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The short-term roles of sectors during a carbon tax on Chinese economy based on complex network: An in-process analysis

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ABSTRACT

The Chinese government may promulgate a carbon tax on the emitters outside the national carbon trading market in the future. The emission reduction strategy needs to consider the specific features of the sectors. However, existing literature on the roles of sectors during a carbon tax on the Chinese economy is insufficient. The aim of this study is to analyze the short-term roles of sectors during a carbon tax on China's economic system via complex network theory. The results show that the small-world nature of intersectoral price change flow network and intersectoral output change flow network is significant, and the key individual sectors play important roles. Second, we investigate the roles of sector groups by network motif analysis. The members of the key sector group are heterogeneous, which mainly exist between the sectors with larger price change or output change and the sectors with lower price change or output change. Although the function of sector groups is significant, the frequency is lower. Finally, we compare the results of the in-process analysis with ex-post analysis and found that there was a significant difference between the two. The biggest difference is that the roles of some low-carbon sectors are ignored in the ex-post analysis. Our study is of valuable reference for policymakers in terms of designing a differentiated sectoral emission reduction strategy.

1. Introduction

China has become the world's largest primary energy consumer and CO_2 emitter since 2007 (BP, 2018). Under the pressure to save energy and reduce CO_2 emissions, the 13th Five-Year Plan of China pledged to reduce CO_2 emission intensity by 60%–65% by 2030 through market-oriented tools relative to the emissions in 2005. More specifically, China has launched a national carbon trading market in 2017 and will consider imposing a carbon tax on emitters outside the market after 2020 (Xie and Li, 2016-08-10). As an important tool for reducing carbon emissions, carbon taxes have been effectively implemented in certain countries (Kuo et al., 2016). Thus, a clear understanding of the impacts of a carbon tax on the Chinese economy is necessary. Considering more than 70% of national carbon emissions come from production fields (Ouyang and Lin, 2015), reasonable emission abatement strategies at the sector level are important for realizing the national target.

Some studies have concluded that the emission abatement costs vary significantly across sectors and the abatement costs of energy-intensive sectors are lower than those of the low-carbon ones (Chen, 2011). Thus, energy-intensive sectors are supposed to take more responsibility (Choi et al., 2010). However, some scholars also claimed that the introduction of a carbon tax will have a severe negative impact on the competitiveness of energy-intensive sectors (Liang et al., 2016). Although the carbon emissions at the sector level are uneven significantly, there are co-movement phenomena between the upstream and downstream sectors. That means condition a policy applied to an individual sector would cause the reactions from related sectors (Ma et al., 2019b). Therefore, to achieve the national reduction target, a sectoral cooperation mechanism needs to be constructed, which should comprehensively consider the heterogeneity and co-movement of the sectors. Meantime, due to the unique features of different sectors, the Chinese government

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promulgated a differentiated green price mechanism in sustainable development in 2018 (National Development and Reform Commission, 2018). Therefore, to make reasonable emission abatement strategies on differentiated sectors, it is necessary to obtain a more comprehensive understanding of the roles of sectors within a carbon tax on the Chinese economy.

The existing research on the roles of sectors can be divided into two parts: ex-ante analysis and ex-post analysis. To evaluate the importance of each sector, ex-ante analysis investigates the characteristics of carbon emissions in various sectors before an emission reduction policy. This part includes the measurement in direct and indirect emissions (Ma et al., 2019a; Schandl et al., 2016), the analysis of emission reduction costs (McLellan et al., 2011), the interaction pattern analysis in the intersectoral carbon flow (Liu et al., 2016), and emission driving forces analysis (Li et al., 2017; Xu and Lin, 2015). Ex-post analysis analyzes the performance difference of sectors after a carbon tax, which mainly includes the competitiveness effects (Liu and Wu, 2017; Liu et al., 2015) and environmental effects (Guo and Liu, 2016). Based on the difference of sectors affected by a carbon tax, scholars have further considered how to make tax exemptions for some specific sectors (Liu and Lu, 2015). To maintain the international competitiveness of some energy-extensive sectors, some scholars suggest releasing border tax adjustments (Lin and Li, 2011). In general, most scholars believe that the economic impacts of a carbon tax on sectors are negative and the energy-intensive sectors are correspondingly more severe than other sectors due to higher carbon tax costs (Liang et al., 2016). As to the environmental effects of a carbon tax, Guo and Liu (2016) found that some energy-intensive sectors have contributed more as compared to other sectors. In addition, most studies believe that the negative impact of a carbon tax could be alleviated by proper exemptions or subsidies (Yi and Li, 2018).

However, the existing research neglects the roles of sectors in the process of a carbon tax on the economy, which makes the economic transmission of a carbon tax on various sectors in “black box”. Process management is also important for a carbon tax policy. In addition, the objective of the existing research is usually an individual sector, which neglects the interactions between sectors. Obviously, due to the close production relationships, there are comovement between the upstream and downstream sectors. If a carbon tax only focuses on the features of individual sectors and ignore the interactions between sectors, it will offset the efficiency of a carbon tax.

On the other hand, the analysis of the economic effects of carbon taxes is generally distinguished between the long and the short term (Arlinghaus, 2015). According to the Porter hypothesis, carbon taxes promote the ability of a country/sector to innovate, which would increase the competitiveness of a country/sector. Thus, this paper only investigates the short-term economic effects of a carbon tax on the economy. According to the research of Ho et al. (2008), the short-term is defined as the time when sectors can increase prices to reflect the higher energy costs, with a corresponding decline in sales as a result of product substitution. Thus, the short-term economic impacts of a carbon tax are measured in terms of price and output change.

The CGE model (Hermeling et al., 2013; Zhang et al., 2017), the MARKAL model (Ekins et al., 2011; Levin et al., 2011) and the input-output (namely, I–O) model (Choi et al., 2010, 2016; Tezuka et al., 2002) are the most applied methods in evaluating the roles of sectors within carbon taxes on an economy. The CGE and MARKAL models focus on the long-term impacts of carbon taxes, while the I–O model considers both long-term and short-term analysis. The I–O model can fully reflect the production relationships among various sectors in the national economy. However, all the above methods provide a snap-shot of an economy in a specific period (Choi et al., 2016) and fail to illustrate the process of exogenous variables on the economy. Considering that, many scholars introduce a complex network theory for in-processing analysis. Complex network theory portrays the topological structure of individual interactions in a system by constructing networks that include nodes and edges. Complexity science devotes to reveal and explain the rules of how the complex systems operate. Some studies uncover that cooperative and competitive interactions between network nodes widely exist in various systems and can be captured by the evolution of network structures. Better characterization of the structure, dynamics and function of networks is the key step to our understanding of cellular functions, species adaptation, social and market changes (Csermely et al., 2013; Newman, 2000). Scholars have applied the complex network theory to the emissions features of sectors/countries in the international trade (Jiang et al., 2019) and the critical transmission paths of economic effects (Wang et al., 2018). Although the complex network theory has deeply described the roles of an individual sector, however, the role of sector groups is not fully explored.

To investigate the function of sector groups during a carbon tax on the economy, this paper introduces the network motif analysis. A motif is defined as a recurring and statistically significant subgraph in complex networks (Milo, 2002). Each motif captures a specific pattern of interconnections between nodes (Barabasi and Oltvai, 2004) and reflects a framework in which particular functions are achieved efficiently (Kashani et al., 2009). Network motif analysis is widely applied to investigate interactions between nodes and their function in directed networks (Bergmann et al., 2013). Some scholars have applied network motif analysis to carbon emissions, international trade (Squartini and Garlaschelli, 2012), traffic (Liu et al., 2013), price spillover (Liu et al., 2019), and biological research (Geard et al., 2011). Thus, network motif analysis is helpful to investigate the interactions between sectors and find the roles of sector groups during a carbon tax on the economy.

