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China's CO_2 emission structure for 1957–2017 through transitions in economic and environmental policies

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A B S T R A C T

This paper provides an insight into the structure of CO_2 emissions in China through transitions in economic and environmental policies for the period of 1957–2017 by using input-output and network analysis with newly compiled environmentally-extended historical input-output tables of China. These tables, which include firm-level, industry-level, and macro-level statistical data, are the first environmentally-extended input-output tables covering the years in the early stage of the People's Republic of China. The results present the following two main findings. The first is due to the stable economic structure associated with the independent economic policy, China's emission structure has been stable for more than 60 years. Heavy industry has contributed about 80% of CO_2 emissions since the 1950s. On a second account, although the emission structure was stable, stricter environmental controls and regulations led to a decrease of the growth rate of CO_2 emissions after 2010. Against this background, as a policy choice of China, instead of carbon leakage that could break up the stable economic structure, balanced technology upgrading across all sectors induced by stricter environmental controls is a realistic way for China to achieve increased energy efficiency, emission mitigation and economic development, so that the country can keep the promise of reducing CO_2 emissions after they peak around 2030.

1. Introduction

As China has pledged to achieve the CO_2 emission peak target of 2030 and exert efforts to reach this target early (Liu et al., 2015a,b), researchers have shown great interest in how this objective can be achieved (Tollefson, 2016; Yu et al., 2018). To reach the mitigation target and build a low-carbon development mode, not only environmental policies but also economic policies will engender profound effects on emission trajectory and structure. *There is no new thing under the sun.* Studying the historical emission path of China can help us forecast the likely trajectory of China's emission in the next decades. Historical facts can shed light on the behavioral principles of the Chinese government. Current carbon mitigation procedures have been built on historical policies, including environmental protection policies as well as other economic policies that have environmental implications. Furthermore, current government principles and policies will greatly influence the direction of future relevant policies.

The most important economic policy in China has been the "independence and self-reliance" policy, which was proposed in the 1950s, regarding "maintaining independence and keeping initiatives in our own hands and relying on our own efforts" (Keith, 1985). Economic aspects of the independence policy came from the heavy industry strategy, an import-substitution policy in place since the 1950s (the 1st five-year plan). Although the economy grew rapidly in China, the core principles of the independence policy have been maintained for the last 60 years. Economic policies, especially historical guidelines, have had remarkable impacts on the current economic structure (Johnson, 1982; Rodrik, 2004), and have subsequently influenced the path of emissions and their control structure. Because of the policy of independence, China has rapidly developed its heavy industry and can now produce almost every category of industrial products. This structure consumes large amounts of energy and has had a strong effect on China's CO_2 emissions structure. As China has attempted to maintain all

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categories of industries, the CO_2 emission structure has remained relatively stable. Therefore, the independence policy has led to inertia in terms of the emission structure. In other words, China's challenges in terms of emissions have a historical origin. Discussing this historical origin is interesting but is also quite data-intensive.

Some previous studies have investigated historical CO_2 emissions. For example, Botzen et al. (2008) analyzed historical CO_2 emissions from the main emitters, including China, since 1900; Wei et al. (2012) quantified CO_2 emissions from developed and developing countries since 1850. However, due to limitations in data availability, most of the studies focused on the perspectives of scale and did not consider the sectoral structure of emissions. Without considering the emission structure, it is difficult to investigate the historical cause of China's CO_2 emission trends.

Input-output analysis (IOA), with multi-sectoral input-output tables (IOTs), is a powerful tool to analyze economic and environmental linkage between sectors. A significant number of studies utilized IOA to study the sectoral structure of CO_2 emissions by using single country (Feng et al., 2015; Zheng et al., 2019), multi-regional (Davis and Caldeira, 2010; Feng et al., 2013; Mi et al., 2017), or international IOTs (Meng et al., 2018; Yi et al., 2019). Among these studies, many investigated the relationship between economic issues and CO_2 emissions in China. IOA, with a well-designed analytical framework for comparative statistics, is an appropriate quantitative tool to assess the impacts of industrial structure changes on emission changes (Guan et al., 2018; Liu et al., 2019). Meanwhile, the use of IOA in existing literature has illuminated the role of key sectors on emission reductions. For example, Nakamoto et al. (2019) estimated the carbon footprint for automobiles; and Wang et al. (2017) illustrated the contribution of the non-metallic sector to global CO_2 emissions. Furthermore, many researchers have acknowledged that economic policies have played an important role in economic structure and engendered different effects on CO_2 emission structures (Peters and Hertwich, 2008; Zheng et al., 2019). For example, Guan et al. (2016) discussed the relation between emissions performance and policy effectiveness, while Zheng et al. (2019) paid attention to CO_2 emissions associated with sectoral policies for new development. In addition, some studies have focused on the relationship between the network structure of industrial supply chains and CO_2 emissions. Davis et al. (2011) presented carbon inventories that span the full supply chain of global CO_2 emissions, to depict the economic and international effects that influence emissions. Song et al. (2019) estimated China's embodied food-related energy consumption throughout the supply chain, to analyze the energy implications.

Network analysis is a method to illustrate the economic and emission structures in greater detail. Due to the nature of intersectoral linkages, input-output datasets can support network analysis, which have been traditionally used to analyze economic relationships (McNerney et al., 2013). Currently, complex network theory is being extended to analyze the energy and emissions network. For example, Chen et al. (2018) proposed global energy flows embodied in international trade, based on environmentally-extended IOA and complex network theory. Kagawa et al. (2015) identified supply-chain clusters with high CO_2 emissions within more than 300 million individual supply chains, based on global supply-chain networks.

As mentioned above, IOA is a potentially powerful tool for analyzing historical CO_2 emission structure and its relationship with economic and environmental policy in China. However, the first semi-official IOT for China is for 1973, and is a physical table. Before this year, the only available IOT was an unofficial table for 1957 provided by Niwa (1970), which has 22 sectors. However, this table was based on roughly estimated data and with a low degree of resolution. To the best of our knowledge, because of the lack of IOTs for the early period of the People's Republic of China, no previous study has considered the emissions structure of China with IOTs. Given this background,the present study estimates the sectoral CO_2 emissions data for the newly compiled China historical input-output tables (CHIOTs) (Lin and Chen, 2018). This CHIOTs project provides hybrid IOTs for the years of 1957, 1963, 1968, and 1973. We extend the CHIOTs to also include CO_2 emissions data. Based on these data and the official IOTs of China since 1987, we form time series IOTs that include CO_2 emissions. Based on the time series IOTs, we analyze the change in the emissions structure of China during recent decades and attempt to determine the historical origin of current emissions problems, by using traditional IOA and network analysis.

The paper is organized as follows. Section 2 describes the methodology and data used in the analysis, Section 3 presents the results, and Section 4 presents the discussion and conclusions.

2. Method and data

Based on the newly compiled CHIOTS, we characterize China's historical CO_2 emission structure using IOA. Before describing the data issue, we first introduce the framework of historical environmental-extended input-output tables (HEEIOTs) and the method used for the analysis.

2.1. Method

2.1.1. The framework of HEEIOT

Table 1 shows the framework of HEEIOT, which combines CHIOTs with CO_2 emissions data. The CHIOTs are hybrid IOTs that include m kinds of commodities in physical units and n types of sectors in monetary units. The m commodities are the major industrial products, while the sectors cover all the other products that are not directly included in the industrial products. $\boldsymbol{X}_{I,I}$ in Table 1 represents intermediate inputs from commodities to commodities, whose element x_{ij} is the intermediate input of commodity i in physical units to the production of commodity j; $\boldsymbol{X}_{I,II}$ represents domestic intermediate inputs from commodities to industries, whose element x_{ij} records the intermediate input of commodity i in physical units to industry j; $\boldsymbol{X}_{II,I}$ is the matrix of intermediate inputs from industries in monetary units for the production of commodities. $\boldsymbol{X}_{II,II}$ is the matrix of intermediate inputs from industries in monetary units to the industries. $\boldsymbol{F}_I$ and $\boldsymbol{F}_{II}$ represent final demands of commodities and industries, respectively; $\boldsymbol{m}_I$ and $\boldsymbol{m}_{II}$ represent the imports of commodities and industries, respectively; $\boldsymbol{V}_I$ and $\boldsymbol{V}_{II}$ represent value-added of commodity and industry production, respectively. Additionally, $\boldsymbol{x}_I$ and $\boldsymbol{x}_{II}$ denote total outputs, while $\boldsymbol{q}_I$ and $\boldsymbol{q}_{II}$ refer to CO_2 emissions.

Furthermore, we transfer the hybrid tables from 1957 to 1973 to monetary value to form a time series of IOTs from 1957 to 2017. The following calculation depends on the monetary value IOTs.

2.1.2. Sectoral CO_2 emission structure changes

To characterize the sectoral contributors to CO_2 emissions during the last half decades, we apply the HEEIOTs to calculate the sectoral CO_2 emissions by means of consumer-based accounting (CBA) and producer-based accounting (PBA). CBA and PBA are two sides of the same coin, in the sense that they determine responsibility for emissions by different principles; both methods reflect the emission structure, although from different perspectives.

Before we explain the mathematical methods, we first clarify the notations used in this paper. Non-bold lowercase letters refer to a scalar quantity; bold lowercase letters refer a column vector; bold uppercase letters denote a matrix; ' means transpose; and ^ means diagonalization. The sectoral CO_2 emissions by means of CBA are

Table 1
Historical environmental extended input-output table.

