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Research article

Critical sectors and paths for climate change mitigation within supply chain networks

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ABSTRACT

Certain sectors and paths along supply chains play a critical role in climate change mitigation. We develope a consumption-based framework, which combines input–output analysis, a power-of-pull approach and structural path analysis, and applied it to supply chain networks derived from 2010 and 2012 Jing-Jin-Ji interregional input–output tables. The aim of this study is to identify (1) the key economic sectors for controlling carbon emissions and their changes, (2) the critical directions from a carbon-pulling sector to the emissions of key economic sectors, and (3) the paths with the largest carbon emissions flux in these critical directions. Our results show that the key sectors are from Hebei and Tianjin, more concentrated in Hebei. Most sectors have the largest pulling power over their own carbon emissions, and within-region connections dominated in the emission network, with a stronger tie between Beijing and the other two regions. Critical paths along carbon-pulling directions are located in tiers 0 and 1. Our framework can provide new insight into the creation of carbon emissions control policies.

1. Introduction

With the implementation of the 13th 5-year plan, promoting energy efficiency and reducing carbon intensity have become binding priorities of the Chinese government. The task of national reduction in carbon emissions is generally allocated to provinces or industries. Currently, these allocations are based on direct geographic or sectoral carbon emissions, using production-based accounting methods (Liang et al., 2017). These methods neglect indirect emissions embodied in the supply chain with informative linkages (Liang et al., 2016), and may create unequal policy pressure on industries in provinces at different stages of development (Du et al., 2017). Considering that the major drivers of carbon emissions include local, domestic, and foreign consumptions, the allocation of the burden of mitigation requires further exploration (Davis and Caldeira, 2010).

Consumption-based accounting methods consider emissions embodied in international or interregional trade (Guo et al., 2012; Mi et al., 2016; Zhang et al., 2015). Since input–output models (IOMs) can capture emissions embodied in trade, an increasing number of studies have focused on consumption-based carbon emissions (Feng et al., 2015; Jakob and Marschinski, 2012). In particular, many studies have focused on China's embodied carbon emissions in trade (Feng et al., 2013; Meng et al., 2013; Mi et al., 2016; Xu et al., 2011; Xu et al., 2017). Using IOMs, it is possible to quantify the transfer of emissions from one region to another. Further, each sector produces goods and services for final consumption and intermediate use in other sectors (Chen et al., 2017b); i.e., sectors are the agents of cross-reginal emission transfer. Therefore, some sectors may play significant roles in contributing, controlling, or brokering emissions for the entire system (Chen and Chen, 2016; Wang et al., 2017a; Wen et al., 2014). Critical sectors were initially identified for their economic importance. For example, Chenery and Watanabe (1958), Rasmussen (1956), and Dietzenbacher (1992) have proposed a series of IOM-based methods for identification of critical economic sectors. More recently, critical sector identification has been applied increasingly to resource or environmental extended input–output tables, in pace with the rapid development of social/ecological network analysis. Alcántara and Padilla (2003) designed a method based on input–output tables and the elasticity of final energy consumption demands to identify which sectors should be controlled in Spain. Chen et al. (2017a) used linkage analysis to pinpoint the critical sectors for urban decarbonization. Chen and his colleges proposed a network control method to assess the level of influence of a sector within a system and applied this method to different subjects, including energy consumption, carbon emissions, and the energy–water nexus (Chen and

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Chen, 2015, 2016; Lu et al., 2015; Wang and Chen, 2016). Wang et al. (2017b) applied several social network analytical methods to interregional carbon flows embodied in domestic trade and identified the roles of critical sectors. Power-of-pull (PoP) approach is a convenient method used for the identification of critical sectors in a systemic view (Wang et al., 2017a), which gives a rank of the most powerful sectors as key nodes that pull others. In addition to node identification in the system, the linkage feature, which identifies flow among sectors, has become a popular research tool in the past few decades. Structural path analysis (SPA) is a method based on IOM that has typically been applied to quantify environmental transmissions and identify important paths along supply chains. Over the past decades, several studies have used SPA (Defourny and Thorbecke, 1984; Khan and Thorbecke, 1989; Lenzen, 2003, 2002; Sonis and Hewings, 1998) to analyze flows of energy (Hong et al., 2016; Zhang et al., 2017), carbon (Acquaye et al., 2011; Liang et al., 2016b; Yang et al., 2015), water (Llop and Ponce-Alifonso, 2015), and other resources (Seung, 2016) or pollutants (Meng et al., 2015; Nagashima et al., 2016) through input–output relationships. The identification of critical sectors and paths has successfully assisted the creation and implementation of policies. Nodes and linkages are two closely connected aspects of this method. For example, a highly ranked sector may play a significant role in the emission transferring process. Critical sectors and paths together affect the environmental performance of the economic system (Hanaka et al., 2017; Liang et al., 2016). However, previous studies have tended to focus on only one of these aspects or on both aspects separately; the influence of a path on the entire system has rarely been addressed. In general, a path with a high amount of embodied emissions is not a critical path *per se* controlling the performance of the entire system. Additionally, the question of which paths would affect the system performance of critical sectors has not been sufficiently discussed in previous studies.

