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Analysis

# Environmentally-Targeted Sectors and Linkages in the Global Supply-Chain Complexity of Transport Equipment☆

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ABSTRACT

This study combined the input-output clustering analysis and structural path betweenness analysis, and identified critical sectors belonging to important emission clusters in the global supply chain networks associated with final demand of transport equipment in five countries (United States, China, Germany, Japan, and France). Clustering analysis can divide the groups constructing the strong connecting supply chain with large emissions from the global supply chain network, and structural path betweenness represents how much $CO_2$ emissions from the supply chain paths a sector has in global supply chain network. I applied the combined method to the EORA database which covers 189 countries and focused on the whole global supply chain networks in detail. The results demonstrate that the global supply chain networks of transport equipment were well separated into emission clusters with higher emissions that consist of sectors with higher structural path betweenness. Chinese emission clusters were identified from the global supply chain networks for the five countries in question and the betweenness of Chinese sectors tend to be higher values in the supply chain networks. In this study, I suggested supply chain management of high priority sectors for a reduction in $CO_2$ emissions of transport equipment in the producing countries.

## 1. Introduction

Although developed countries such as those included in the Kyoto Protocol Annex I have been striving to reduce territorial $CO_2$ emissions, the emissions arising from international trade have been rapidly increasing in countries with lax environmental regulations with the expansion of trade and the international fragmentation of production (Peters et al., 2011). Peters et al. (2011) demonstrated that $CO_2$ emissions associated with international trade have increased from 4.3 Gt in 1990 to 7.8 Gt in 2008. With this background, the Paris Agreement at the 21st Conference of the Parties of the UNFCCC extended emission regulations to developing countries that are *not* included in Annex I (UNFCCC, 2015). In reducing the global $CO_2$ emissions, developed countries need to consider consumption-based emissions (i.e., emissions arising from domestic final demand) and emission transfers (i.e., emissions produced overseas arising from domestic demand) (e.g., Wiedmann, 2009) and effective cooperation between developed and developing countries is crucial in reducing $CO_2$ emissions through supply chain engagement (e.g., Kagawa et al., 2015).

In particular, in recent decades, a large part of the value chains associated with the automotive industry in developed countries such as Germany, has been shifted overseas and thus automotive supply-chains have contributed to the world economy (Pavlinek and Zenka, 2011; Timmer et al., 2015; Los et al., 2015). Thus, it can be said that the automotive industry supply chain network is complex and global. The manufacture of transport equipment uses more indirect energy to produce chemical products, metal products, and electricity across its supply chain than directly onsite (Kagawa et al., 2013a, 2013b). The shift from conventional gasoline-powered cars to the next generation of more fuel-efficient vehicles, such as hybrid, electric and hydrogen vehicles, will reduce $CO_2$ emissions from the driving phase. On the other hand, this shift will increase $CO_2$ emissions in the production phase (TOYOTA, 2015). Therefore, detecting key ‘upstream’ sectors and decreasing their manufacturing emissions is crucial for reducing global $CO_2$ emissions. To the best of our knowledge, there are few studies analyzing the life-cycle of $CO_2$ emissions that focus on global automotive supply chains. This paper focused on the supply chain associated with final demand for production in the “Transport Equipment” sector.

Many studies on the calculation of consumption-based emissions and emission transfers have been done by using Multi-Regional Input-Output (MRIO) Analysis (e.g., Peters et al., 2011; Du et al., 2011). To

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apply the results of these studies to policy making, policy makers need to focus on high-priority key stakeholders within the global supply chain (Karstensen et al., 2013). Identifying the key sectors in supply chain networks is important to advance negotiations for climate mitigation, as it can help inform policy makers about issues such as the transfer of greener technologies.

