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Understanding international trade network complexity of platinum: The case of Japan

Shohei Tokito [a,*], Shigemi Kagawa [a], Keisuke Nansai [b]

[a] Faculty of Economics, Kyushu University, Fukuoka, Japan
[b] Center for Material Cycles and Waste Management Research, National Institute for Environmental Studies, Tsukuba, Japan

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ABSTRACT

In recent decades, platinum-group metals have become increasingly important to the development and diffusion of cleaner technologies being developed to achieve a “low carbon” society. Countries engaged in the development and diffusion of new energy technologies are concerned about steadily importing scarce rare metals. Nevertheless, the question of what kind of competitive relationships exist among demand countries is not well addressed. This study focused on platinum primary product used to produce greener products like next-generation vehicles and analyzed the international trade network complexity of the platinum primary product using the clustering method. From the results, we found that (1) there exit well-separated nine trade clusters (i.e., trade networks with higher exchanges) in the international trade network of 2005, (2) the group including South Africa and the group consisting of Western countries together account for approximately half the total international trade flow in platinum primary products, and (3) international coordination of purchases and sales of platinum among relevant trade partners in the identified largest cluster: South Africa, Russia, Japan, China, Hong Kong, and Switzerland is crucial in securing the stable supply and demand for platinum.

1. Introduction

In recent decades, the world demand for platinum-group metals has increased to double (Wilburn and Bleiwas, 2005), as they have become increasingly important to the development and diffusion of cleaner technologies being developed to achieve a “low carbon” society and mitigate the effects of global warming (Nansai et al., 2014). The rapid shift from conventional gasoline-powered cars to next-generation vehicles, such as highly fuel efficient, low CO_2-emission hybrid cars and electric vehicles is one example of the changes driving this increase in this demand. In addition, a growing market for precision electronic components in smartphones, tablets, and personal computers is also contributing to this demand for rare metals (e.g., platinum, cobalt, palladium) (Nassar, 2015, Shigetomi et al., 2015).

For Japan, a country actively engaged in the development and diffusion of new energy technologies, procuring a stable supply of rare metals is an important and high-priority challenge (Agency for Natural Resources and Energy., 2014). However, at present, almost all of the rare metals used for manufacturing in Japan are imported (O’Connell et al., 2014). Rare metals are scarce and very unevenly distributed around the world. Consequently, their supply is subject to considerable uncertainty, mainly due to factors such as changing political conditions and resource nationalism in supply countries, trade restrictions, and price rises (Agency for Natural Resources and Energy., 2014). For this reason, countries with a high demand for these resources (demand countries) are concerned about securing reliable supplies. Demand countries therefore need to implement suitable resource procurement strategies to ensure the stable supply of rare metals.

In establishing such a resource procurement strategy, it is crucially important to understand the market—that is, which supply countries are currently trading with which demand countries, and what kind of competitive relationships exist among demand countries (Koyama, 2011). Untangling and understanding the complexity of this international trade network is very important for any resource procurement policy.

An important study on the international trade of rare metals is Nansai et al. (2014), that used the Base pour l’Analyse du Commerce International trade statistics (BACI) database and content of rare metals in a trade commodity to explore the international flows of rare metals—in particular, neodymium, cobalt, and platinum—in international trade between 231 countries. Nansai et al. (2014) not only identified the material footprints on rare metals for Japanese economy with a global link input-output model

* Correspondence to: Faculty of Economics, Kyushu University, 6-19-1 Hakozaki, Higashi-ku, Fukuoka, 812-8581, Japan.
E-mail address: stkyuuni103@gmail.com (S. Tokito).

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(GLIO) (Nansai et al., 2009) incorporating the explored international trade of the metal, but it also quantified the trade risks associated with international supply chains connected with final demand in Japan. There are many studies examining global flows in other metals. Cullen et al. (2012) examined trade flows of steel. Nakajima et al. (2011) also analyzed the material footprints relating to iron and aluminum, and other studies analyzed the international flows of tungsten, chromium, and rare earth metals (Johnson et al., 2006, Du and Graedel, 2011, Leal-Ayala et al., 2015). These studies identified international flows of metals from the production of ores to final consumption, and analyzed the environmental impact on the global supply-chains. Graedel et al. (2015) analyzed the risks of various factors affecting rare metals trade by proposing useful indexes, such as the Policy Potential Index, which is a measure of political stability, and the Human Development Index, which is a measure of standards of health, education, and quality of life of a country, to assess the political and economic risks associated with resource supply countries. By focusing on resource trade flows of particular countries to analyze export and import volumes, these earlier studies have identified the major bilateral resource flows within the international trade network. However, since these studies have not been able to identify which countries account for the biggest flows in the international trade network, it is difficult to determine which countries need to focus on increasing effective resource utilization or on reducing procurement risk.

In the present study, we identified "trade networks with higher exchanges" (trade clusters) formed by a particular resource supply country with a particular resource demand country, to determine which bilateral trade flows (trade between two countries) account for the largest and most dominant resource flows internationally. We also analyzed the primary products of the rare metal platinum, which is widely used in the manufacture of precision electronic components and electric vehicle catalysts. We also analyzed the risk characteristics of each cluster in order to identify the important stakeholders in terms of securing a stable supply of resources from each country, and we discussed the need for international coordination in the coming years.