		Intermediate demands		Final demands	Import	Total output
		Commodity	Industry			
		1 … m	1 … n			
Intermediate inputs	Commodity 1	$\boldsymbol{X}_{I,I}$	$\boldsymbol{X}_{I,II}$	$\boldsymbol{X}_{I,F}$	$\boldsymbol{m}_I$	$\boldsymbol{x}_I$
	Commodity m	$\boldsymbol{X}_{II,I}$	$\boldsymbol{X}_{II,II}$	$\boldsymbol{X}_{II,F}$	$\boldsymbol{m}_{II}$	$\boldsymbol{x}_{II}$
	Industry 1					
	Industry n					
Primary inputs	Operating surplus	$\boldsymbol{V}_I$	$\boldsymbol{V}_{II}$			
	Tax					
	Wage					
	Depreciation					
Total input		$\boldsymbol{x}_I$'	$\boldsymbol{x}_{II}$'			
CO_2 emissions		$\boldsymbol{q}_I$	$\boldsymbol{q}_{II}$			

derived by the following equation:

$$\boldsymbol{\alpha}' = \boldsymbol{e}'(\boldsymbol{I}-\boldsymbol{A})^{-1}\widehat{\boldsymbol{f}}, \tag{1}$$

where vector $\boldsymbol{e}$ refers to the direct coefficient of CO_2 emissions; $\boldsymbol{I}$ is the identity matrix; $\boldsymbol{A}$ is the matrix of direct input coefficients; $\boldsymbol{L} = (\boldsymbol{I}-\boldsymbol{A})^{-1}$ is the Leontief inverse; $\boldsymbol{f}$ refers to the column vector of final demand. Because the diagonalization is on $\boldsymbol{f}$, the final demands, the *j*th element of $\boldsymbol{\alpha}$ refers to the CO_2 emissions induced by the final demand of sector *j*. Therefore, Eq. (1) attributes the emission responsibility to final demanders.

On the other side, the sectoral CO_2 emissions by means of PBA is given by the following equation:

$$\boldsymbol{\beta}' = \widehat{\boldsymbol{e}}(\boldsymbol{I}-\boldsymbol{A})^{-1}\boldsymbol{f}. \tag{2}$$

In Eq. (2), the diagonalization is on $\boldsymbol{e}$, instead of $\boldsymbol{f}$ in Eq. (1). Therefore, the *j*th element of $\boldsymbol{\beta}$ refers to CO_2 emissions emitted from sector *j*.

By using the CBA and PBA models of IOT, we disaggregated the CO_2 emissions to the sectoral level from two different perspectives. In other words, these methods disaggregate the total emissions, a scalar quantity, into an *n*-dimensional vector of sectoral emissions. To show more information on the emission structure, the IOA can disaggregate the emission data into an $n \times n$ matrix, based on network analysis.

2.1.3. Network analysis

Network analysis is a sector level analysis, which can be used to explain the influence that one sector exerts on other sectors, within the overall system configuration (Song et al., 2019). Compared with emission flow analysis, network analysis depicts the interrelationship among sectors more clearly and provides more structural information. As an extension of Eqs. (1) and (2), the CO_2 emissions can be disaggregated by the following equation:

$$\boldsymbol{\Theta} = \widehat{\boldsymbol{e}}(\boldsymbol{I}-\boldsymbol{A})^{-1}\widehat{\boldsymbol{f}}. \tag{3}$$

here we diagonalize both $\boldsymbol{e}$ and $\boldsymbol{f}$. The *ij*th element of $\boldsymbol{\Theta}$, θ_{ij}, refers to the CO_2 emitted from sector *i* to satisfy the final demand of sector *j*. It represents the complete linkage between sector *i* and *j*. We call it "emission linkage from sector *i* to sector *j*". Meanwhile, the $n \times n$ matrix, $\boldsymbol{\Theta}$, also illustrates a network with regard to CO_2 emissions. By using the elements of $\boldsymbol{\Theta}$, we can define both self effect and sectoral spillover effects. Self effect (ε) are the elements on the main diagonal of the matrix $\boldsymbol{\Theta}$, whose *i*th element $\varepsilon_i = \Theta_{ii}$, representing the emissions caused by self production of sector *i*. Sectoral spillover effects are the non-diagonal elements of matrix $\boldsymbol{\Theta}$, and include the sending and receiving effects. The sending effect refers to the emissions from a sector that are induced by the final demand of the other sectors, which is defined by $\rho_i = \Sigma_{j \neq i}\theta_{ij}$. In other words, ρ_i refers to the CO_2 emitted from sector *i* to satisfy the final demand of the sectors other than sector *i*. The sending effect is also referred to as forward linkage in IOA literature. Meanwhile, the receiving effect is the impact of one sector's final demand on the emissions from all the other sectors. The receiving effect of sector *i* is defined by $\gamma_i = \Sigma_{j \neq i}\theta_{ji}$, and is referred to as backward linkage in the IOA literature.

The network shown in $\boldsymbol{\Theta}$ also reflects the size of final demand *f*. Additionally, we considered the pure technical linkage without considering the demand size. As the counterpart of Eq. (3), we use the following equation to define the pure technical linkage with regard to CO_2 emissions

$$\boldsymbol{\Phi} = \widehat{\boldsymbol{e}}(\boldsymbol{I}-\boldsymbol{A})^{-1}. \tag{4}$$

Instead of the "linkage" defined in Eq. (3), we call the *ij*th element of $\boldsymbol{\Phi}$, φ_{ij}, "linkage density from sector *i* to sector *j*". Similarly, we can define the sending density of sector *i* as $\lambda_i = \Sigma_{j \neq i}\varphi_{ij}$ and receiving density of sector *i* as $\mu_i = \Sigma_{j \neq i}\varphi_{ji}$, respectively. The sending density represents CO_2 emissions from a sector that are induced by a unit of the final demand of the other sectors. The receiving density refers to the impact of a unit of one sector's final demand on the emissions from all the other sectors.

Furthermore, following the tradition of network and block models (White et al., 1976; Snyder and Kick, 1979), we divided the sectors into 4 types in terms of the directions of linkages: sending sectors, receiving sectors, intermediary sectors, and independent sectors. Sending sectors have great sending density but less receiving density. They send inputs to the other sectors and emit CO_2 directly by themselves. In contrast, receiving sectors have less sending density but greater receiving density, and receive inputs from the other sectors. Intermediary sectors act as bridges between sectors, while independent sectors are relatively isolated. Generally, the sending sectors are needed by other sectors, such as the electric sector, while the receiving sectors, which need more input from other sectors, are always downstream in the industrial chain.

By using the above mentioned methods, we described the CO_2 emission challenges for China over the last 60 years by using 1, *n*, and $n \times n$-dimensional approaches.

2.2. Data

For this study, we obtained IOTs for 1957, 1963, 1968, and 1973 from the CHIOTs project (Lin and Chen, 2018). The final year of the CHIOTs project was selected as 1973, because the Chinese Academy of Science and National Bureau of Statistics compiled a physical IOT for the year 1973. The objective of the CHIOTs project was to extend the IOTs for China back to 1950s, from the existing IOTs. The initial year was selected as 1957 instead of 1958, because a great leap forward began in 1958 and ended by 1960. However, the statistical data for this period was not reliable. The compilation work of CHIOTs was based on macro-level, industry-level, and firm-level statistical data. For details regarding CHIOTs, please refer to Lin and Chen (2018).

The CHIOTs are hybrid IOTs that include 161 commodities in physical units and 18 sectors in monetary units. The 161 commodities are the major industrial products, while the 18 sectors cover all the other products that are not directly included in the 161 industrial products. For example, "chemical industry" in the 18 sectors refers to the part of the chemical industry that excludes the chemical products that have already been included in the 161 commodities, such as sulfuric acid, sodium carbonate, chemical pesticide, and so on. Please refer to Appendix A for the details regarding the sector classification for the CHIOTs.

Additionally, this study calculates the sectoral CO_2 emissions based on the data of energy usage and corresponding CO_2 emission intensity. For the sectoral energy usage, 19 types of fossil fuels are considered, including: raw coal, cleaned coal, other washed coal, briquettes, coke, coke oven gas, blast furnace gas, converter gas, other gas, other coking products, crude oil, gasoline, kerosene, diesel, fuel oil, LPG, refinery gas, other petroleum products, and natural gas. The data of energy consumption from 1958 to 1973 are obtained from the China industrial, transportation & energy statistical information collection (from 1949 to 1999), while the data of energy consumption from 1992 to 2017 are derived from the China energy statistical yearbooks (National Bureau of Statistics (1992–2018)). The CO_2 emission intensity of corresponding energy is estimated by the inventories from the Intergovernmental Panel on Climate Change (2006).

Finally, by using the price information provided by Liu (1990) and the price indices for later years published by National Bureau of Statistics, we transferred the hybrid tables from 1957 to 1973 to monetary value and harmonized the sector classifications of the CHIOTs with the IOTs for 1992, 1997, 2002, 2007, 2012 and 2017 (National Bureau of Statistics, 1994, 2019) to form a time series of IOTs from 1957 to 2017 with 18 sectors in constant price of 2000. Based on the approach proposed by Weber et al. (2008), we complied the non-competitive IOTs.

3. Results

3.1. Sectoral CO_2 structure analysis

We first show the sectoral CO_2 emissions from 1957 to 2017 according to PBA and CBA, which are shown in Figs. 1 and 2. In Fig. 1, we aggregate the sectoral CO_2 emissions according to PBA into 7 categories: agriculture, mining, light industry, heavy industry, electricity, construction, and tertiary industry. Under the framework of PBA, from 1957 to 1973, China's CO_2 emissions increased from 54.03 million tonnes (Mt) to 322.74 Mt, with an average growth of 17.64% per year. From 1957 to 1973, CO_2 emissions from the mining, heavy industry and electric power sectors increased by 598.05%, 504.94%, and 567.39%, respectively. However, emissions from light industry were relatively stable, increased by only 66.85%. This is consistent with China's development strategy. Five-year plans in this period focus more attention on the heavy industry and military industry. In 1963, after China finished the 2nd five-year plan, the CO_2 emissions from heavy industry accounted for 82.90% of the total emissions.