Identifying key sectors is nontrivial because of the complexity of the global supply chain network. Methodologies for identifying key sectors and the paths of supply chains, such as Structural Path Analysis and Structural Path Decomposition Analysis, have been proposed (Lenzen, 2003; Peters and Hertwich, 2005; Wood and Lenzen, 2009; Oshita, 2012; Nagashima et al., 2017). However, analyzing global supply chains using these methods is not easy due to the large computation time (e.g., Kagawa et al., 2015).

Studies applying network centrality analysis and clustering analysis to such complex industrial networks have been performed to mechanically elucidate the main characteristics of networks (Amador and Cabral, 2016) and visualize network structures. Various indicators have been proposed (McNerney, 2009; Zhao, 2015; Amador and Cabral, 2016; Liang et al., 2016; Xing, 2017) to enable the application of methodology originally intended for the analysis of somewhat sparse social networks to supply chain networks that are nearly complete graphs. In this way McNerney (2009), Zhao (2015), Amador and Cabral (2016) and Xing (2017) have used giant MRIO tables to elucidate global value chain structures.

Kagawa et al. (2013a, 2013b, 2015) and Okamoto (2015) identified $CO_2$ emission-intensive supply-chain groups using cluster analysis to understand the structure of production networks and enable the detection of the key sectors of the global supply chain network. Their methodology can quickly and consistently identify key sectors and clusters. Kagawa et al. (2015) analyzed the World Input-Output Database (WIOD) and identified 4756 significant $CO_2$ clusters from the global supply-chain network associated with the final demand countries. However, they focused on only the 40 countries and regions covered in the WIOD, and many other countries in Asia and Africa that are still developing were not considered in their supply chain analysis. In addition, Kagawa et al. (2015) did not consider sectors that belong to multiple clusters. Thus, understanding the global supply chain network in more detail is necessary to suggest climate policy for all $CO_2$ emitting countries.

The clustering method enables us to detect sectors that are large emitters and strongly connected in the supply chain networks *but* are not suitable targets for reducing $CO_2$ emissions because there is little inter-industry linkage, and thus less opportunity for emission reductions from adopting greener technology in such sectors, due to their fewer connections to other sectors.

Liang et al. (2016) proposed the concept of structural path ‘betweenness’ to identify sectors transmitting large amounts of $CO_2$ emissions throughout their supply chains. Applying a policy to sectors with higher betweenness is much more effective across the whole network, because global $CO_2$ emissions are efficiently reduced through the inter-industry linkages centered around the key sectors with higher betweenness. A combination of the clustering analysis and the structural betweenness analysis can identify the environmentally important clusters including the key sectors with higher betweenness.

This paper aimed to identify key sectors and clusters for effective reduction in $CO_2$ emission from the supply chain of transport equipment by applying a spectral clustering method and structural path betweenness analysis to the comprehensive EORA database (Lenzen et al., 2012, 2013). Using the EORA database, which covers 189 countries and regions, enables us to analyze whole supply chain networks in more detail and detect key sectors and clusters more precisely. From the results of this study, I discussed the need for international coordination in the relevant supply chains.

The remainder of this paper is organized as follows: Section 2 explains the methodology used here, Sections 3 and 4 present and discuss the results, and Section 5 presents the conclusions.

