Carbon emissions in China's thermal electricity and heating industry: An input-output structural decomposition analysis

Abstract

CO_2 emissions from China accounted for 27 per cent of global emisions in 2019. More than one third of China's CO_2 emissions come from the thermal electricity and heating sector. Unfortunately, this area has received limited academic attention. This research aims to find the key drivers of CO_2 emissions in the thermal electricity and heating sector, as well as investigating how energy policies affect those drivers. We use data from 2007 to 2018 to decompose the drivers of CO_2 emissions into four types, namely: energy structure; energy intensity; input-output structure; and the demand for electricity and heating. We find that the demand for electricity and heating is the main driver of the increase in CO_2 emissions, and energy intensity has a slight effect on increasing carbon emissions. Improving the input-output structure can significantly help to reduce CO_2 emissions, but optimising the energy structure only has a limited influence. This study complements the existing literature and finds that the continuous upgrading of power generation technology is less effective at reducing emissions and needs to be accompanied by the market reform of thermal power prices. Second, this study extends the research on CO_2 emissions and enriches the application of the IO-SDA method. In terms of policy implications, we suggest that energy policies should be more flexible and adaptive to the varying socio-economic conditions in different cities and provinces in China. Accelerating the market-oriented reforms with regard to electricity pricing is also important if the benefits of technology upgrading and innovation are to be realised.

Keywords

Carbon dioxide reduction; Energy intensity; Energy structure; Electricity; Decomposition analysis; China

1 Introduction

Currently, China's electricity supply structure is primarily dominated by thermal electricity, which accounts for more than 70 per cent of the total electricity generated in the country; more than 60 percent of thermal electricity is generated by burning coal (National Bureau of Statistics, 2016). In 2016, China's electric power industry consumed 52 percent of the country's coal and released 34 per cent of the country's CO_2 emissons (Yang and Lin, 2016). The International Environment Agency (IEA) reported that China's electric power industry released 48.6 per cent of the country's CO_2 in 2015, which is higher than the global average of 41.9 per cent during the same period (IEA, 2016). In order to facilitate a move away from high carbon dependency, China has been promoting a non-fossil energy substitution policy in order to transform the energy sector and accelerate the upgrading of technology used within the industry.

During the 11th period (2006-2010) and the 12th period (2011-2015) of the five-year plan[1], the Chinese government introduced a series of carbon reduction policies in order to accelerate the upgrading of technology, reduce energy consumption and optimise the energy structure in the thermal and heating sector. One of the key tasks undertaken during the 12th period of the five-year plan was to advance the reforms in energy production, prioritise and strengthen the energy conservation strategy, and comprehensively improve the efficiency of energy conversion and utilisation (National Energy Administration, 2013). However, despite these efforts, carbon emissions from the thermal and heating sector continued to rise significantly during the period between 2007 and 2015 (National Energy Administration, 2016).

The contradiction between China's energy policy goals and the reality of the situation has put great pressure on the country to achieve its carbon emission reduction targets. In response to the huge pressures created by the low-carbon movement, the National Development and Reform Commission (NDRC) held a press conference on 19th December 2017 at which they announced the official launch of the national carbon emission trading system, and issued the 'national carbon emission trading market construction plan (electricity generation industry)'. As the only industry to be included in the early stages of creating the national carbon market, the electricity power industry has formally entered the era of carbon constraints. In 2017, approximately 1,700 electrical enterprises were included in the national carbon market, emitting about 3 billion tons of carbon dioxide annually. However, due to the existing energy structure and the historical electricity installation layout, it is likely that the domestic electricity production structure will continue to be dominated by coal-fired plants. In other words, it is difficult for China to effectively change its electricity supply structure, which means that it will remain a predominantly high-carbon based system in the short term. In addition to the current constraints on the electricity production structure, China's electric power industry also has to contend with a significant carbon lock-in effect. Through the use of measures such as the replacement of non-fossil energy, improving the utilisation of coal, and upgrading the technology used to generate thermal electricity,

[1] The five-year plan is a blueprint that sets out goals and directions for the long-term development of China's national economy.

the industry succeeded in reducing carbon dioxide emissions by 13.7 billion tons from 2006 to 2018. However, the average operating lifespan of coal-fired generating units in China is about 12 years, and the average operating lifespan of million-kilowatt units is about 5 years; consequently, it is difficult to eliminate the carbon lock-in effect of thermal electricity generation in the short term.

Previous studies have aimed to investigate the relative contributory factors to CO_2 emissions (Ang,1999; Sun, 2005; Zhang et al., 2008, Mi, et al., 2017; Mi, et al., 2020; Zheng et al., 2019). The most frequently used methods include the IPCC method (IPCC, 2006), the IPAT method (Fu et al., 2015), the metafrontier non-radial MCPI method (Zhou, 2012); the DEA method (Yang, 2009); and the LMDI method (Zhou, 2014; Liu, 2015). However, although these studies have examined various impact factors such as the energy intensity and energy structure of energy-related CO_2 emissions, they have a drawback in that they have mainly focused on a single CO_2 emissions index and failed to comprehensively reflect the linkages between the different industrial sectors. Therefore, it is hard to assess the impact of sectoral connection and economic structural factors on carbon emissions.