In this year, China's GDP per capita was only 181 RMB (1963 value), which is the equivalent of only 142.02 USD (2010 value) per capita. If we compare the situation in China in 1963 with the other low and middle income countries, the CO_2 emission structures are totally different. For example, the GDP per capita of India and Indonesia in 1995 were 622 and 2219 USD (2010 value), while the shares of CO_2 emissions from heavy industry were 24.08% and 33.03%, respectively (according to a calculation based on world input-output database, Timmer et al. (2015)). Those values are much lower than those for China in 1963. This means that the development model for China was different from those two other countries. The different development models resulted in differences in the structure of CO_2 emissions. In recent years, the GDP per capita of China exceeded that of India and Indonesia, and the share of emissions from heavy industry in China is still higher than in those countries. In 2009 the share of emissions from heavy industry was 43.22% in China, while the shares of emissions from heavy industry in India and Indonesia were 22.07% and 23.18%, respectively.[1]

Additionally, the Hoffmann coefficient, proposed by Hoffmann (1958), calculated by the proportion of net output from consumer goods to the net output from capital goods, was used to measure the industrial stages. Generally, the output of light industry was used to measure consumer goods, while the output of heavy industry was used to measure capital goods. The lower the value was, the more developed the economic structure was. The path of industrial development is from low levels to high levels and from light industry to heavy industry (Hoffmann, 1958). Consistent with this trend, the Hoffmann coefficient was from large to small. The Hoffmann coefficient in China during the 1970s was about 0.6 (National Bureau of Statistics, 1994), which reached the level of developed countries and was close to the Hoffmann coefficient for Japan Wu and Wen (2006). As the government placed great emphasis on heavy industry during China's industrialization before 1973, the imbalance between light industry and heavy industry has always existed.

From 1973 to 1992, China's CO_2 emissions increased by 1706.92 Mt, with an average annual growth of 10.16%. As the imbalance between light industry and heavy industry was further aggravated at the end of 1978, industrial transformation and promotion of light industry were significantly important (Deng, 1994). In line with the industrial development, CO_2 emissions resulting from agriculture, light industry, electric power and the tertiary industry increased rapidly. Specifically, the growth rates of electric power and light industry were 112.67% and 119.06%, respectively. The share of emissions caused by electric power increased from 5.04% to 34.92%, and the share of emissions caused by light industry raised from 0.82% to 5.66%. Although the share of emissions induced by heavy industry declined, heavy industry was still the most important contributor to CO_2 emissions. After China's economic reform began in 1978, the growth rate of CO_2 emissions decreased and tended to be stable. From 1992 to 2017, CO_2 emissions increased by 8285.62 Mt, with an average growth rate of 6.72% per year.

The annual growth rate of CO_2 emissions during the period 1992–1997 (mainly in the 8th five-year plan) was 6.29%. At this stage, expanding industrial scale was important, and the relation between light industry and heavy industry was relatively balanced. The proportion of light industry to heavy industry increased from 0.76 to 0.96, because of the expanding demand, pluralistic investment from private enterprises, and international trade. As export-oriented light industries grew rapidly in this period, which consumed less energy and produced less emissions, the growth

[1] The shares of emission from heavy industry in India and Indonesia are from the environmental accounts of world input-output database and the latest sectoral environmental data is for the year of 2009.

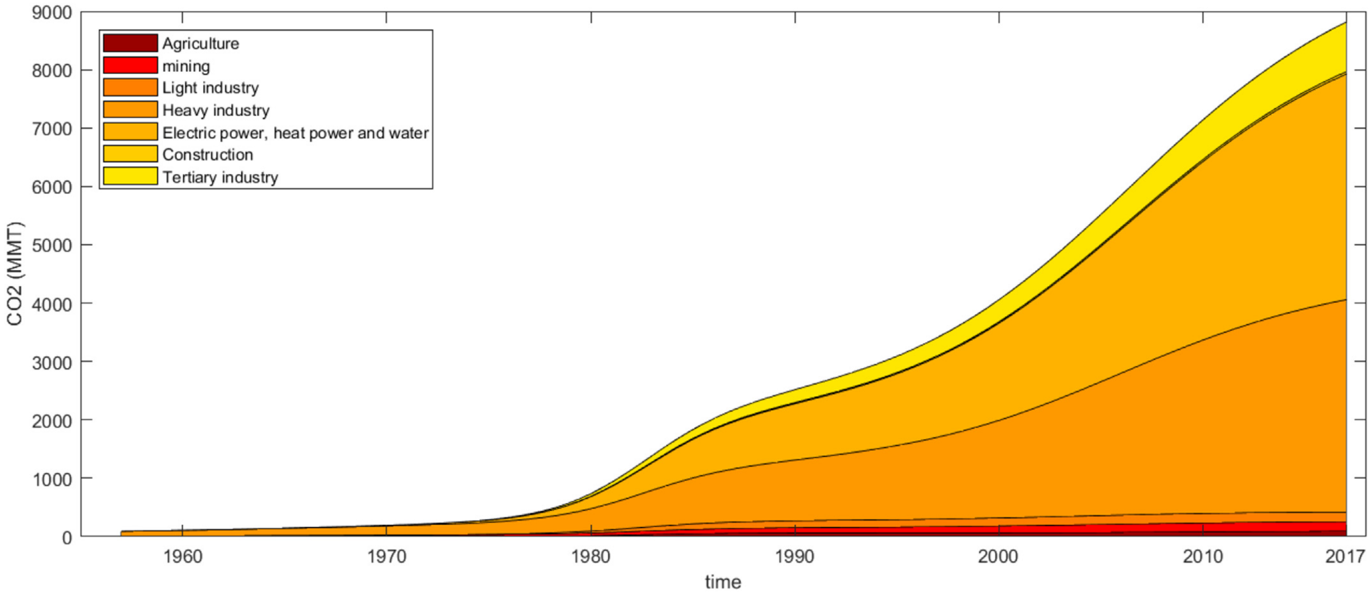


Fig. 1. Sectoral CO_2 emissions 1957–2017 under the framework of PBA.

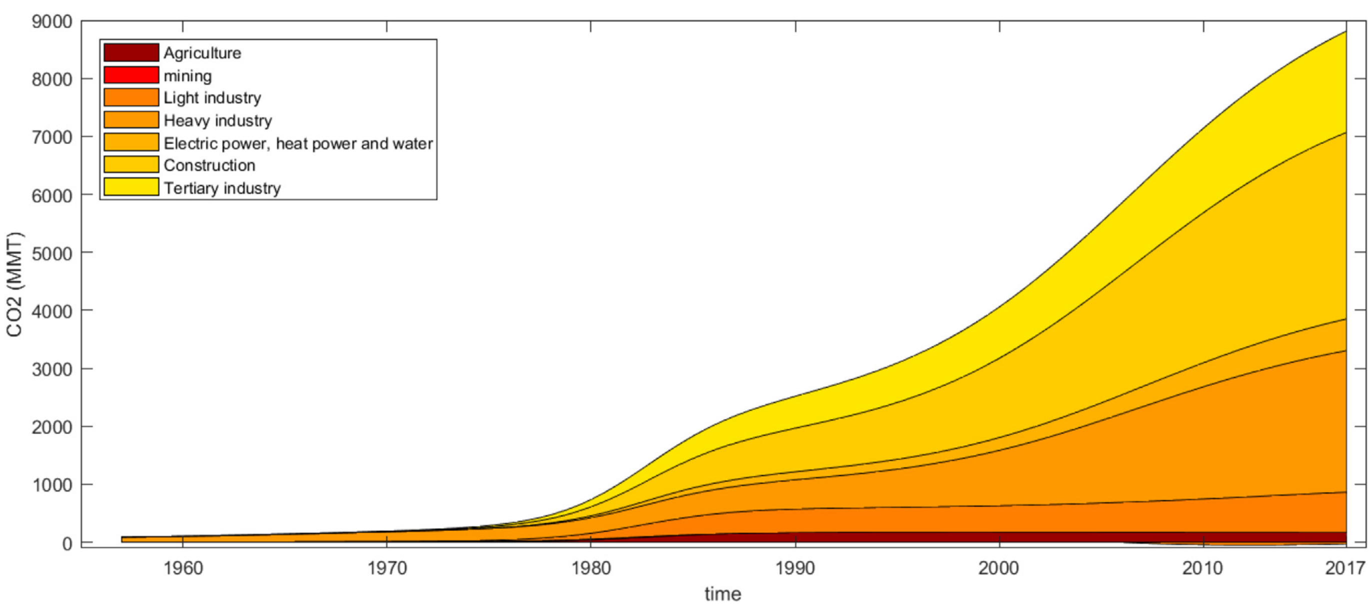


Fig. 2. Sectoral CO_2 emissions 1957–2017 under the framework of CBA.

rate of emissions was slower than before, even with this extensive development. Note that emissions from electric power had the fastest growth rate (9.01%) in this stage with heavy industry in second place (6.17%). The share of emissions from heavy industry and electric power, at this time, was larger than 80%. Specifically, most of the emissions were caused by the industrial investment to expand the production scales and the government paid little attention to environmental problems or mitigation issues. In 1997, sustainable development was confirmed by the Chinese government as one of the basic national strategies. The annual growth rate of CO_2 emissions during the period 1997–2002 dropped to 4.31%. Improving energy efficiency was conducive to reducing emissions in this stage.