This paper aims to assess the short-term roles of sectors during a carbon tax on Chinese sectors via complex network analysis. First, we analyze the short-term economic effects of a carbon tax on Chinese sectors by using the I–O analysis. The short-term economic effects of carbon tax include price change and output change. Second, we explore the roles of individual sectors in the process of price and output change transmissions via the complex network theory. Third, the roles of sector groups are identified through network motif analysis. Finally, we compare the results of the in-process analysis with the ones of ex-post analysis. Through the above analyses, this paper provides guidance for decision-makers in terms of designing a differentiated sectoral emission reduction strategy.

The rest of this paper is structured as follows. Section 2 introduces the methodologies and data used in this study. Section 3 describes results and analysis. Section 4 presents the discussion. Section 5 provides conclusions and policy implications.

2. Methodology and data

2.1. The short-term economic impacts of a carbon tax on a system

The Leontief price model is generally used to measure the impact on prices throughout the economy of a change in the value added component (labor costs, depreciation of fixed assets, production tax and business surplus per unit of output) for one or more sectors (Miller and Blair, 2009). The production cost increases are passed along completely as the intermediate input price increase to all purchasers, who in turn pass on these increases by raising their output prices accordingly. In this cost-push I–O price model, the physical quantities are fixed and relative prices change. It has been extensively used to measure the price effects of changes in corporate income taxes, technology, waste management, carbon pricing.

We used the method proposed by Choi et al., 2010, Choi et al. (2016) to investigate the short-term impacts of a carbon tax (for details on the analysis process, see Fig. 1). When a carbon tax is imposed on sectors (e.g., Step 1 in Fig. 1), the production costs rise accordingly, which causes the commodity prices to increase in all sectors in the intermediate commodity market. That process is the cost pass-through the system (e.g., Step 2 in Fig. 1). The Leontief price model was used to capture direct and indirect changes in commodity prices that resulted from the imposition of a carbon tax on the various sectors. As commodity prices increase, consumers adjust their short-term consumption demand, which was estimated through the price elasticity of demand (e.g., Step 3 in Fig. 1). These changes in the quantity of the final demand resulted in changes in the total output of each sector, which were captured by the Leontief demand model (e.g., Step 4 in Fig. 1). Finally, the economic system reached new stability. In the medium and long term, the mix of input, capital allocation, and energy-saving technologies may change, which leads to new changes in the sector value-added. Thus, a new round of economic system changes will be triggered (e.g., Step 5 in Fig. 1).

Both the monetary I–O table (namely, MIOT) and the physical I–O table (namely, PIOT) were involved in this study (for details on table structure, refer to Fig. 2). The variables Z_0,Y_0, V_0 andX_0 represent the monetary value of intermediate commodities, final demand, value added and total output in baseline MIOT, respectively. The variables s_0,f_0 and q_0 represent the physical value of intermediate commodities, final demand and total output in baseline PIOT, respectively. The subscript denotes time: 0 denotes the period of baseline; 1 denotes the period step 2, and 2 denotes the period step 4.

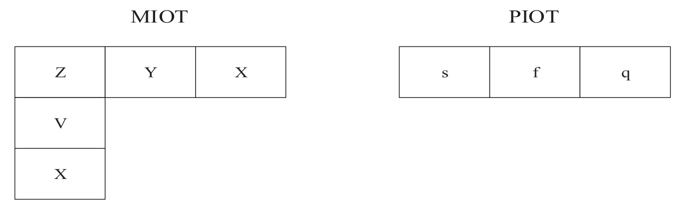


Fig. 2. The structures of MIOT and PIOT.
Note: MIOT, PIOT represent the monetary and physical I–O table, respectively.

2.1.1. Exogenous value added (step 1): carbon emissions and carbon tax

Direct carbon emissions refer to the carbon emissions caused by fossil energy that is directly used by a sector. Sectoral direct carbon emissions are calculated from the amount of energy they consume multiplied by their corresponding CO_2 emission factor (Liu et al., 2016; Meng et al., 2016; Shi et al., 2019). The formula can be written as:

$$DC_j = \sum_{\kappa} (E_{j\kappa} \times EF_k) \tag{1}$$

where DC_j denotes the direct carbon emissions of sector j; E_{jk}denotes the energy κ input of sector j; and EF_kdenotes the CO_2 emission factor of energy κ from the IPCC emission factors. Primary energies include coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil and natural gas. Because electricity is secondary energy and thermal power generation is the primary proportion in China, carbon emissions will be double-calculated from coal consumption. Therefore, only the former eight energies were calculated in this paper.

Then, a carbon tax is levied on the system. For sector j, the

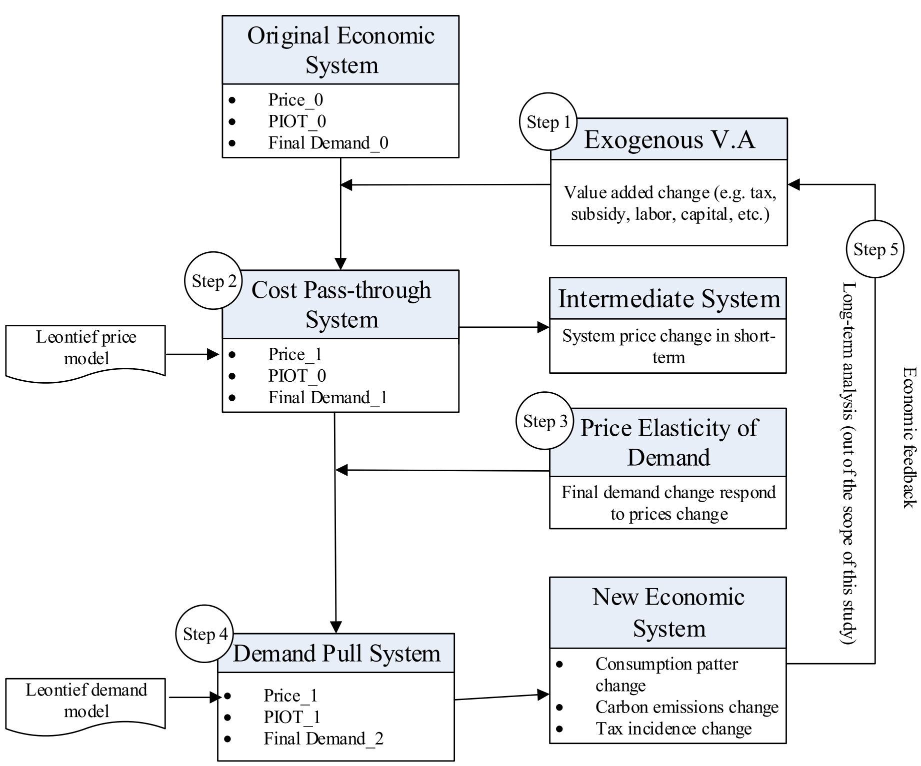


Fig. 1. The transaction process of the economic effects of a carbon tax.
Note: 0 represents the value of the economic variables in the original economic system; 1 represents the value after the economic variables have changed.

carbon tax can be written as:

$$Tax_j = t \times DC_j \tag{2}$$

where Tax_j denotes the amount of carbon tax levied on sector j, and t denotes the carbon tax rate.

Thus, the carbon tax per unit of output of sector j can be written as:

$$\beta_j = t \times DCI_j \tag{3}$$

where $DCI_j = \frac{DC_j}{X_j}$, as X_j is the output of sector j, DCI_j is the direct monetary carbon emission intensity of sector j, $\beta_j$denotes the carbon tax per unit of output.

2.1.2. Cost pass-through system (step 2)

According to the Leontief price model, the total price change can be expressed as:

$$\Delta P = \left(I - A_0^T\right)^{-1}(\Delta A_W + \Delta A_d + \Delta A_t + \Delta A_s) \tag{4}$$

where ΔP is the price change vector of the sectors; ΔA_W, ΔA_d, ΔA_t and ΔA_s denote the change in the compensation of labor, depreciation of fixed assets, production tax and business surplus per unit of output, respectively.