In this study, we propose a framework based on IOM, the PoP approach, and SPA to identify critical sectors of interregional carbon emissions transfer and to indirectly identify the important carbon transfer paths across the Jing-Jin-Ji (Beijing-Tianjin-Hebei) region in China. Viewed from the demand side, we focused on the key sectors and their critical paths through supply chain among the regions. This study was the first application of our proposed framework at an interregional scale, and we expect this framework to provide new and promising insights into the creation and implementation of policies. This paper is organized as follows: Section 2 provides a detailed introduction to the methods and data, Section 3 elaborates the results of the Jing-Jin-Ji area case study, Section 4 provides a discussion of the results, and finally, we draw brief conclusions in Section 5.

2. Methodology and data

2.1. Methodology

The first step of our framework was to apply PoP to the emission technical coefficient matrix of the Jing-Jin-Ji area to identify the key sectors of the system. IOM was then used to extract the induced carbon transfer networks. PoP was applied to the networks again to determine the relative importance of pulling sector i to the carbon emissions performance of sector j, yielding a pulling direction $i \rightarrow j$. Along this direction, the critical paths from i to j were identified by SPA. This procedure allowed us to identify the important paths for the key sectors. To avoid confusion, we define several concepts in Table 1.

Table 1
Definitions of the terms frequently used in this paper. PoP: power-of-pull approach; SPA: structural path analysis.

Keywords	Meaning
Key sector	A sector identified by PoP for the whole system
Pulling sector	A sector identified by PoP for a targeted sector
Direction	The effect from pulling sector *i* to key sector *j*, as identified by PoP
Path	Structural path derived from SPA

2.1.1. Input–output model

In a three-region interregional input–output table, sectors have the following relationships:

$$x = Ax + y = (I - A)^{-1}y = Ly \tag{1}$$

$$A = \begin{bmatrix} A^{rr} & A^{rs} & A^{rt} \\ A^{sr} & A^{ss} & A^{st} \\ A^{tr} & A^{ts} & A^{tt} \end{bmatrix} \tag{2}$$

where x is the total output vector (of, say, $3n$ sectors for 3 regions each with n sectors), A is the technical coefficient matrix ($3n \times 3n$) for the entire system, and r, s, and t represent the three different regions, each with n sectors. A^{rr} and A^{rs}, for example, describe the purchases for unit production within region r and from regions r to s, respectively. The total final-use (of three regions) vector is y ($3n \times 1$), and I is the identity matrix of A. The matrix $L = (I - A)^{-1}$ is known as the Leontief inverse, reflecting the total requirement of the sectors.

Based on Eq. (1), the induced final-use output can be allocated to each sector as

$$X = (I - A)^{-1}\hat{y} \tag{3}$$

where X is the total output matrix, the ith column of which X denotes the output derived from the final use of the ith sector; the accent "ˆ" on a vector denotes the diagonal form of the vector. For transforming the input-output relationships into a carbon-emission network, we assume that the derived outputs are all distributed for intermediate use, the final-use induced carbon flows form a network as follows:

$$G_i = \hat{c}A\hat{X}_{,i}, \tag{4}$$

where G_i is the final use of the i^{th} sector induced network, and $\hat{c}$ is the diagonal matrix form of the direct carbon coefficient vector c ($3n \times 1$). Based on this network, the embedded carbon linkages between sectors can be extracted with PoP and SPA methods.

2.1.2. Power-of-pull approach

PoP, first proposed by Dietzenbacher (1992), is an eigenvector-based method that is similar to eigenvector centrality in social network analysis (Luo, 2013b). PoP often uses a technical coefficient matrix or weighted relationship matrix as input, whereas a binary-adjacent matrix is used in eigenvector centrality. According to PoP, the power of a sector is determined by the powers of the sectors to which it is connected. In turn, the power indexes of these sectors are determined by their connected sectors. Therefore, PoP is an infinite regress problem and can be written as Eq. (5):

$$\lambda p' = p'M, \tag{5}$$

where M is the weighted relationship matrix, in this study the network of emission transfer through sectors ($3n \times 3n$), p' ($1 \times 3n$) is the transpose of the vector of power indexes for the X matrix, and λ is the dominant eigenvalue, also as a scalar constant. The solution for p' is the left-hand Perron eigenvector for key sector identification in the consumption-based input–output relationships. The normalized power indexes are calculated as follows:

$$z' = mp'/(p'e), \tag{6}$$

where m is the number of sectors, e is the column summation vector where all $e_i = 1$, and is the vector of standardized power indexes with an average of 1, denoting how powerfully the activities of specific sectors can pull the activity of the overall system. Without loss of generality, sectors with an above-average pulling power ($z_i > 1$) are