After 2000, China's comparative advantages changed because of capital accumulation, and the industry structure shifted, becoming heavier than during the early stage of economic reform. One consequence of this change was the expansion in coal consumption (Green and Stern, 2016). Although technological development and increased R&D activities facilitated emission reduction, parts of reduction were offset by the additional energy consumption. Therefore, since 2002, CO_2 emissions have increased much more rapidly than during the 1990s. The annual growth rate of CO_2 emissions during the period 2002–2007 was 13.67%. Large scale investments in heavy industry increased the energy consumption and related emissions, and then offset the emission mitigation obtained from the emission efficiency improvement. This was a phenomenon named "output effect". As economic growth was still much more important than the environment during this stage, enterprises specialize in production-biased technology, rather than environment-biased technology (Song et al., 2019). The improvement of energy efficiency induced decreases in the real price of energy, resulting in producer substituting energy for other inputs to lower the price. This phenomenon was called "substitution effect", which also increased CO_2 emissions. Both the "output effect" and the "substitution effect" expanded the consumption of coal and led to high-speed growth of emissions during 2000–2010, consistent with the results proposed by Green and Stern (2016) and Zhang et al. (2017).

After 2010, China enhanced efforts in emission mitigation and the government promised to reduce CO_2 emissions and CO_2 emission intensity by the signing of Paris Agreement in 2015. In pursuit of emission reduction, stricter environmental controls and regulations were implemented. Therefore, the growth rate of CO_2 emissions has decreased year-on-year after the rapid growth spanning more than five decades. The annual growth rate of CO_2 emissions during the period 2007–2012 was 6.45%. In 2016, the government promulgated green development plans for industries. The plan, China Industrial Green Development Plan 2016–2020, was promulgated to implement environmental-friend, energy-saving technology in industrial production. Meanwhile, environmental concerns in China were relatively higher than before, which was impel enterprises to improve emission efficiency. Both of them promoted the emission mitigation in this period. During 2012–2017, the annual growth rate was 3.18%. The growth trend of emissions was consistent with the trajectory of Chinese emissions calculated by Guan et al. (2018). Emissions from mining and light industries are less than before, and the growth rates of emissions in heavy industry, electric power and tertiary industry are slower. That is, the environmental regulations as well as the promotion of emission efficiency is conductive to the CO_2 emission reduction.

According to the PBA, heavy industry was the most significant polluter, contributing almost 80% of the emissions for the years before the economic reform. After the economic reform, the share of emissions produced directly by heavy industry was reduced, with a decrease of 40% by 2017. However, this reduction was largely eliminated by increased emissions from electric power generation. About 45% of the emissions in 2017 were from electric power and heat power. This is because in these three decades, China achieved notable success in the construction of electricity generation capacity. The increase in the share of emissions from the electricity sector implies technological progress in China, because in many cases, electrically powered machines have replaced the labor force. The increase in the share of emissions from electricity generation sector encroached on the share of emissions from heavy industry. However, this does not imply that there has been a decrease in the importance of heavy industry in the CO_2 emission structure in China, because part of the increase in electricity was to satisfy the demand from heavy industry.

As evidence, the shares of agriculture and light industry were relatively stable, while the sum of the shares from heavy industry and electricity generation remained around 85.18%. In other words, a portion of CO_2 emitted directly by the electricity sector should be attributed to the heavy industry sectors. To illustrate this point, we show the share of emissions from heavy industry and the share of emissions from both heavy industry and electric power generation in Fig. 3. The red line in Fig. 3 refers to the share of emissions from heavy industry, while the black line shows the sum of emission share from both heavy industry and electric power generation. We observed that after economic reform, the share of emissions from heavy industry was clearly reduced, however, the share of emissions from both heavy industry and electric power combined, were relatively stable. This indicates that the increase in the amount of CO_2 directly emitted due to electric power generation was mainly induced by the demand by heavy industry. In the following section, we quantitatively prove this argument.

Additionally, energy usage also influenced CO_2 emissions. Due to the industry-oriented pattern of China's economy, industrial energy consumption made up over 60% of the total energy consumption (National Bureau of Statistics, 2019). We calculated the emissions caused by different types of energy, as shown in Fig. 4. Although the energy structure was still dominated by coal-type fossil fuels, the emissions caused by coal gradually decreased. That is, with the implementation of industrial green development, the energy structure was reversed gradually. Optimizing energy structure also facilitated CO_2 emission mitigation.

There were different stages of CO_2 emission changes that occurred through transitions in economic and environmental policies. Before 1997, as environmental protects were not the major aims in China, environmental policies had few effects on emission changes. The consequences of this growth mode were expanding energy consumption and environmentally unsustainable development. After sustainable development was proposed by the Chinese government in 1997, the government focused on adaptation actions. However, to promote economic growth, expanding investment was another feature of this period. Although technological development and increased R&D activities facilitated energy efficiency, parts of the emission reduction were offset by the additional energy consumption that occurred between 1997 and 2010. Since 2010, the government has pursued efforts to produce environment-biased technology and has improved energy efficiency. Meanwhile, the stricter environmental controls and regulations were implemented to restrain the blind expansion of investment scales and decrease the rebound effects of energy efficiency. Since then, the growth rate of CO_2 emissions has decreased year-on-year. That is, promoting energy efficiency was conducive to emission mitigation. Concurrently, the increase of electricity generation capacity also influenced the emission structure. As shown in Fig. 3, electricity generation gradually became the second important emitter of CO_2 emission. Under the independent industrial policies, China maintained a relatively stable industrial structure for about six decades. As the economic policies in China were still centered on heavy industries, it was impossible for China to remove the largest emission emitter outside the country. In line with the stable industrial structure, the CO_2 emission structure would also maintain a relatively stable status. Therefore, to achieve the emission mitigation target, the government needed to pursue efforts to promote energy efficiency as well as to diversify the energy mix. Furthermore, the stricter environmental controls and regulations implemented by the government to restrain the blind expansion of investment also promoted emission mitigation.

Fig. 2 shows the CO_2 emissions for 1957–2017 according to the CBA. In other words, this result disaggregates the CO_2 emissions in China by shifting the responsibility for emissions to final consumers instead of direct emitters. In contrast with the results of PBA, the CBA indicated that the shares of construction, light industry, and tertiary industry increased markedly, since 1992. The increase in the share of construction was due to the infrastructure investment boom. The increases in the shares of light industry and tertiary industry were because of the change in export and domestic final demand structures. Although the emission structure, according to the CBA, is more volatile than with the PBA, due to the change in consumption structure, it is nevertheless observable that a significant part of CO_2 emissions since the 1950s is attributable to heavy industry. Finally, we also compared our results with other literature focusing on the relationship between China's changing economy and its implications on CO_2 emissions. From 1992 to 1997, the emission structure is similar to that proposed by Guan et al. (2008) and Zhang et al. (2017); and since 2000, the emission structure is

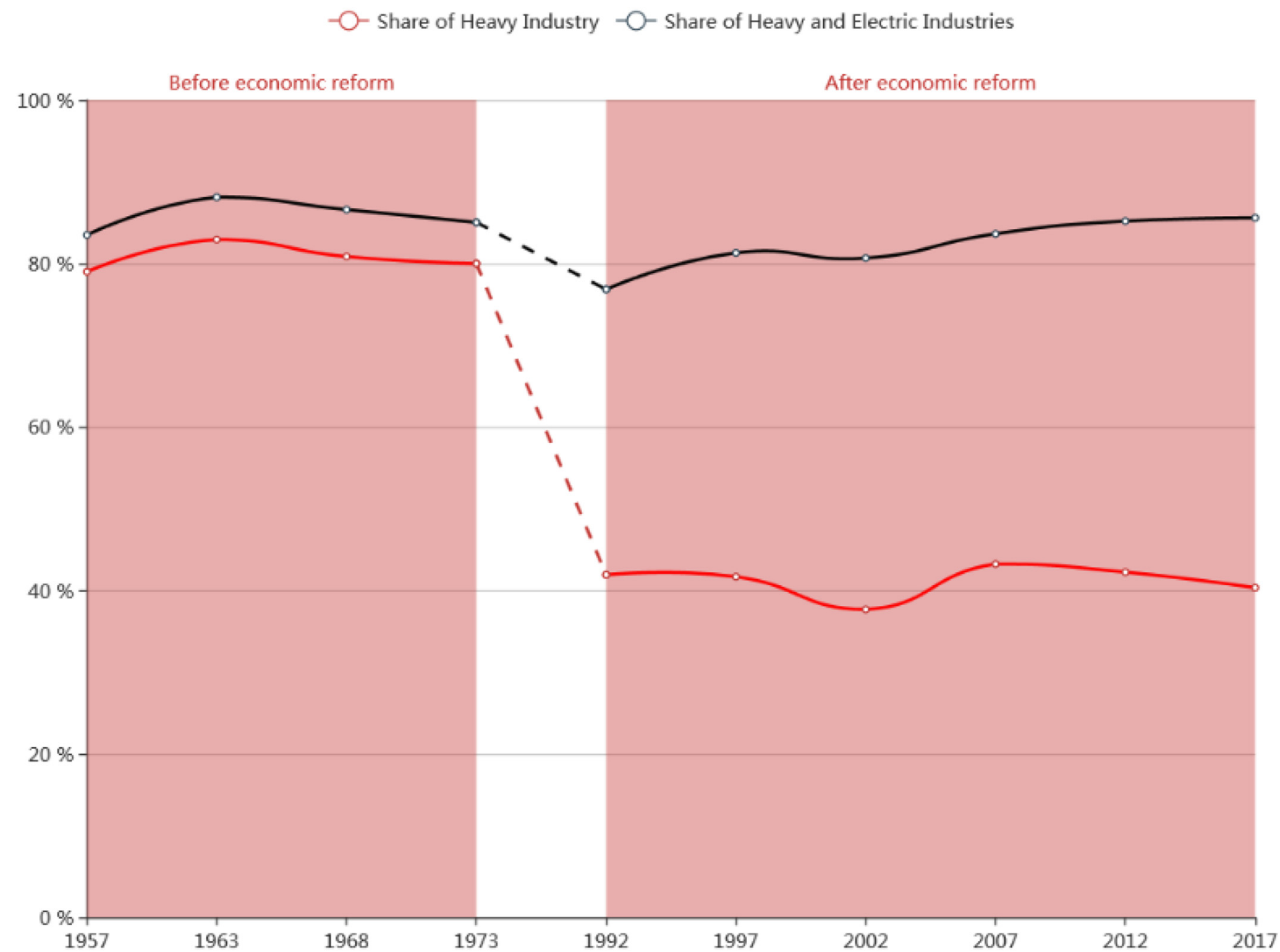


Fig. 3. The shares of CO_2 emissions for heavy industry and electric power.

consistent with the analysis made by Grubb et al. (2015), Green and Stern (2016), and Guan et al. (2018).