In period step 2, when the cost pass-through system is complete, the new direct requirements matrix can be written as:

$$A_1 = \frac{(\mathrm{I} + \Delta\widehat{P})Z_0}{(\mathrm{I} + \Delta\widehat{P})X_0} = (\mathrm{I} + \Delta\widehat{P})A_0(\mathrm{I} + \Delta\widehat{P})^{-1} \tag{5}$$

where A_1 represents the new direct requirements matrix. It is crucial to note that the change in the values of the direct requirement matrix should not be considered as a structural change in the economy. The change in the value of the direct requirement matrix is purely due to the change in commodity price, while the structural change is the change in the physical input of production.

2.1.3. Price elasticity of demand and demand pull system (step 3 and step 4)

Price elasticity of demand is the ratio of the change in the physical quantity of demand to the corresponding change in commodity prices. Suppose the price elasticity of demand for sector j is $\varepsilon_{d,j}$, according to the definition the formula can be written as:

$$\varepsilon_{d,j} = \frac{dQ_j/Q_j}{dp_j/p_j} = \frac{\frac{f_2 - f_0}{f_0}}{\Delta P_j} = \frac{\frac{P_1 f_2 - P_1 f_0}{P_1 f_0}}{\Delta P_j} = \frac{\frac{Y_2 - Y_1}{Y_1}}{\Delta P_j} \tag{6}$$

where Q_j denotes sector j's physical quantity of demand; dQ_j/Q_jdenotes the ratio of the change in sector j's physical quantity of demand; P_j denotes the price of sector j; dp_j/p_j denotes the ratio of the change in price of sector j. In this study, price elasticity data were obtained from previous studies and historical reference data (Ho et al., 2008; Yan et al., 2017) (see Table B.1 in Appendix B).

Additionally, f_0 is equal to f_1 since the physical values of final demand have not changed in the period step 2. The change in the monetary value of final demand (ΔY) can be estimated using Eq. (14). The formula is as following:

$$\Delta Y = \widehat{\varepsilon}_{d,j}\Delta\widehat{P}Y_1 \tag{7}$$

According to the Leontief I–O model, the change in the physical demand of commodities influences a total economic system (Leontief, 1936). The changes in total output (ΔX) and inter-industry transaction matrix (ΔZ) can be written as:

$$\Delta X = (I - A_1)^{-1}\Delta Y \tag{8}$$

$$\Delta Z = A_1 \Delta\widehat{X} \tag{9}$$

where $\Delta\widehat{X}$ denotes the diagonal matrix of the total output change vector.

2.2. Intersectoral price change and output change flow networks

According to section 2.1.2, each sector corresponds to a node, and the flow of price change from one sector to another is set as an edge. Then, an intersectoral price change flow network (namely, the IPCFN) is built (see Fig. 4a), as shown in Eq. (10):

$$G1 = (N, C) \tag{10}$$

where $G1$ represents a complex network; N denotes the set of nodes in the network; and C represents the set of edges in the network, which is the quantity of the price change.

The matrix of the inter-industry price change flow between sectors can be expressed as:

$$C = \begin{bmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nn} \end{bmatrix}, C_{ij} = \Delta p_i \times a_{ji} \tag{11}$$

where $a_{ij} = \frac{x_{ij}}{X_i}$, as a_{ij} is the direct requirement coefficient.

According to Section 2.1.3, each sector corresponds to a node, and the flow of output change from one sector to another is set as an edge. Then, an intersectoral output change flow network (namely, the IOCFN) is built (see Fig. 4b), as shown in Eq. (12):

$$G2 = (N, D) \tag{12}$$

where $G2$ represents a complex network; N denotes the set of nodes in the network; and D represents the set of edges in the network, which is the quantity of output change.

The matrix of the intersectoral output change flow can be expressed as:

$$D = \begin{bmatrix} d_{11} & \cdots & d_{1n} \\ \vdots & \ddots & \vdots \\ d_{n1} & \cdots & d_{nn} \end{bmatrix}, d_{ij} = |\Delta x_i| \times a_{ij,1} \tag{13}$$

2.2.1. The roles of individual sectors

(1) Influence strength

The influence strength of a sector is the quantity of the economic effects that a sector has on other sectors, which can be defined as follows:

$$d_j^{wout} = \sum_{i=1}^{N} \left(C_{ji}, d_{ji} \right) \tag{14}$$

where d_j^{wout} is the influence strength of sector j. C_{ji} is the quantity of the price change from j to i. d_{ji} is the quantity of the output change from j to i.

(2) Sensitivity strength

The sensitivity strength of a sector is the quantity of the economic effects that a sector is affected by others, which can be defined as follows:

$$d_j^{win} = \sum_{i=1}^{N} \left(C_{ij}, d_{ij} \right) \tag{15}$$

where d_j^{win} is the sensitivity strength of sector j. C_{ij} is the quantity of the price change from i to j. d_{ij} is the quantity of output change from i to j.

(3) Intermediate strength

Betweenness usually measures the media capability of nodes in the network. If a sector has a high betweenness, it can greatly pass through the economic effects it received. Betweenness is calculated as follows:

$$T_i = \sum_i \sum_j g_{ikj} \Big/ g_{ij},\ \ i \neq j \neq k \tag{16}$$

2.2.2. The roles of sector groups

This paper explores 3-motifs, which are common motifs in directed networks. 3-motifs are the natural generalization of directed clustering coefficients and the starting point for understanding complex network communities (Guan et al., 2017; Liu et al.,2018; Squartini and Garlaschelli, 2012). This paper applies an extended definition proposed by Onnela et al. (2005) that motifs are the subgraphs with the independence of their statistical significance.

Network motif analysis explores interaction patterns by classified nodes and edges in a network. In this paper, we average and classify the whole edges of IIPCFN and IIPOFN into three groups: strong $\left(min(E) + \frac{2}{3}\nabla,\ max(E) \right]$, medium $\left(min(E) + \frac{1}{3}\nabla, min(E) + \frac{2}{3}\nabla \right]$ and weak $\left[min(E), min(E) + \frac{1}{3}\nabla \right]$ three groups. $\nabla = max(E) - \min(E)$. As to the nodes, we average and classify the whole nodes of IIPCFN and IIPOFN into three groups: strong $(min(\Delta P, \Delta x_i) + \frac{2}{3}\Delta,\ \max(\Delta P, \Delta x_i)]$, medium $(min(\Delta P, \Delta x_i) + \frac{1}{3}\Delta,\ min\left(\Delta P, \Delta x_i \right) + \frac{2}{3}\Delta \right]$, and weak $[min(\Delta P, \Delta x_i),\ min(\Delta P, \Delta x_i) + \frac{1}{3}\Delta \Big]$ three groups.

Then, the motif statistical significance analysis is as follows:

(1) *Z-score*

Z-score is widely used to measure the statistical significance of motifs. The larger the *Z-score* is, the more important the motif is. When the *Z-score* is less than or equal to 0, the motif structure fails. The formula can be written as:

$$Z_i = \frac{N_{real_i} - N_{rand_i}}{\sigma_{rand_i}} \tag{17}$$

where N_{real_i} denotes the number of occurrences of motif i in the real network. N_{rand_i} denotes the number of occurrence of motif i in the randomized network. N_{rand_i} denotes the average value of N_{rand_i}. σ_{rand_i} denotes the standard deviation of N_{rand_i}.