## 2. Methodology

### 2.1. Clustering Method

In this section, I define adjacency matrices of the $CO_2$ emissions associated with global commodity flows. An intermediate input from industry $i$ in country $r$ to industry $j$ in country $s$ is defined as $Z_{ij}^{rs}(i,j = 1,\ldots,M; r,s = 1,\ldots,N)$. The final demand from industry $i$ in country $r$ to final consumers in country $s$ is defined as $F_i^{rs}(i = 1,\ldots,M; r,s = 1,\ldots N)$. As a result, the total output of industry $i$ in country $r$ is defined as $x_i^r = \Sigma_{s=1}^N \Sigma_{j=1}^M Z_{ij}^{rs} + \Sigma_{s=1}^N F_i^{rs}$. If intermediate input coefficients $a_{ij}^{rs} = Z_{ij}^{rs}/x_j^s$ are defined, the widely used MRIO model can be formulated as $\mathbf{x} = \mathbf{Ax} + \mathbf{f}$ in matrix notation (e.g., Kagawa et al., 2015), where $\mathbf{x} = (x_j^s)$, $\mathbf{A} = (a_{ij}^{rs})$ and $\mathbf{f} = (\Sigma_{s=1}^N F_i^{rs})$. The MRIO model, $\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} = \mathbf{Bf}$, can show the extension of the final demand that directly and indirectly generates the industrial output. Here, $\mathbf{I}$ is the identity matrix, and $\mathbf{B} = (\mathbf{I} - \mathbf{A})^{-1} = (b_{ij}^{rs})$ is the direct and indirect requirement matrix that represents how many units of a product of industry $i$ in country $r$ are needed to produce one unit of a product of industry $j$ in country $s$. If the industrial $CO_2$ emission per unit of output of industry $i$ in country $r$ is defined as the vector $\mathbf{e} = (er_i)$, then the global $CO_2$ emission transaction matrix can be represented with the following equation:

$$\mathbf{x} = \hat{\mathbf{e}}\mathbf{B} \;\; \text{diag} \;(\mathbf{f}) \tag{1}$$

where $\hat{\mathbf{e}}$ is a diagonal matrix whose diagonal elements are the $CO_2$ emissions per unit of output of industry $i$ in country $r$.

Ozaki (1990) introduced the unit structure model that represents the economic transactions associated with the final demand for products for a specific industry $j$ in a specific country $s$. Using this model, I can obtain the induced demand for the products of industry $j$ in country $s$, described as $\mathbf{x}_j^s = \mathbf{b}_j^s \mathbf{f}_j^s$, where $\mathbf{b}_j^s$ represents the direct and indirect requirement for one unit of production of industry $j$ in country $s$, which is the $\{(s-1) \times M + j\}$th column vector in $\mathbf{B}$. $f_j^s$ is the final consumption of products of industry $j$ in country $s$. Consequently, the study presented a new version of the economic network model, $\mathbf{X}_j^c = \mathbf{A} \;\; \text{diag}\,(\mathbf{b}_j^s f_j^s)$, which shows the economic transactions that are triggered by the final demand for industry $j$ in country $s$.

Using the emission intensity vector, the global $CO_2$ emissions $\mathbf{X}_j^s = (x_{ij}^{rs})$ induced by the geographical inter-industry deliveries from industry $i$ in country $r$ to industry $j$ in country $s$ and associated with the final demand for a specific industry $j$ in a specific country $s$ can be formulated as follows (Kagawa et al., 2015):

$$\mathbf{X}_j^s = \hat{\mathbf{e}}\mathbf{A} \;\; \text{diag}(b_j^s f_j^s). \tag{2}$$

This study considered the directed graph of the $CO_2$ emissions associated with the geographical flow between industry $i$ in country $r$ and industry $j$ in country $s$. Each sector is defined as a vertex, and the emission transfers between sectors are indicated by arcs weighted by the total emissions.

This paper focused on the “Transport Equipment” sector. Over 60% of the global production of transport equipment was attributed to five countries in the EORA database: the United States, China, Germany, Japan and France. Thus, this study considered their country codes in the EORA database—$s = 40, 62, 67, 87, 181$, corresponding to “China”, “France”, “Germany”, “Japan” and the “United States”— and the industry code $j = 10$, “Transport Equipment”.

Following Kagawa et al. (2013b) and Tokito et al. (2016), I used a cluster analysis method based on nonnegative matrix factorization (NMF). I partitioned the $CO_2$ emission flow network of international trade $\mathbf{G} = (g_{ij}^{rs})$ into $K$ groups (hereafter $K$ clusters). Here, $g_{ij}^{rs}$ represents the $CO_2$ emission flow associated with trade volume between sector $i$ in country $r$ and sector $j$ in country $s$ (exports from sector $i$ in