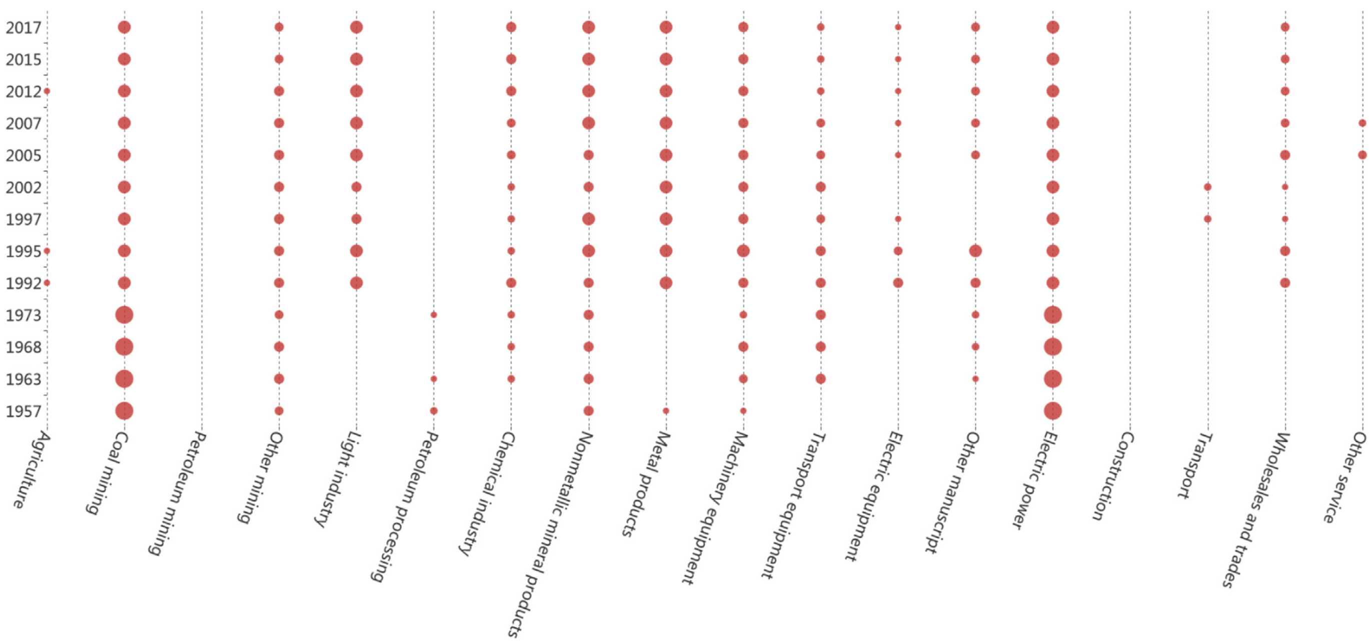
3.2. Stability

To prove the stability of the emission structure, we calculated the Pearson correlation coefficients between the sectoral CO_2 emissions for different years, which were used to measure the linear correlation between two variables. In this analysis, we considered two kinds of sector classifications: the original 18 sector classification, as well as a 6 sector classification. As shown in Fig. 3, emission structure was stable if heavy industry and electric power sector were aggregated. The 6 sectors are agriculture, mining sector, light industry, heavy industry and electric power, construction, and service. In the 6 sector classification, heavy industry and electric power generation are considered as one sector. This is because emissions from electric power generation encroached on the direct emissions from the heavy industry. Our quantitative analysis supports the observation from Fig. 3 that the emission structure of China was stable for more than 60 years-given that heavy industry and electric power generation are aggregated under the PBA framework-although after the economic reform the emission share of heavy industry decreased, while that of the electric power sector increased. A possible explanation is that the increase in CO_2 emitted directly from electric power generation was mainly induced by the demand from the heavy industry. To prove this mechanism, it is necessary to study the intersectoral linkage. However, it is difficult to observe the intersectoral linkage under the PBA framework. Therefore, we will return to this topic in the network analysis to discuss the emissions that are directly from electricity production, but induced by heavy industry production. For details, please see the Appendix.

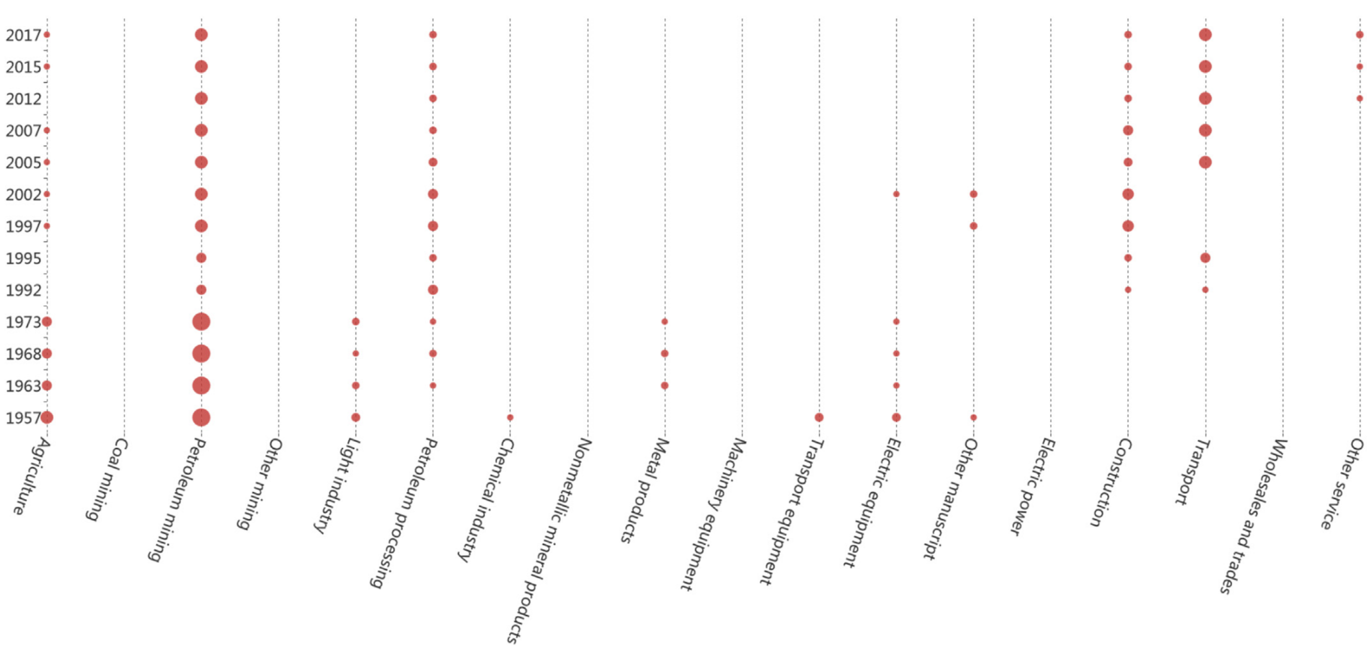
3.3. Network analysis

The previous sections decompose CO_2 emissions in a $1 \times n$ dimensional way; however, this representation fails to characterize the inter-sectoral linkage. For instance, the result of PBA shows that CO_2 emitted directly from the electricity generation sector encroached on that from the heavy industry after China's economic reform. If the inter-sectoral linkage can be calculated, then it is possible to understand whether part of the CO_2 emitted directly from electricity generation was induced by the electricity demand from heavy industries. If so, heavy industry was still the most important contributor of CO_2 emissions after the economic reform.

Fig. 5 visualizes matrix $\mathbf{\Phi}$ to show the inter-sectoral linkage density for 1957, 1973, 2002, and 2017. To visualize the emission network, sectors of the IOTs were treated as nodes and the

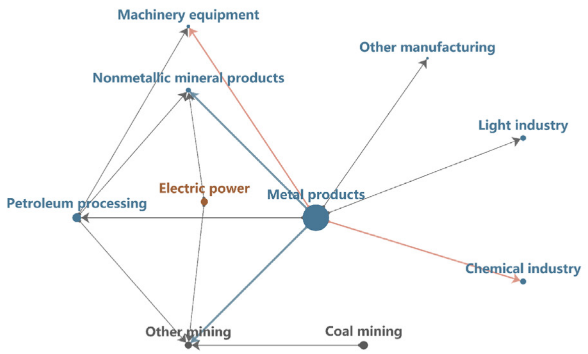


(a) The shares of sectoral CO2 emissions caused by coal

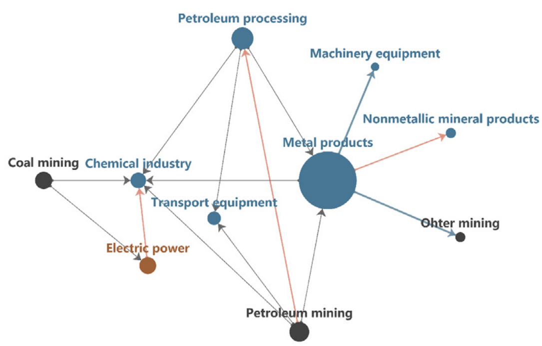


(b) The shares of sectoral CO2 emissions caused by oil and gas

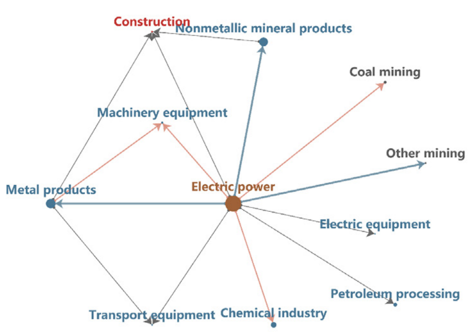
Fig. 4. The shares of emissions caused by different energy for different sectors.