(2) Motif load capacity index

Different from biological networks, motifs in social networks do not have a clear specific function. Due to some functionally important motifs do not have statistical significance (Milo, 2002), a motif load capacity index is proposed to investigate the function of motifs in both weighted edges and frequency. For motif i, the motif load capacity index is defined as the ratio of the weighted edges in proportion to the frequency. The formula can be written as:

$$f_i = \frac{m_i}{M} \tag{18}$$

$$L_i = \frac{\sum_{j=1}^{m} sum(E_j)}{\sum_{q=1}^{M} sum(E_q)} \tag{19}$$

$$LI_i = \frac{L_i}{f_i} \tag{20}$$

where f_i denotes the frequency of motif i;m_i denotes the number of occurrences of motif i; M denotes the number of occurrences of all subgraphs in a real network. $L_i$denotes the weighted edges proportion of motif i; E_j denotes the weighted edges of subgraphs j in motif i; $sum(E_j)$ denotes the sum of the weighted edges of subgraph j in motif i, also called the load capacity of subgraph j; $\sum_{j=1}^{m} sum(E_j)$ denotes the sum of the weighted edges of m_i subgraphs in motif i, also called the load capacity of motif i; E_q denotes the weighted edges of subgraphs q in the real network; $sum(E_q)$ denotes the sum of the weighted edges of subgraph q in the real network; $\sum_{q=1}^{m} sum(E_q)$ denotes the sum of the weighted edges of M subgraphs in the real network, and LI_i denotes the motif load capacity index of motif i.

If the motif load capacity index LI_i is greater than 1, then motif i can play an increasing role in the network. The larger the LI_i is, the stronger its increasing function is. Such motifs are regarded as increasing function motifs. In contrast, if the motif load capacity index LI_i is less than 1, then the motif i can play a decreasing role in the network. The smaller the LI_i is, the stronger its decreasing function is. This kind of motif is regarded as a decreasing function motif.

2.3. Data

The Chinese I–O table for the year 2015 was retrieved from the China National Bureau of Statistics (http://www.stats.gov.cn/english/Statisticaldata/AnnualData/). Original energy data used in this study were derived from the China Energy Statistical Yearbook of 2017 (National Bureau of Statistics, 2017). Because the sector classifications of the basic I–O tables are not identical to those of the energy balance sheets, we combined them into a 31-sector table for the convenience of data processing while still including all important information (see Table A.1 in Appendix A).

The carbon tax rate was assumed to be 50 yuan/ton CO_2, following the proposal for 2020 from the Ministry of Environmental Protection of China (Xie and Li, 2016-08-10).

Table 1
Percentage price change and sector classification.

Classification	Sector	△P	Classification	Sector	△P
Strong	Electricity Production	2.07%	Weak	Other Manufacturing	0.46%
	Fuel Processing	2.02%		Education-related Products	0.45%
Medium	Metal Smelting	1.14%		Special Machinery	0.45%
	Coal Mining	0.92%		Repair services	0.41%
Weak	Nonmetallic Products	0.75%		Transport Equipment	0.41%
	Chemical Industry	0.69%		Wholesale Trade	0.40%
	Metal Products	0.67%		Instrumentation	0.35%
	Electrical Equipment	0.57%		Textile	0.33%
	Metal Mining	0.56%		Other Electronic Equipment	0.33%
	P&G Extraction	0.55%		Furniture Manufacturing	0.32%
	Recycling	0.53%		Leather Manufacturing	0.25%
	Gas Production	0.51%		Transport	0.23%
	Nonmetal Mining	0.51%		Food	0.19%
	Construction	0.50%		Agriculture	0.18%
	Water Production	0.50%		Services	0.18%
	General Machinery	0.50%			

Note: All sectors are divided into strong, intermediate and weak groups according to the magnitude of price change.

3. Results and analysis

3.1. The measurement of sector price changes and output changes

Table 1 illustrates the sectoral breakdown of the increased price percentage and sector classification. The price increase in all sectors averaged 0.58%. The price increase was mainly affected by two factors: the direct carbon intensity and the total forward linkage (see Table C.1 in Appendix C for total forward linkage). The total forward linkage in the I–O method is used to measure the interconnection between a sector with a supply change and other sectors that use its good in their production (Miller and Blair, 2009). Obviously, the price changes of sectors with higher carbon intensity and total forward linkage were relatively larger. For example, electricity production is dominated by thermal power generation and coal consumption contributed 44% of the country's total in 2016 (National Bureau of Statistics, 2018). As a result, the carbon intensity was high due to the extensive energy consumption. In addition, as a vital secondary energy producer for most sectors, electricity production has extensive impacts on the industrial chain. Thus, electricity production had the largest price increase.

As shown in Fig. 3, the percentage of output change varies significantly between sectors. Services had the largest decline in output because most of the products were directly aimed at residents. As a result, the share of final demand was the largest in all sectors. Once residents adjusted consumption patterns due to the commodity prices increase, the services would be shocked greatly. Other electronic equipment had a larger decrease in output because of its highest price-demand elasticity coefficient (see Table B.1 in Appendix B), which reached −2.596. Therefore, even a smaller increase in prices led to a larger decrease in output. As to the chemical industry, the larger decrease in output is due to its higher carbon emission intensity and price-demand elasticity.

IPCFN and IOCFN are shown in Fig. 4a-b. Both of IPCFN and IOCFN had a high clustering coefficient of 0.955 and a short average path length of 1.045. This indicated that all sectors were almost directly connected, and its network structure was like that of a globally coupled network. Compared with other networks, globally coupled network has the smallest average distance and the largest clustering coefficient (Guo and Lu, 2012). Considering that, the small-world nature of IPCFN and IOCFN was very significant. The small-world phenomenon is defined that the nodes are usually linked by a short chain of neighbor (Watts and Strogatz, 1998). Small-world usually shows smaller average path length and higher average clustering coefficients. In such a system, because the average path length of the network is short, the speed of

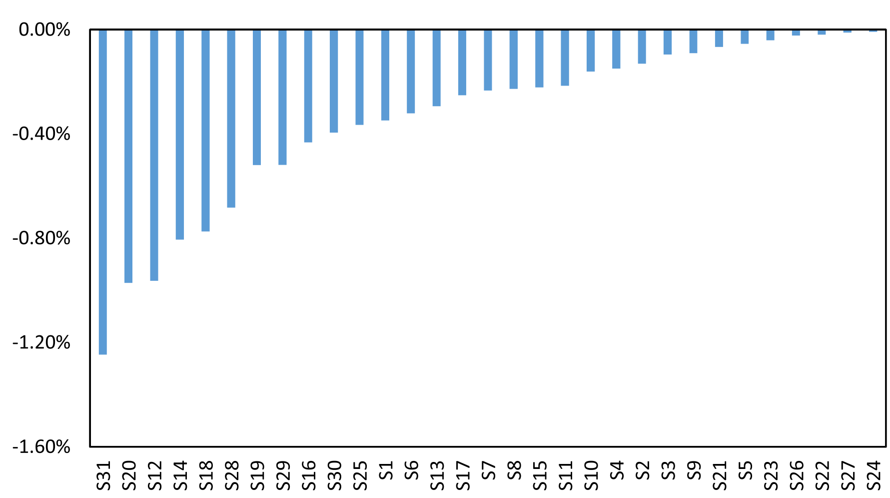
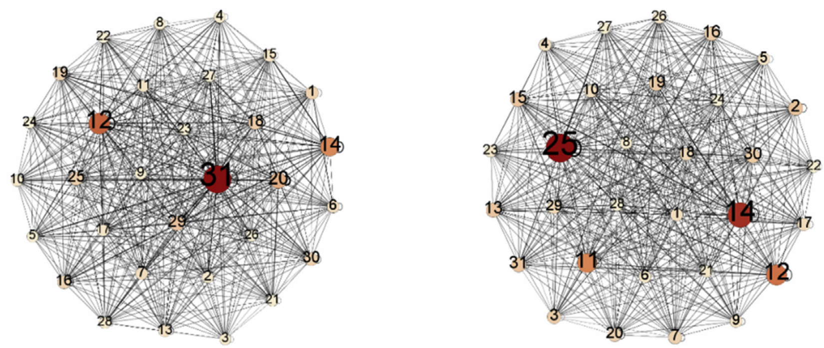


Fig. 3. The sectoral breakdown of the percentage output change.
Note: The output change is derived from the demand pull system (Step 4 in Fig. 1).



a. The intersectoral price change flow network.

b. The intersectoral output change flow network.

