade competitiveness. Not surprisingly, countries with larger trade scales will dominate international markets. How to achieve resources trade scale for countries to be put less at risk—in some ways risk may increase—is important. For countries with original ore resources for the LIB industry and high resource endowments can easily have high trade competitiveness. Practically, they may—and probably should be limited—due to environmental concerns that may restrict the trade scale from these countries. For instance, the high nickel ore concentrated country of Indonesia maintained a leading export position from 2010 to 2012, and its trade competitiveness was high. However, in terms of environmental concerns and socio-political instability, the government of Indonesia banned the export of ores from 2014 to 2016, and the Philippines became the top exporter in this period and its trade competitiveness is high based on our results (Survey, 2011-2019). Thus, environmental and socio-political instability is likely to have repercussions for resources management and international competitiveness that limits trade quantities and trying to maintain competitiveness. Various international trade practices of developed countries may also limit some of the developing country trade competitiveness due to ownership of supply chain infrastructure and operations.

The implication from these and other situations is that *sustainable* resource mining activities should be encouraged and promoted globally, so that the *equitable* and *just* trade scale of countries can be assured. Careful monitoring, dialogue, and relationship development across these issues involving multiple stakeholders—governmental agencies, manufacturers, exporters and importers, NGOs, and academia need to exist. Multiple perspectives need to be expressed given that these are not simple issues with complex historical, cultural social, economic, and political relationships. Also, many resource export developing countries should build up their own industrial capabilities and extend their supply chains within their territories, eventually leading to less competitiveness and loss of jobs (Wilkinson et al., 2000). For instance, if an ore concentrated country such as Chile extends its refinery industry of original ore and exports refined metal instead of its original ore, it can improve economic benefits while mitigating industrial carbon emissions (Sturla-Zerene et al., 2020).

Improving the LIB chemical compound trade supply chains can help promote trade scale and country trade competitiveness. For instance, Asian countries such as China, Japan and Korea are identified as some of the most competitive countries in the LIB industry. They compete on quality and price of LIBs due to their long-term experiences of manufacturing and well-developed LIB supply chains (Sun et al., 2019). Therefore, the potential ways to improve industrial supply chains may include establishing value added domestic manufacturing and make sure supply chain partners should be cost-effective (Wilkinson et al., 2000).

The LIB original ore material supply is critical for the whole supply chain. For example, disturbances in material supply can lead to short-term supply gaps, which can create significant price volatility and commodity price uncertainty (Craighead et al., 2007). Stakeholders along the LIB supply chain should collaborate to sustain resource trading—where long-term economic and resource sustainability should be a goal. Countries should consider forming relevant trade agreements to facilitate participation of these countries in the global value chain and induce more innovations through close cooperation between upstream, middle stream and downstream players, and reduce trade barriers.

4.3 Improving country resilience

The LIB sector has become a key sector for low carbon development globally; this situation can also lead to potential supply risks (Maxwell, 2015). It is necessary to promote country natural resources and supply chain resilience. Our major results show that a crisis can be prevented only when each country's critical threshold value of trade is higher. These higher values indicate that a country's trade partners should be diverse and should not be concentrated in a single country. Thus, each country involved in this international trade network should establish information systems, including data integration with upstream and downstream supply partners. This system can help evaluate performance of critical resource use, which provides valuable insights to trade policy decision-makers and increase country contingency for sourcing materials and delivering to markets. For example, the EU has a system to evaluate critical resource use since 2010 (EC, 2020). Unfortunately, most developing countries—especially least developed countries—do not have these capabilities and lack access to this data. It is necessary for countries or private supply chain to construct a dynamic monitoring system of critical resources using digital technology using first-hand information of changes of resources and industries worldwide and promoting country crisis resilience for these natural resources.

Another way to promote country resilience capabilities for these resources is through circular economy pathways. Rapid LIB demand—especially from renewable vehicles and electronic products—requires relevant critical resource increases for production (Hao et al., 2019). Almost one quarter of components require critical resources in automotive, energy and utilities, infrastructure, and renewable energy sectors (Schoolderman and Mathlener, 2011). In these industries it is likely that high recycling rates will be even more critical. Such an action not only saves the virgin minerals, but also meets country demands from domestic end-of-life supply chains. In these circumstances, country resilience improves if global trade network suffers from a crisis (Nandi et al., 2021). Government should consider improving incentive implementations such as subsides for recycling industries for overall resources resilience and security of countries.

Circular economy (CE) principles can be an effective strategy to support fewer material and energy resource flows and closing materials cycles. These activities are likely to lead to improved product and material utilization and resource efficiency. CE-related technologies, such as internet-connected equipment, big data for reuse and recycling, internet of things, and blockchains can provide improved information for resources efficiencies (Esmaeilian, et al. 2020; Gaustad et al., 2018). Investment and technological capabilities can also enable countries to deal with technological change through learning by doing, behaviors changes, expanded scales, upgrading of technological competence and business activities. These capabilities eventually form a foundation for further technology improvement (Geng et al., 2019).

4.4 Limitations

Several limitations exist in this current study. First, the relevant LIB resources are based on the UN Commodity Trade Database. This database limits exploration of lithium ore and cobalt ore resources. This database does not contain original data of lithium ore in this database in order to keep the consistence of data source we exclude this ore. The database lacks the trade volumes from one key source reporter of cobalt ore—The Democratic Republic of the Congo—therefore we exclude this ore. Lithium resource and cobalt resource are explored via Material Flow Analysis in our previous studies (Hao et al., 2017; Sun et al., 2018; Sun et al., 2019). As soon as suitable data is available future research on these two resources networks will be completed.

Data availability also limits analysis for key aggregated data for the trade networks. In future research more detailed, granular, data from other sources can be integrated to achieve more refined and accurate accounting. This study only considers direct competition relationships between different countries. It would be helpful to investigate the indirect competition relationships between different countries.

The global trade network is more complex in reality when compared to this study. Many driving forces and interactions exist. Incorporating such driving forces into our simulation model, for example market growth rates may provide varying dynamic results. We may consider incorporating game theoretic simulations and other tools to improve our simulation model and provide future resource forecasts.

5 Conclusions

Critical resources are essential for global low carbon development—especially for products that provide better environmental performance. This study tries to identify the features of critical resource trade networks—including lithium carbonate, cobalt oxide, nickel sulfate, manganese sulfate, nickel ore and manganese ore. It identifies the roles of different countries within these networks during 2010 to 2018.

Our major findings show that the stability of country relationships decreased from 2010 to 2018 in the resources trade networks. Countries that have high trade volumes are more competitive in the network. Countries that had more trade partners and high trade volumes in the export trade networks have the greatest impacts on the whole network if a crisis occurs.

The nickel ore trade network shows China, Korea, Australia and Indonesia are dominant countries. China, India, Ukraine, South Africa and Brazil are dominant manganese ore countries. The lithium carbonate trade network has China, Germany, Chile, and Belgium as dominant countries. The cobalt oxide trade network includes China, Korea, the US, UK and Belgium as dominant countries. The nickel sulfate trade network has

Japan, Germany, and Belgium as dominant countries. Finally, for the manganese sulfate trade network, Malaysia, China and Germany are the dominant countries. As can be seen, overall, China plays an extensive role in almost all these critical resources.

Several policy recommendations are presented using the research results. Effective and more appropriate policies can be prepared to promote sustainable resource trade and use. Future research is required for more nuanced policy and practice insights.

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