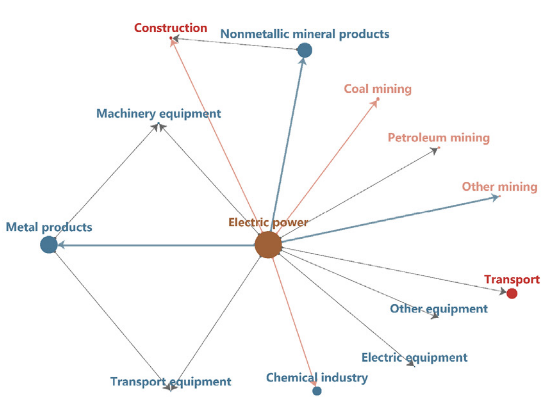
(a) 1957



(b) 1973



(c) 2002



(d) 2017

Fig. 5. Sectoral CO_2 emissions links 1957-2017
notes: The blue arrows recorded the top 1% greatest elements, the red arrows denoted the top 1.5% greatest elements, and the grey arrows represented the remaining top 5% greatest elements, respectively. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

elements of the matrix $\mathbf{\Phi}$ were treated as arrows. The size of the node represents the quantity of the direct emissions from the corresponding sectors, while the color of the arrow denotes the values of the elements of matrix $\mathbf{\Phi}$. To differentiate the sending and receiving sectors, directional arrows were used. An arrow begins from the sector that emits CO_2 directly and points to the sector that drives the demand. In other words, the arrow is from the sending sector to the receiving sector. Let us consider φ_{ij}, the ijth element of $\mathbf{\Phi}$, as an example. The value of φ_{ij} decides the color of the arrow from sector i to sector j. Sectors largely dependent on other sectors will be in the center, while sectors on the periphery are trivial. The sectors in the center are the core sectors. As there are too many $(n \times n)$ elements to be visualized, we chose the top 5% greatest elements in the matrix $\mathbf{\Phi}$ to show the main linkages.

From Fig. 5(a) and (b) it is clear that metal products constituted the core sector, and the emission network dominated by heavy industry was gradually established. Metal products was the most important core sector of the networks for 1957 and 1973. On the one hand, the emissions from metal products were larger than for other sectors; on the other hand, most arrows-especially those representing core linkage density-were associated with metal products. Some sectors, such as the manufacture of electric equipment, transport equipment, and machinery equipment, are integrated into industrial chains and contact other sectors that are based on metal products. Mining sectors and electric power generation provide energy for other sectors, and in this period, mining sectors are more important than electric power. After economic reform, as shown in Fig. 5(c) and (d), the network transformed from having one core to two cores, as the electric power sector gradually became another key node. Heavy industries, such as metal products manufacturing, transport equipment manufacturing, and petroleum processing, surrounded the electric power sector. This implies that heavy industry was the main consumer of electricity. This finding confirms that the increase in CO_2 directly emitted from electric power generation was mainly caused by the demand of heavy industry. Therefore, the stability described by the 6 sector classification with aggregated heavy industry and electric power sector is robust. Heavy industry will always be the most important contributors to CO_2 emissions. From the network Fig. 5, it is also possible to observe the change in the energy structure. In the period 1957–1973, a large portion of coal was used directly in the manufacturing sectors. In contrast, however, a significant portion of coal was used by the electric power sector in the period 1992–2017; the electricity, as secondary energy, served as energy input to the other sectors. Therefore, the core status of coal mining declined in the network after the economic reform, while that of electric power increased.

Furthermore, we also relaxed the filter condition and visualized the networks including the top 50% greatest elements of the matrix $\mathbf{\Phi}$; these are shown in Fig. C1 of the Appendix. By considering more linkages in the matrix, the networks become more complex. Heavy industry was still located in the core of the network and a relatively close cluster formed among heavy industry. The chemical industry was another core sector, and agriculture and other services formed a small cluster together with the chemical industry. The mining sectors associated with each other and made up a small cluster during the period 1957–1973. However, this cluster was disaggregated and the sector was gradually marginalized after 1992. Transport and other service sectors were close to the center of the network after economic reform.

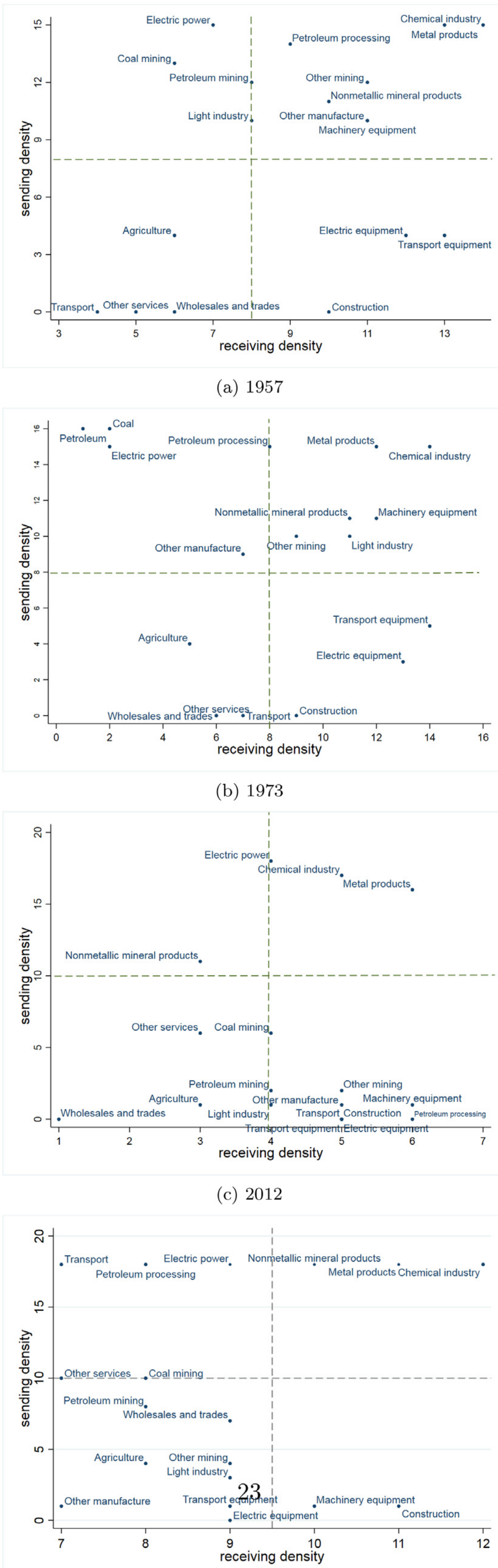


Fig. 6. Pathway of the sector position changes 1957–2017.

Based on the sectoral linkage density, the block model was used to analyze the positions of the sectors in China's emission structure (White et al., 1976). The results are shown in Fig. 6. The horizontal and vertical axes represent the sending and receiving density respectively. The scatter diagram was then divided into four quadrants, with each quadrant corresponding to one of the four types. The high-high (upper right) quadrant indicates the sectors that have the most connections with each other. As these sectors play a "bridge" role, thereby uniting sectors and enhancing the network, they are named intermediate sectors. The low-low (lower left) quadrant indicates the sectors that have the minimal connection with other sectors and are named independent sectors. The high-low (lower right) and low-high (upper left) quadrants exhibit more receiving or sending density and are named receiving sectors and sending sectors, respectively. Fig. 6 shows the 4 types of sectors for the years of 1957, 1973, 2012, and 2017. From this perspective, the industry characteristics remained relatively stable during the period 1957–2017. Metal products and chemical industry are important intermediate sectors, as the products of these sectors are dependent on other sectors and these sectors also supply materials for other sectors. The mining and electric power sectors supply energy inputs, and are characterized as sending sectors; CO_2 emitted directly from these sending sectors. Manufacturing industries are receiving sectors, as the production of these industries is dependent on raw material and components provided by other sectors. The results also confirm the status of heavy industry in the Chinese industry structure. Heavy industry sectors, such as metal production, the machinery industry, and the chemical industry, have been located at the core of the sectoral network and have been closely related with other sectors since the 1950s. Considering the economic situation of the core sectors in the economy, China can change the spatial structure for heavy industry but cannot remove them from the economic system.

In addition to the linkage density given by $\mathbf{\Phi}$ in Eq. (4), the linkage given by $\mathbf{\Theta}$ in Eq. (3) was also considered. In contrast with linkage density, linkage takes the size of the final demand into account. Generally, sectors that have strong sending effects also have a large sending density. However, the size of the final demand also matters. Metal products, petroleum mining, and processing had the most remarkable sending effects during the period 1957–1973, although this status was replaced by electric power after 1992. Meanwhile, nonmetal products also had significant sending effects together with the development of the construction sector, and the receiving effects from transport increased noticeably. Heavy industry at the upstream of the industrial chain has significant sending effects. This is because most heavy industries provide raw materials and semi-finished products, such as metal products, nonmetallic mineral products, and the chemical products, while heavy industries at the downstream of the industrial chain have significant receiving effects, such as the manufacture of machinery and equipment, electric equipment, and transportation equipment. This is the same as the case for the tertiary industry. Service sectors, such as wholesales trades and other services, exert receiving effects and transport increases greatly within the scope of the receiving effects. Construction has been the most important receiving sector since 1992.