Fig. 4. IPCFN and IOCFN.

Note: The node represents the sector. The node's size denotes the influence strength; the larger the influence strength is, the larger the node is. The color's depth denotes the influence strength; the larger the influence strength is, the deeper the color is. The edge's thickness denotes the intersectoral price change and output change flow's weight; the thicker the line is, the greater the intersectoral price change and output change flow is. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

information transmission is very fast. Therefore, in the short term, the speed of price change and output change transferring between sectors caused by a carbon tax was very rapid.

In addition, the small-world nature indicates that there are powerful nodes in networks. Changes in several key nodes or linkages will greatly affect the function of the whole system (Watts and Strogatz, 1998). Therefore, it is necessary to further identify key sectors and sector groups. Considering that Guan et al. (2009) choose the top five export production sectors from 42 sectors and Cheng et al. (2018) choose the three industries with the greatest net CEs- PT from 40 sectors as key sectors, we categorize the top 10% of sectors as key sectors in the following analysis.

3.2. The roles of individual sectors

3.2.1. The roles of individual sectors in cost pass-through system

The top 10% of sectors with the largest influence strength, sensitivity strength and intermediate strength in IPCFN are shown in Table 2. The top 10% of sectors with influence strength in cost pass-through system included electricity production, metal smelting, chemical industry, and fuel processing. These four sectors were energy and basic industrial commodity suppliers, which were the source of price increases due to higher carbon costs. In addition, the total forward linkage of these four sectors in the cost pass-through system is relatively higher (see Table C.1 in Appendix C). This meant that these four sectors had a wide impact on the downstream sectors in the industry chain. As a result, the above four sectors had the most influence on the price changes of the other sectors.

The top 10% of sectors with sensitivity strength in cost pass-through system included electricity production, metal smelting, metal products, and fuel processing. There was a self-loop phenomenon in electricity production, metal smelting, and fuel processing. The self-loop is defined that a sector has a large intermediate input demand for its own commodities. Considering the above three sectors had the largest price change, the price changes received from themselves were the largest accordingly. As a direct downstream sector of metal smelting, the metal products industry was greatly affected. Moreover, the metal products industry was a high sensitivity sector due to the higher total backward linkage. As a result, the sensitivity strength of metal products was relatively higher.

The top 10% of sectors with intermediate strength in cost pass-through system played a strong bridge role. According to the features of those sectors, the top 10% of sectors can be divided into two categories: the first was the sectors providing the upper or middle capital goods and raw materials, which were in better supply and demand conditions, such as metal smelting, chemical industry, fuel processing, metal products, and nonmetallic products. Because of the better supply and demand conditions, these sectors could quickly transfer the price change received. The second category was the sectors providing production equipment in the middle of the industrial chain, including general machinery, transport equipment, and special machinery. Because the goods provided by these sectors were essential to the production or operation of downstream sectors, they also had the strongest intermediate strength.

As shown in Fig. 5, influence, sensitivity, and intermediate strength of the top 10% sectors were huge, accounting for 53.43%, 22.94%, and 51.50% of total strength, respectively. This meant that a small number of key sectors played an important role in IPCFN. Changing price increases in key sectors or dependence on energy-

Table 2
The top 10% of sectors with influence strength, sensitivity strength and intermediate strength in IPCFN.

Sector	Influence strength	Sensitivity strength	Intermediate strength
The top 10% of sectors	Electricity Production Metal Smelting Chemical Industry Fuel Processing	Electricity Production Metal Smelting Metal Products Fuel Processing	Metal Smelting Chemical Industry Fuel Processing Metal Products Nonmetallic Products General Machinery Transport Equipment Special Machinery

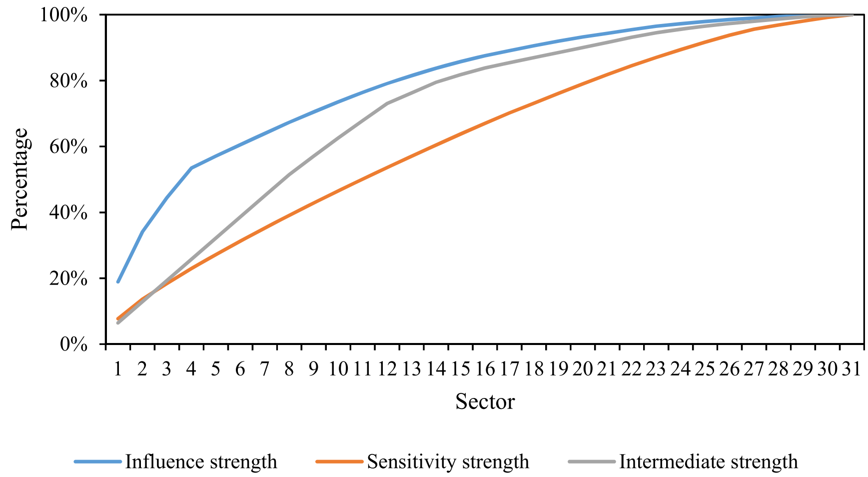


Fig. 5. The cumulative distribution of sector influence, sensitivity, and intermediate strength in the cost pass-through system.
Note: The sector influence, sensitivity, and intermediate strength are the indices measuring the role of the individual sector. On the horizontal axis, we process sectors using the following procedures: (1) ranking sectors in descending order according to their influence strength and (2) calculating the cumulative percentage of influence strength. These process procedures apply similarly to Fig. 6.

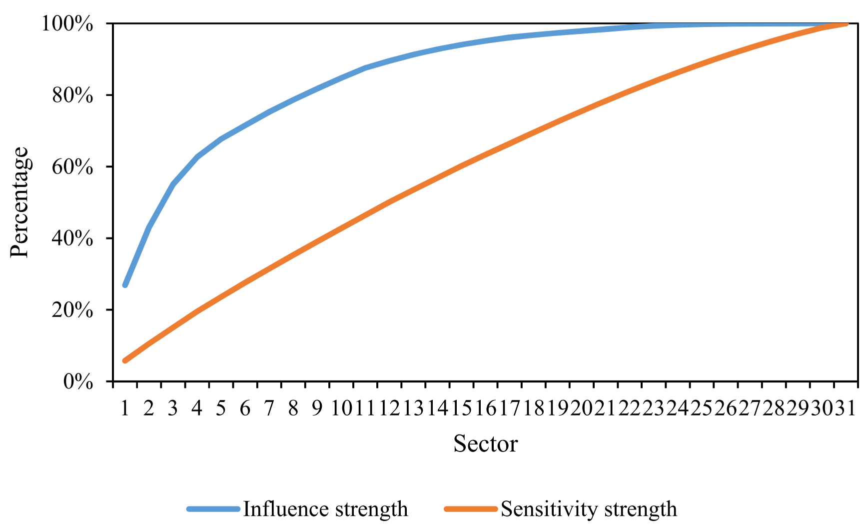


Fig. 6. Cumulative distribution of sector influence and sensitivity strength in the demand pull system.
Note: The sector influence and sensitivity are the indices measuring the role of the individual sector.

intensive sectors in a few key sectors would significantly reduce the scale of price increases across the economy. For electricity production, metal smelting, chemical industry, and fuel processing, accelerating the transformation to ultra-low emission production technology should be focused. Moreover, considering the price increase caused by the self-loop, it is an inevitable trend to develop the cycle economy within the sector to reduce the internal high carbon cost.

Table 3
The top 10% of sectors with influence strength, sensitivity strength and intermediate strength in IOCFN.