The remainder of this paper is organized as follows: Section 2 explains the methodology, Section 3 describes the data, Section 4 presents and discusses the results, and finally Section 5 offers a conclusion.

2. Methodology

We used a graph partitioning method widely used in image segmentations (e.g., Shi and Malik, 2000), social networks (e.g., Newman and Girvan, 2004), and supply-chain networks (e.g., Kagawa et al., 2013a, 2013b, 2015). In previous studies (Kagawa et al., 2013a, 2013b, 2015; Okamoto, 2015; Chen et al., 2016), supply-chain networks were analyzed using a clustering analysis and CO_2 emissions-intensive supply-chain groups were identified. In the present study, we also employ cluster analysis to analyze the clusters extracted from international platinum trade networks and assess the interdependency relationships in the international trade of platinum.

Following Kagawa et al. (2013b), we use a cluster analysis method based on Nonnegative Matrix Factorization (NMF). We want to partition the network of international trade in platinum $\mathbf{G} = \left(g_{ij}\right)$ into K groups (hereafter K clusters). Here, g_{ij} represents the total rare metal trade volume between country i and country j (exports from country i to country j+imports from country j into country i), and matrix $\mathbf{G}$ is the adjacency matrix, so the values of the matrix elements g_{ij} and g_{ji} are equivalent. It should be noted that the trade volume is defined as total amount of the traded specific rare metal in physical base (tonnes). The diagonal components of $\mathbf{G}$ are zero and we excluded the domestically-used platinum from the network data. Here, we define an index to express the degree to which the K groups are cut from the network as $Cut = \sum_{k=1}^{K}\left(\sum_{i\in V_k, j\in V} g_{ij} - \sum_{i\in V_k, j\in V_k} g_{ij}\right)$, where the value of the index is called the cut value (Wu and Leahy, 1993). Here, $V = \{1,\ 2,\ \ldots,\ N\}$ represents a set of vertexes (corresponding to countries in this study), and V_k is the set of vertexes belonging to the kth cluster. It should be noted that we have the following mathematical relationship: $V = \bigcup_{k=1}^{K} V_k$. By finding the combination of vertexes for which the cut value is minimized, we can determine the rare metals trade clusters that have close international flows.

However, if we divide the network in order to minimize the cut value, there is a tendency to arrive at a cluster with a single vertex (country) (Shi and Malik, 2000). Here, we defined d_i as degree of node i which represents the total connections of node i estimated by $\sum_j g_{ij}$. To resolve this limitation, we can simultaneously try to maximize the aggregate value of the degrees of vertexes belonging to a particular cluster, $\sum_{i\in V_k} d_i$. In other words, we can define a normalized cut value (Eq. (1)) that applies an additional condition to maximize the total connections of each cluster, and apply grouping in order to minimize this value.

$$Ncut = \sum_{k=1}^{K} \frac{\sum_{i\in V_k,\, j\in V} g_{ij} - \sum_{i\in V_k,\, j\in V_k} g_{ij}}{\sum_{i\in V_k} d_i} = \sum_{k=1}^{K} \frac{\mathbf{h}_k^T(\mathbf{D}-\mathbf{G})\mathbf{h}_k}{\mathbf{h}_k^T\mathbf{D}\mathbf{h}_k} \tag{1}$$

Here, $\mathbf{h}$ is the indicator vector associated with cluster k, defined as shown below. The superscript symbol T indicates transposition.

$$\mathbf{h}_k = \left(h_{i,k}\right) = \begin{cases} 1 & (i \in V_k) \\ 0 & (i \notin V_k) \end{cases}$$

$\mathbf{D}$ in Eq. (1) stands for the degree matrix having degree d_i as diagonal components.

However, the problem with minimizing Eq. (1) is that each vertex needs to be assigned to one of the k clusters. Within the context of computation time, this minimization problem is referred to as an NP-complete problem (Shi and Malik, 2000). By expanding the values obtained for this discrete indicator vector $\mathbf{h}$ over real-n space, the discrete optimization problem of Eq. (1) can be reduced to the Nonnegative Matrix Factorization (NMF) problem of Eq. (2); see Ding et al. (2005) for details.

$$\min_{\mathbf{H}\geq 0}\left\|\mathbf{D}^{-\frac{1}{2}}\mathbf{G}\mathbf{D}^{-\frac{1}{2}} - \mathbf{H}\mathbf{H}^T\right\|_F^2 \tag{2}$$

Here, $\mathbf{H}$ is a non-negative matrix. If the number of vertexes that constitute the network is N and the number of clusters is K, this becomes the rectangular matrix $(N \times K)$.

$$\mathbf{H} = \left[\mathbf{h}_1\ \ \mathbf{h}_2\ \ \cdots\ \ \mathbf{h}_K\right]$$

If we use the algorithm proposed by Lee and Seung (1999, 2001), we can determine the matrix $\mathbf{H}$ that minimizes the norm of Eq. (2). The result is that the ith row vector of matrix $\mathbf{H}$ (h_i) becomes a feature vector of vertex i, and by identifying the vertex points of similar feature vectors as belonging to the same cluster, we can identify the K clusters; the identification method used in this study is the K-means technique (Bolla, 2011). In this technique, mean values are randomly assigned to a certain number of sets. The data sets are then partitioned into K clusters, and then, using the mean values of the partitioned sets, the partitioning process is repeated until the mean values converge.

In cluster partitioning that combines NMF and the K-means