3.4. Mitigation pathway analysis

Due to the stable industrial and emission structure, heavy industries of China that perform as core sectors for CO_2 emission could not shrink significantly in near future. Increasing energy efficiency and reducing emissions directly and indirectly from these heavy industries are the keys for Chinas carbon mitigation. As shown by our network analysis, the core heavy industries of emission network are metal products, nonmetallic mineral products, and chemical industries. These sectors are also considered as the key sectors for pollution control by Chinese government (Guan et al., 2018). The main primary energy used by these sectors was coal, while the secondary energy (electricity) used by these sectors were also mainly from coal-fired stations (Zhang et al., 2012). Replacing coal by other cleaner energy sources, such as natural gas, could significantly reduce CO_2 emissions from these sectors. However, China is endowed with coal but not natural gas (Hu, 2016). Meanwhile, considering the size of China's demand, if China conducts a replacement for a vast quantity of coal by natural gas, the international natural gas price would increase sharply (Lin and Wang, 2012). Therefore, the policy of complete substitution toward natural gas in China is unrealistic (Lin and Wang, 2012; Shaikh et al., 2016). Based on this background, a realistic and effective approach of pollution control in near future is to increase the energy efficiency of coal-powered furnaces and electrical generators by weeding out lower efficient facilities (Liu et al., 2015a,b).

If the energy efficiency of these key sectors, such as metal and nonmetallic mineral production sectors, could be increased, the CO_2 emissions induced by the downstream sectors in China, such as machinery and equipment manufacture, electric equipment manufacture, and transportation equipment manufacture sectors, could be reduced. More importantly, China is a major exporter of metal products. An energy efficiency improvement in metal production sector in China could lead to a significant reduction on the emissions induced by the downstream products of the other countries. For electric power sector, both environment-biased technology and energy-saving equipment are conductive to decreasing the CO_2 emissions (Tang et al., 2019). Under the constraint of energy endowment, electric generation process in China would still depend on coal-fired stations in the near future (Zhang et al., 2012). Phasing out older, smaller and inefficient coal-fired power plants and keeping large coal-fired power plants with energy-saving equipment could exert significant effect on emission mitigation (Minx et al., 2011).

4. Discussions and conclusions

This study compiled HEEIOTs of China for the period of 1957–2017. These tables, which include firm-level, industry-level, and macro-level statistical data, are the first HEEIOTs covering the years in the early stages of the People's Republic of China. Analysis of the CO_2 emission structure of China in 1957–2017, based on these tables, reveals that the CO_2 emission structure is relatively stable, due to the stable economic structure associated with the independent economic policy. Consequently, China had a stable economy for more than 60 years. Furthermore, this study visualized the inter-sectoral linkage of emissions and constructed an emission network dominated by heavy industry, which confirmed that the increase in the amount of CO_2 directly emitted from electric power generation was mainly caused by the demand of heavy industry. Correlation coefficients were used to study the stability over time, which implied that if heavy industry and electric power generation are not separated, the emission structure is stable for more than 60 years. Based on the above analysis, we put forth the following discussion points.

First, the stable economic system and emission structure had historical origins. The economic aspect of the independent policy dated from the heavy industry strategy—an import-substitution policy since the 1950s. Although China has officially abandoned the heavy industry strategy, this country still tries to maintain the ability to produce almost every category of products. Therefore, the emission structure was relatively stable for more than 60 years both from the $1 \times n$ dimensional emissions and the $n \times n$ dimensional emission network. Despite the large amount of imports in China after the economic reform, each industry still had a significant part of domestic share. That is, imports and domestic products coexisted in the market and both imported and domestic products were distributed in the whole industry in a well-balanced manner. Due to the stable industrial structure, China could not adopt the policy that suggested importing products from high pollution industries, thus transferring the "dirty" industry to other places. Strengthening technological innovation and encouraging environment-biased technology from the developed countries to improve CO_2 emission efficiency could be more significant for China.

Second, as a large country with significant internal disparity regarding income level, factor endowment, and geographical conditions, China could change the spatial structure of heavy industry. As the core sectors in the economy, heavy industry might transfer from the municipalities and highly developed east provinces to China's central and western provinces. Compared with simply transferring the "dirty" industry to other places without mitigation, facility changes and technology to promote emission efficiency should be accompanied with the industrial spatial changes. In addition, as the comparative advantages of China's different regions are different, China could maintain all types of industry in an efficient way by adjusting and optimizing the industrial layout around the country.

Finally, energy mix also influences emission mitigation in industrial production, and thus, promoting renewable energy and reducing the inputs of fossil fuels are necessary to optimize the energy mix and reduce CO_2 emissions. As heavy industry in China depends heavily upon fossil fuels, especially coal, effective measures should be taken by the government to reduce the cost of renewable energy and encourage enterprises to adjust the energy consumption structure.

Hence, as discussed in the previous sections, the stability of the economic structure leads to the stability of the CO_2 emission structure. Against this background, instead of carbon leakage, technology upgrading is the realistic way for China to achieve increased energy efficiency, emission mitigation and economic development, so that it can keep the promise of reducing CO_2 emissions after they peak around 2030. As one ancient Chinese official stated, "A smart man changes his approach as circumstances change; a wise person alters his means as times evolve." China has entered the new normal of economic development, under this new normal, the economy is shifting from a high to a medium-high rate of growth, from a growth model that emphasized scale and rate to one that emphasizes quality and efficiency, from an economic structure in which economic growth was mainly fueled by the increment and increased industrial capacity to one in which the existing capacity is adjusted and the increment is put to best use, and from being driven by production factors such as resources and low cost labor to being driven by innovation. Today, the country is a world factory; China has taken and will continue to take the responsibility of carbon mitigation as a world factory.

Author contributions section

Jing Li: Methodology, Writing- Original draft preparation. **Shigemi Kagawa:** Software, Writing- Original draft preparation. **Chen Lin:** Conceptualization, Data, Writing- Reviewing and Editing.

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.

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Appendix

Appendix A. Sector classification

Table A1 shows the sector names of 6, 7, and 18 sector classification.

Table A1
Sector classification

6 sector classification	7 sector classification	18 sector classification
Agriculture	Agriculture	Agriculture
Mining sectors	Mining sectors	Coal Mining and Processing
		Petroleum and Natural Gas Extraction
		Other mining
Light industry	Light industry	Light industry
Heavy industry and electric power heat power & water	Heavy industry	Coking gas and processing of petroleum
		Chemical industry
		Manufacture of nonmetallic mineral products
		Manufacture and processing of metals and metal products
		Manufacture of machinery and equipment
		Manufacture of transport equipment
		Manufacture of electric equipment
		Other manufacture
	Production and supply of electric power, heat power & water	Production and supply of electric power, heat power & water
Construction	Construction	Construction
tertiary industry	tertiary industry	Transport, storage, post, information transmission, computer services & software
		Wholesales, retail trades, hotels and catering service
		Other services

Appendix B. Stability

Table B1 shows the correlation coefficients between the sectoral CO_2 emissions of different years according to the PBA. Lower-triangular cells of table B1 report Pearson correlation coefficients for the 6 sector classification, while upper-triangular cells are Pearson correlation coefficients for the 18 sector classification. In the 18 sector classification, the correlation coefficient between the sectoral emission structures for 1957 and 1973 was 0.991. Its counterpart of the 6 sector classification was 0.999, and all of them were statistically significant with a confidence level of 99%. After the economic reform, in the 18 sector classification, the correlation coefficient between the sectoral emission structures of 1992 and 2017 was 0.980. Its counterpart in the 6 sector classification is 0.998. All of them are significantly positive with a confidence level of 99%. These results imply that if we study the two periods (before economic reform and after economic reform) separately, the emission structures would be stable for each period. However, if the two periods are considered together, then the situation is entirely different. In the 18 sector classification, the correlation coefficient between the sectoral emission structures for 1957 and 2017 is 0.332, which is non-significant. This means that the emission structure for 1957 was different than that of 2017 if heavy industry and electric power sector are separated. When the heavy industry and electric power sectors are aggregated in the 6 sector classification, the correlation coefficient between the sectoral emission structures of 1957 and 2017 becomes 0.981, which is significant with a confidence level of 99%. The result is consistent with the observation shown in Fig. 3: if heavy industry and electric power generation are not separated, then the emission structure was stable for more than 60 years. In order to test whether the aggregation of the sectors other than heavy industry and electric power sector affects the significance of the correlation coefficients, a 7 sector classification was also tested, in which heavy industry and electric power sector were separated based on the 6 sector classification. In the 7 sector classification, the correlation coefficient between the sectoral emission structures for 1957 and 1973 is 0.631, which is non-significant. The conclusion is consistent with that of the 18 sector classification. The separation of heavy industry and electric power sector caused the instability during 1957–2017. The results are shown in Table B2.

We also calculated the correlation coefficients between the sectoral CO_2 emissions of different years according to the CBA. For both the 18 and 6 sector classifications, the sectoral CO_2 emissions for each period (before economic reform and after economic reform) were significantly correlated. However, regardless of whether heavy industry and electric power sector are aggregated or not, the emission structure of 1957 is not significantly correlated with that of 2017. It implies that the consumption, investment, and export structure changed fundamentally after the economic reform. In addition, the shares of CO_2 emissions induced by construction, light industry, and tertiary industry increased markedly. Table B3 and B4 in the Appendix shows the correlation coefficients between the sectoral CO_2 emissions of different years under the framework of CBA.

In summary, our quantitative analysis supports the observation from Fig. 3 that the emission structure of China was stable for more than 60 years-given that heavy industry and electric power generation are aggregated under the PBA framework-although after the economic reform the emission share of heavy industry decreased, while that of the electric power sector increased. A possible explanation is that the increase in CO_2 emitted directly from electric power generation was mainly induced by the demand from the heavy industry. To prove this mechanism explicitly, it is necessary to study the intersectoral linkage. However, it is difficult to observe the intersectoral linkage under the PBA framework. Therefore, we will return to this topic in the network analysis to discuss the emissions that are directly from electricity production, but induced by heavy industry production.