Sector	Influence strength	Sensitivity strength	Intermediate strength
The top 10% of sectors	Construction Chemical Industry Metal Smelting Wholesale Trade	Water Production Chemical Industry Transport Equipment Electrical Equipment	Metal Smelting Chemical Industry Fuel Processing Metal Products Nonmetallic Products General Machinery Transport Equipment Special Machinery

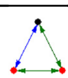
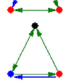
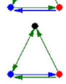
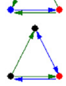
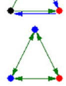
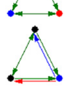
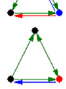
3.2.2. The roles of individual sectors in demand pull system

As shown in Table 3, the influence and sensitivity strength of the top 10% sectors in demand pull system are significantly different from those in cost pass-through system. Obviously, the response of the same sector to changes in price and output was different. The top 10% of sectors with influence strength in demand pull system included construction, chemical industry, metal smelting, and wholesale trade. Construction had the largest influence strength because China's economy was driven by infrastructure investment, and construction was the largest indirect carbon emissions accepter. As a result, once the output dropped down greatly, construction would have an extensive influence strength and range in the industrial chain. Since the larger scale of output decrease and high total forward linkage (see Table C.1 in Appendix C), chemical industry, metal smelting, and wholesale trade had a high influence on the downstream sectors.

The top 10% of sectors with sensitivity strength in demand pull system included water production, chemical industry, transport equipment, and electrical equipment. The self-loop phenomenon also existed in water production, chemical industry, and transport equipment. Thus, the output decrease of sectors would have a significant impact on the intermediate goods of enterprises within the sectors, resulting in a rapid decline in the overall output of the sectors. For the low-carbon sectors like water production and transport equipment, such kind of sectoral characteristics are obviously detrimental, and future tax subsidies policies should be considered to reduce the negative impacts. In contrast, as a high-carbon sector, chemical industry needed to develop a cycle economy to reduce energy consumption internally. Because of the high dependence on metal smelting, electrical equipment had a significant output decrease.

The top 10% of sectors with intermediate strength in demand pull system were the same as the ones in cost pass-through system. This was mainly because the structure of PIOT in cost pass-through and demand pull system did not change in the short-term. Considering the basic production relations persisted, the rank of sectors in intermediate strength did not change.

Table 4
Key motifs with the top 7 *Z-scores* in IPCFN.

No.	ID	Adj	Sector 1-2-3	*fi* (%)	*Li* (%)	LI_i
1.	238		S3–S11–S25	0.02%	0.21%	9.44
2.	174		S23–S14–S25	0.02%	0.11%	4.94
3.	174		S23–S2–S25	0.02%	0.10%	4.49
4.	174		S3–S30–S11	0.02%	0.20%	8.99
5.	238		S2–S14–S11	0.02%	0.07%	3.15
6.	238		S5–S27–S25	0.02%	0.15%	6.74
7.	174		S4–S30–S11 S23–S30–S11	0.04%	0.04%	1.00

Note: The node denotes the sector in IPCFN. Red nodes represent strong group sectors. Blue nodes represent medium group sectors. Black nodes represent weak group sectors. The edge denotes the flow of the intersectoral price change from one sector to another. Red edges represent strong group edges. Blue edges represent medium group edges. Green edges represent weak group edges. The motif name is the standard motif ID number from the software fanmod tool.

As shown in Fig. 6, compared with the cost pass-through system, the influence and sensitivity strength of the top 10% sectors were more concentrated, accounting for 62.63% and 31.43% of total strength, respectively. Therefore, to reduce the impact of key sectors on the output decrease of the economy, it is necessary to design low-carbon policies based on the specific features of key sectors, which will greatly reduce the economy-wide output decline.

3.3. The roles of sector groups

3.3.1. The roles of sector groups in cost pass-through system

There were 74 motifs in IPCFN and we regarded the top 10% of motifs with the largest *Z-score* as key motifs, accounting for 7 motifs. As shown in Table 4, the members of all key motifs in IPCFN were heterogeneous, with a clear sign that the price changes between motif members were different. The linkages between the members in key sector groups were generally strong or medium.

The key motifs with statistical significance were those with higher *LI*, but not the ones with higher frequency. It was obvious that all key motifs in IPCFN were the increasing function motifs with *LI* was greater than 1. In other words, these sector groups played an increasing role in the process of price change transferring between sectors, which were the driving force of price change transmission.

The most powerful motif was the sector group of P&G extraction-fuel processing-electricity production (for sector position please refer to Fig. 7), with a *LI of* 9.44, which led the price change transmission in IPCFN. This matched the features of electricity production and fuel processing as the sectors with the largest price increase. For P&G extraction, although it was a lower price change sector, it had a strong co-movement linkage with fuel processing as the upstream sector. As a result, this motif was the most functionally important. All other sector groups were based on electricity production or fuel processing. The other members in key sector groups could be divided into two categories: the first category was the upstream or downstream sectors related to electricity production or fuel processing, for example, P&G extraction and metal mining. The second category was the co-movement sectors related to electricity production or fuel processing, such as recycling and wholesale trade.

Sole and Valverde (2006) and Ma et al. (2019b) pointed out that massive network motifs contribute small to the network and should be considered as the byproducts during network construction. Thus, when designing low-carbon policy in the future, the key sector groups should be paid full attention to. In addition, since strong co-movement sectors were generally low-carbon and easy to be ignored in the design of carbon tax, according to the above analysis, this kind of sectors should be looped in the future.

3.3.2. The roles of sector groups in the demand pull system

There were 73 motifs in IOCFN and we regarded the top 10% of motifs with the largest *Z-score* as key motifs, accounting for 7 motifs. As shown in Table 5, the members of key motifs in IOCFN

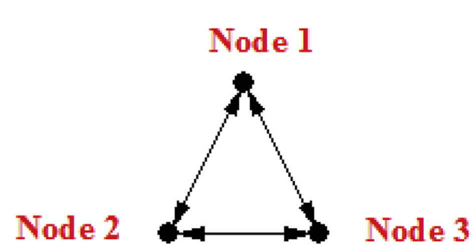


Fig. 7. Node positions of 3-motifs.

Table 5
Key motifs with the top 7 *Z-scores* in IOCFN.

No.	ID	Adj	Sector 1-2-3	*fi* (%)	*Li* (%)	LI_i
1.	174		S4–S20–S31	0.02%	0.09%	4.22
2.	174		S1–S6–S21 S1–S6–S24	0.04%	0.12%	2.69
3.	38		S4–S1–S20 S3–S1–S20	0.04%	0.00%	0.03
4.	238		S22–S12–S31 S10–S12–S31	0.04%	0.24%	5.28
5.	46		S3–S29–S31 S3–S27–S31	0.04%	0.22%	5.02
6.	46		S23–S29–S31 S23–S27–S31	0.04%	0.29%	6.61
7.	238		S17–S14–S31 S6–S1–S31	0.04%	0.18%	3.98

Note: The node denotes the sector in IOCFN. Red nodes represent strong group sectors. Blue nodes represent medium group sectors. Black nodes represent weak group sectors. The edge denotes the flow of the intersectoral price change from one sector to another. Red edges represent strong group edges. Blue edges represent medium group edges. Green edges represent weak group edges. The motif name is the standard motif ID number from the software fanmod tool.

were mixed. Like IPCFN, the linkages between the members in key sector groups in IOCFN were strong or medium.

There were two types of motifs in IOCFN: the increase function and the decreasing function motif. The increasing function motifs were the sector groups based on services, other electronic equipment, and chemical industry, while the decreasing function motifs were the No.3 motif, containing two-sector groups of metal mining-agriculture-other electronic equipment and P&G extraction -agriculture-other electronic equipment.

The members of key sector groups in IOCFN could be divided into two categories: energy material providers and low-carbon sectors. This indicated that the carbon tax was efficient for the effects finally transferred to the energy material providers. However, many low-carbon sectors were shocked by this process, for example, services and transport equipment, which had a larger decrease in output than energy-intensive sectors. Therefore, the tax exemption should be considered for these low-carbon sectors in the future.

3.4. Comparative results of the in-process and ex-post analysis

According to the price and output changes, the distribution of key sectors and sector groups is shown in Fig. 8. The abscissa is the price changes, and the ordinate is the output changes. The vertical line in red indicates the neutrality line of the sector price changes, and the horizontal line is the neutrality line of output changes.

The biggest difference between in-process and ex-post analysis was that some sectors with lower price/output changes in the quadrant II played an important role in the in-process analysis. And this part of sectors was easily neglected in ex-post analysis, for example, metal product as the key sensitive sector, wholesale trade as the key influential sector, special machinery as the key intermediate sector. On the other hand, the in-process analysis found the key interaction patterns were between sectors with larger price/output change and the ones with lower price/output change, such as the two driving sector groups of P&G extraction-fuel processing-electricity production and metal mining-other electronic equipment-services. This interaction pattern analysis could easily trace the sectors in the quadrant II that were usually overlooked, which played a key role during a carbon tax on the economy.

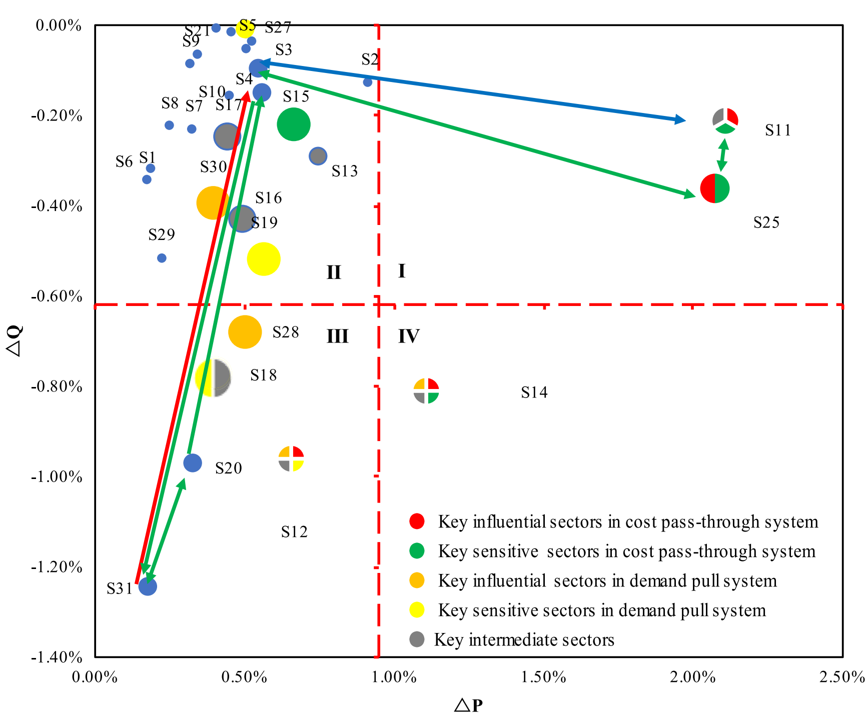


Fig. 8. The distribution of key sectors and sector groups.

In addition, more functions of some key sectors, in quadrant I, III and IV, were explored in an in-process analysis. For example, metal smelting and chemical industry had four key roles, fuel process had three key roles, and electricity production and transport equipment had two roles. The identification of these key sectors considered both the carbon cost and co-movement relationships in the industrial chain, which expanded people's understanding of the key sectors. Thus, carbon tax design will be more comprehensive accordingly. In summary, the in-process analysis is a necessary supplement for the existing ex-ante and ex-post analysis.

4. Discussion

Our contributions are as follows: first, this paper expands the impact analysis of a carbon tax policy on the economic transaction which used to be in a "black box" via investigating the roles of sectors. Second, this paper provides an analysis method in the roles of sector groups by using a network motif analysis, which is helpful for understanding the interactions between sectors in the process of a carbon tax on the economy. Third, this paper offers a scientific solution for designing more suitable differentiated sectoral emission abatement measures according to the specific features of sectors and establishing cooperation mechanisms across sectors by an in-process analysis of the roles of sectors. The network science methodology can be applied to the emission abatement strategies in international trade, regional trade, and transportation networks.

The main limitation of this paper is that the cost pass-through is a complete cost-transfer model. However, in reality, the carbon tax cost cannot be 100% transferred to the commodity price due to the different market power of sectors. For example, the fuel process and chemical industry, the cost pass-through rates are lower than 100% (Alexeeva-Talebi, 2011; Oberndorfer et al., 2010). However, electricity and thermal and steel are greater than 100% (De Bruyn et al., 2010; Sijm et al., 2006). Additionally, there are large differences between countries. Future research can be improved by further examining the Leontief price model.

5. Conclusions and policy implications

Based on the I–O model and the complex network method, this paper analyzed the short-term roles of sectors during a carbon tax on China's economy. The key sectors and sector groups in the transaction process were identified. According to our results, we come to the following conclusions:

(1) The small-world nature of IPCFN and IOCFN is significant and key sectors play an important role. Therefore, reducing price and output changes in a few key sectors could significantly reduce the negative shock on the whole economy.
(2) Sector group analysis investigates the interactions between sectors during a carbon tax on the economy. The results show that the key sector groups with high *LI* play a functionally important role. The *LI* of most of the key sector groups is greater than 1, which drives the transmission of price and output change. The members of almost all key sector groups are heterogeneous, including the sectors with higher price/output change and the ones with lower price/output change.
(3) There was a significant difference between the in-process and ex-post analysis. Some sectors which are not much important in an ex-post analysis play an important role in the in-process analysis. In addition, due to combining the carbon cost and interactions between sectors, more functions of some key sectors are explored in an in-process analysis. Our study is of valuable reference for policymakers in terms of designing a differentiated sectoral emission reduction strategy.

Based on the above results and discussions, we present the following policy implications for mitigating carbon emissions and designing the carbon tax policy:

(1) For key influential sectors in the cost pass-through system, the main reason for the price increase is the high carbon tax costs and total forward linkage. Thus, more consideration should be concentrated on accelerating the transformation to ultra-low emission production technology. Moreover, it is urgent to prompt the clean utilization of coal and speed up the resolution of wind, light, and hydropower consumption problems.
(2) For the key influential sectors in demand pull system, the main reason for the output decrease dues to the infrastructure driving mode and high total forward linkage. More consideration is to promote resource conservation and developing green buildings.
(3) Regarding the high-carbon sectors with self-loop phenomena, developing the cycle economy is proposed to reduce the high carbon cost embodied in the internal intermediate inputs. For low-carbon sectors with self-loop phenomena, tax complementary measures should be placed to alleviate the negative impacts.
(4) As to the key intermediate sectors, the dependence on the energy-intensity sectors is suggested to be reduced so as to abate the intermediate strength from the source.
(5) For the sectors with lower price/output change, such as metal mining and P&G extraction, switching to clean energy is proposed to reduce the share of fossil energies in the future.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Confirmed by Ning Ma, Huajiao Li, Yuhai Wang, Jinwei Zhang, Zhenhua Li, Asma Arif.

CRediT authorship contribution statement

Ning Ma: Conceptualization, Methodology, Software, Writing - original draft. **Huajiao Li:** Conceptualization, Writing - original draft. **Yuhai Wang:** Validation, Investigation. **Jinwei Zhang:** Resources, Supervision. **Zhenhua Li:** Software, Validation. **Asma Arif:** Writing - review & editing.

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Appendix A

Table A.1
Sector classification, abbreviations and codes.