Table B1
Pearson correlation coefficients between the sectoral CO_2 emissions of different years under the framework of PBA

years	1957	1963	1968	1973	1992	1997	2002	2007	2012	2017
1957	1	0.998***	0.994***	0.991***	0.274	0.28	0.272	0.389	0.365	0.332
1963	1.000***	1	0.998***	0.996***	0.279	0.289	0.28	0.397	0.373	0.342
1968	1.000***	1.000*	1	0.998***	0.285	0.296	0.288	0.403*	0.379	0.348
1973	0.999***	0.999***	0.999***	1	0.269	0.282	0.274	0.39	0.366	0.334
1992	0.985***	0.988***	0.986***	0.980***	1	0.995***	0.986***	0.983***	0.980***	0.980***
1997	0.987***	0.990***	0.988***	0.983***	0.999***	1	0.994***	0.990***	0.991*	0.992***
2002	0.982***	0.986***	0.984***	0.979***	0.999***	0.999***	1	0.991***	0.994***	0.997***
2007	0.983***	0.987***	0.985***	0.980***	0.999***	1.000***	1.000***	1	0.999***	0.997***
2012	0.984***	0.987***	0.985***	0.980***	0.999***	1.000***	1.000***	1.000***	1	0.999***
2017	0.981***	0.985***	0.982***	0.977***	0.998***	0.999***	1.000***	1.000***	1.000***	1

Notes: Lower-triangular cells report Pearson correlation coefficients of 6 sectors, upper-triangular cells are Pearson correlation coefficients of 18 sectors. *** represents $p < 0.01$, ** represents $p < 0.05$ and * represents $p < 0.1$.

Table B2
Pearson correlation coefficients between the sectoral CO_2 emissions of different years under the framework of PBA for the 7 sector classification

years	1957	1963	1968	1973	1992	1997	2002	2007	2012	2017
1957	1									
1963	0.999***	1								
1968	1.000***	1.000***	1							
1973	0.999***	0.999***	0.999***	1						
1992	0.726*	0.740*	0.741*	0.728*	1					
1997	0.668	0.684*	0.685*	0.673*	0.995***	1				
2002	0.572	0.589	0.591	0.578	0.976***	0.992***	1			
2007	0.670*	0.686*	0.687*	0.675*	0.995***	0.999***	0.991***	1		
2012	0.631	0.649	0.65	0.637	0.988***	0.998***	0.997***	0.998***	1	
2017	0.579	0.597	0.598	0.585	0.977***	0.992***	0.999***	0.993***	0.998***	1

Notes: *** represents $p < 0.01$, ** represents $p < 0.05$ and * represents $p < 0.1$.

Table B3
Pearson correlation coefficients between the sectoral CO_2 emissions of different years under the framework of CBA

years	1957	1963	1968	1973	1992	1997	2002	2007	2012	2017
1957	1	0.29	0.545**	0.821***	−0.171	−0.176	−0.18	−0.18	−0.239	−0.136
1963	0.446	1	0.788***	0.759***	−0.065	0.031	0.014	0.131	0.096	0.131
1968	0.543	0.970***	1	0.802***	−0.13	−0.058	−0.056	0.019	−0.005	0.036
1973	0.491	0.991***	0.977***	1	−0.232	−0.163	−0.167	−0.096	−0.145	−0.062
1992	−0.515	0.396	0.207	0.306	1	0.965***	0.940***	0.894***	0.877***	0.851***
1997	−0.58	0.413	0.242	0.331	0.967***	1	0.982***	0.963***	0.950***	0.943***
2002	−0.615	0.376	0.24	0.294	0.947***	0.969***	1	0.968***	0.965***	0.961***
2007	−0.495	0.519	0.369	0.44	0.946***	0.989***	0.969***	1	0.989***	0.978***
2012	−0.478	0.546	0.406	0.473	0.916**	0.979***	0.955***	0.997***	1	0.983***
2017	−0.427	0.587	0.47	0.513	0.878**	0.950***	0.942***	0.984***	0.992***	1

Notes: Lower-triangular cells report Pearson correlation coefficients of 6 sectors, upper-triangular cells are Pearson correlation coefficients of 18 sectors. *** represents $p < 0.01$, ** represents $p < 0.05$ and * represents $p < 0.1$.

Table B4
Pearson correlation coefficients between the sectoral CO_2 emissions of different years under the framework of CBA for the 7 sector classification

years	1957	1963	1968	1973	1992	1997	2002	2007	2012	2017
1957	1									
1963	0.44	1								
1968	0.53	0.969***	1							
1973	0.488	0.990***	0.970***	1						
1992	−0.59	0.249	0.094	0.139	1					
1997	−0.622	0.329	0.187	0.229	0.964***	1				
2002	−0.711*	0.224	0.108	0.125	0.941***	0.960***	1			
2007	−0.522	0.484	0.351	0.392	0.917***	0.978***	0.942***	1		
2012	−0.564	0.457	0.323	0.371	0.883***	0.964***	0.935***	0.993***	1	
2017	−0.523	0.489	0.38	0.401	0.849**	0.942***	0.925***	0.984***	0.992***	1

Notes: *** represents $p < 0.01$, ** represents $p < 0.05$ and * represents $p < 0.1$.

Appendix C. Network with more linkages

Fig. C1 relaxed the filter condition and visualized the networks including the top 50% greatest elements of the matrix $\boldsymbol{\Phi}$. In this part, we relax the filtration criterion and show network figures with more linkages. The darker arrows denote greater linkage density: the black arrows indicate greatest linkage density: $\varphi_{ij} > 0.0001$; red and blue arrows denote relatively smaller linkage densities, $\varphi_{ij} > 0.00005$ and $\varphi_{ij} > 0.00001$, respectively; grey arrows represent the remaining linkages.

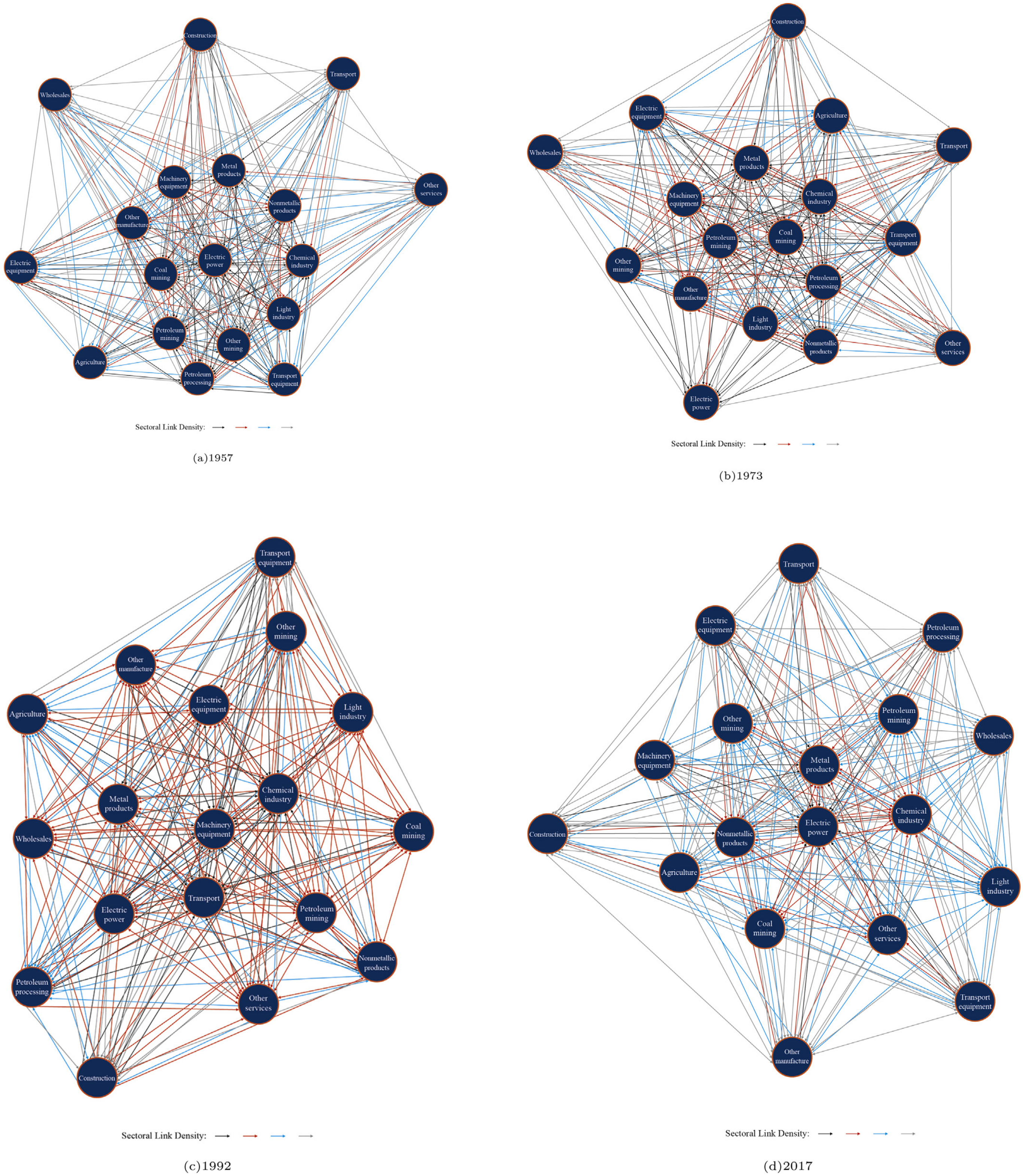

Fig. C1. Sectoral CO_2 emissions links 1957–2017

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