Final classification (sector code)	Sector Abbreviations	Sub-sectors (Sector code)
Agriculture (S1)	Agriculture	Farming (1-01) Forestry (1–02) Animal Husbandry (1–03) Fishery (1–04) Water Conservancy (1–05)
Coal Mining (S2)	Coal Mining	Mining and Washing of Coal (2–01)
		Petroleum and Gas
Petroleum and Gas Extraction (S3)	P&G Extraction	Extraction of Petroleum and Natural Gas (3–01)
Metal Ores Mining (S4)	Metal Mining	Mining and Processing of Ferrous Metal Ores (4–01) Mining and Processing of Non-Ferrous Metal Ores (4–02)
Nonmetal Ores and Other Mining (S5)	Nonmetal Mining	Mining and Processing of Nonmetal Ores (5–01) Mining of Other Resources (5–02)
Food Manufacturing (S6)	Food	Processing of Food from Agricultural Products (6–01) Manufacture of Foods (6–02) Manufacture of Beverages (6–03) Manufacture of Tobacco (6–04)
Textile Manufacturing (S7)	Textile	Manufacture of Textile (7–01)
Textile Wearing and Leather Manufacturing (S8)	Leather Manufacturing	Manufacture of Textile Wearing Apparel, Footwear, and Caps (8–01) Manufacture of Leather, Fur, Feather and Related Products (8–02)
Timber Processing and Furniture Manufacturing (S9)	Furniture Manufacturing	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products (9–01) Manufacture of Furniture (9–02)
Manufacture of Paper and Education-related products (S10)	Education-related Products	Manufacture of Paper and Paper Products (10–01) Printing, Reproduction of Recording Media (10–02) Manufacture of Articles for Culture, Education and Sport Activity (10–03)
Petroleum Processing, Coking, and Nuclear Fuel (S11)	Fuel Processing	Processing of Petroleum, Coking, Processing of Nuclear Fuel (11–01)
Chemical Industry (S12)	Chemical Industry	Manufacture of Raw Chemical Materials and Chemical Products (12–01) Manufacture of Medicines (12–02) Manufacture of Chemical Fibers (12–03) Manufacture of Rubber (12–04) Manufacture of Plastics (12–05)
Manufacture of Nonmetallic Mineral Products (S13)	Nonmetallic Products	Manufacture of Nonmetallic Mineral Products (13–01)
Smelting and Pressing of Metals (S14)	Metal Smelting	Smelting and Pressing of Ferrous Metals (14–01) Smelting and Pressing of Non-ferrous Metals (14–02)
Manufacture of Metal Products (S15)	Metal Products	Manufacture of Metal Products (15–01)
Manufacture of General Purpose Machinery (S16)	General Machinery	Manufacture of General Purpose Machinery (16–01)
Manufacture of Special Purpose Machinery (S17)	Special Machinery	Manufacture of Special Purpose Machinery (17–01)
Manufacture of Transport Equipment (S18)	Transport Equipment	Manufacture of Transport Equipment (18–01)
Manufacture of Electrical Machinery and Equipment (S19)	Electrical Equipment	Manufacture of Electrical Machinery and Equipment (19–01)
Manufacture of Communication Equipment, Computers and Other Electronic Equipment (S20)	Other Electronic Equipment	Manufacture of Communication Equipment, Computers and Other Electronic Equipment (20–01)
Manufacture of Instrumentation and Machinery (S21)	Instrumentation	Manufacture of Instrumentation and Machinery for Cultural Activity and Office Work (21–01)
Other Manufacturing (S22)	Other Manufacturing	Manufacture of Artwork and Other Manufacturing (22–01)
Recycling and Disposal of Waste (S23)	Recycling	Recycling and Disposal of Waste (23–01)
Repair services for metals, machinery and equipment (S24)	Repair services	Repair services for metals, machinery and equipment (24–01)
Production and Distribution of Electricity and Thermal (S25)	Electricity Production	Production and Distribution of Electricity and Thermal (25–01)
Production and Distribution of Gas(S26)	Gas Production	Production and Distribution of Gas (26–01)
Production and Distribution of Water (S27)	Water Production	Production and Distribution of Water (27–01)
Construction (S28)	Construction	Construction (28–01)
Transport, Storage and Post (S29)	Transport	Transport, Storage (29–01) Post (29–02)
Wholesale, Retail Trade and Hotel, Restaurants (S30)	Wholesale Trade	Wholesale, Retail Trade and Hotel, Restaurants (30–01)
Services (S31)	Services	Information, Transmission, Computer Services &Software (31–01) Real Estate, Leasing and Business Services (31–02) Financial Intermediation (31–03) Other Services (31–04)

Appendix B

Table B.1
Demand Elasticity for Output.

Sectors	Elasticity
Agriculture	−0.812
Coal Mining	−0.106
P&G Extraction	−0.296
Metal Mining	−0.633
Nonmetal Mining	−0.633
Food	−0.638
Textile	−1.139
Leather Manufacturing	−2.418
Furniture Manufacturing	−0.698
Education-related Products	−0.698
Fuel Processing	−0.071
Chemical Industry	−0.987
Nonmetallic Products	−0.827
Metal Smelting	−0.953
Metal Products	−0.505
General Machinery	−1.662
Special Machinery	−1.662
Transport Equipment	−2.485
Electrical Equipment	−1.662
Other Electronic Equipment	−2.596
Instrumentation	−1.662
Other Manufacturing	−1.662
Recycling	−1.662
Repair services	−1.662
Electricity Production	−0.160
Gas Production	−0.566
Water Production	−0.745
Construction	−0.744
Transport	−0.833
Wholesale Trade	−0.745
Services	−0.745

Appendix C

Table C.1
Total forward linkage and total backward linkage in cost pass-through system and demand pull system.

Cost Pass-through System			Demand Pull System		
Sector	Total Forward Linkage	Total Backward Linkage	Sector	Total Forward Linkage	Total Backward Linkage
Services	10.47	2.31	Services	10.43	2.32
Chemical Industry	9.42	3.73	Chemical Industry	9.43	3.73
Metal Smelting	7.24	4.12	Metal Smelting	7.27	4.11
Electricity Production	5.87	3.58	Electricity Production	5.93	3.55
Agriculture	5.06	2.18	Agriculture	5.05	2.18
Transport	4.91	2.09	Transport	4.90	2.09
Wholesale Trade	4.49	2.85	Wholesale Trade	4.49	2.85
Other Electronic Equipment	4.44	4.02	Other Electronic Equipment	4.43	4.03
Food	4.09	2.97	Food	4.08	2.97
Fuel Processing	3.53	3.22	Fuel Processing	3.56	3.20
Textile	3.42	3.53	Textile	3.42	3.53
General Machinery	3.24	3.91	General Machinery	3.23	3.91
Electrical Equipment	3.09	4.01	Electrical Equipment	3.09	4.02
Coal Mining	3.05	3.15	Coal Mining	3.05	3.15
P&G Extraction	2.85	2.51	P&G Extraction	2.85	2.52
Metal Products	2.76	3.95	Metal Products	2.77	3.95
Transport Equipment	2.75	3.83	Transport Equipment	2.75	3.84
Metal Mining	2.53	3.38	Metal Mining	2.53	3.38
Nonmetallic Products	2.48	3.68	Nonmetallic Products	2.48	3.68
Education-related Products	2.41	3.67	Education-related Products	2.41	3.67
Special Machinery	2.14	3.78	Special Machinery	2.14	3.78
Furniture Manufacturing	2.02	3.52	Furniture Manufacturing	2.02	3.53
Nonmetal Mining	1.84	3.25	Nonmetal Mining	1.83	3.26
Leather Manufacturing	1.63	3.41	Leather Manufacturing	1.63	3.41
Instrumentation	1.59	3.70	Instrumentation	1.59	3.70
Recycling	1.51	3.79	Recycling	1.51	3.79
Gas Production	1.36	3.28	Gas Production	1.36	3.29
Construction	1.34	3.63	Construction	1.34	3.64
Water Production	1.14	2.94	Water Production	1.14	2.94
Other Manufacturing	1.12	3.50	Other Manufacturing	1.12	3.50
Repair services	1.11	3.42	Repair services	1.11	3.42

Note: $\delta_{j,0}$ represent total forward linkage in cost pass-through system. represent total backward linkage in cost pass-through system, Considering the PIOT is not changed in the short-term impacts of a carbon tax on economic system, the differences in total forward linkage and total backward linkage between two systems are small.

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