To this end, this study is designed to explore two main perspectives: first, it examines the energy structure, energy intensity, and electricity generation technology on the production side; and second, it analyses electricity and heating demand on the demand side. In order to identify the cause of the conflict between the objectives of China's energy policy and the reality, it is important to quantify the drivers and assess the impact of energy policy on each driver. Currently, CO_2 intensity and per capita CO_2 emissions are commonly used to assess CO_2 emissions (Fan et al., 2007; Jobert et al., 2010). Based on the Input-Output (IO) tables that link the thermal electricity and heating sector and other sectors, this study assesses the key factors that contribute to generating CO_2 emissions, by examining the energy structure, energy intensity, and electricity generation technology (Paul, 2016; Wang, 2010; Wang et al., 2019).

Although China is committed to optimising its energy structure and constantly developing new thermal electricity generation technologies, carbon emissions from the thermal electricity and heating sector have continued to rise. This study aims to examine the key drivers of CO_2 emissions in the thermal electricity and heating sector, as well as investigating how energy policies affect those drivers. In this study, we use an input-output structural decomposition analysis (IO-SDA) method to investigate the drivers of CO_2 emissions in China's thermal electricity and heating sector from 2007 to 2018. First, we calculate the CO_2 emissions as well as assessing the energy structure. Second, the study investigates the contribution and the evolutionary trend of the demand structure of different industry sectors with regard to CO_2 emissions in China's thermal electricity and heating sector. Third, the slack based measurement data envelopment analysis (SBM-DEA) model with unexpected output, and the Adjacent Malmquist model, are used to evaluate the energy efficiency and technical efficiency values for each of the provinces, respectively. Finally, this study analyses the key drivers of CO_2 emission and the internal causes of changes in each driver, as well as assessing the impact of energy policy on each driver. The effect of optimising the energy structure of China's thermal electricity and heating sector is also taken into consideration.

This research contributes to the existing literature regarding the reduction of CO_2 emissions from the electricity sector in the following ways. First, it complements the relevant literature on the impacts of upgrading electricity generation technology on reducing carbon emissions by introducing the Adjacent Malmquist model (Zhang, 2013; Wang et al., 2019). The existing research argues that the continuous upgrading of electricity generation technology has significantly reduced carbon emissions in China (Zhang, 2013; Wang et al., 2019). Nevertheless, our study finds that the reality does not conform to expectations of previous scholars, by capturing the actual suitation regarding emissions reduction in the thermal electricity and heating sector during the period from 2007 to 2018, based on the three-yearly IO data. This finding helps to offer insight into the potential conflict between energy policy and the reality of the situation in practice. In addition, the dynamic analysis the of technical efficiency of the thermal electricity and heating sector can help to predict further trends and enable energy policy to be tailored accordingly.

Second, this study expands the literature on CO_2 emissions from electricity generation in China (Zhang et al., 2013; Paul, 2016; Wang et al., 2019) by applying the SBM-DEA model with unexpected output to assess the effects of energy structure optimisation in the thermal electricity and heating sector for 30 procvinces between 2007 and 2018. The existing research has only focused on the overall effect on emissions reduction of optimising the energy structure, but without measuring the slack and redundancy of the input and output variables. This aspect of the study complements the existing related research, and provides a valuable reference that the government can use to adjust the energy structure of the thermal electricity and heating sector in a scientific and rational way, and to formulate appropriate energy structure optimisation strategies.

Third, this study enriches the application of the IO-SDA method (e.g., Su and Ang, 2012; Su et al., 2013; Wei et al., 2017). By refining the decomposition, we clarify the mechanism by which the industrial sectors' final demand is transmitted to the reduction of emissions in the thermal electricity and heating sector. In addition, the impacts of adjustments in energy consumption on the energy structure and the impact of energy intensity on carbon emissions in different regions are also evaluted. The use of provincial-level data and the refined analysis help to reveal differences between various regions and thus provide a more detailed reference for formulating carbon emission reduction policies. This part of the research also complements the Karmellos et al.'s (2016) study by providing theoretical support for promoting the achievement of CO_2 reduction targets, specifically with regard to the thermal electricity and heating sector in developing countries.

The paper is organised as follows: Section 2 reviews the literature in relation to energy intensity, energy efficiency, electricity generation technology and energy structure. Section 3 explains the data and methodology. Section 4 presents the results. Section 5 offers a discussion and suggests policy implications. Section 6 summarises the key findings of the paper and highlights the main contributions of this research.

2 Literature review

Carbon emissions from electricity generation dominate China's energy-related CO_2 emissions. Evaluating the performance of fossil fuel electricity generation and its potential for reducing carbon emissions are of great significance with regard to promoting low-carbon development (Zhou, 2012). Many studies have explored potential ways of reducing CO_2 emissions from electricity generation and provided policy suggestions. For example, Maruyama and Eckelman (2009) estimated long-term reduction trends in 138 countries and regions, with an emphasis on non-Organization for Economic Cooperation and Development (OECD) countries, and Ang et al. (2011) assessed CO_2 reduction in 129 countries, excluding the six Gulf Cooperation Council member countries, recorded by the IEA statistical database. Unlike the benchmark studies described above, Zhou (2012) applied a non-radial direction distance function method to evaluate the effectiveness of CO_2 emission reduction strategies and found that OECD countries performed better in terms of reducing CO_2 emissions from electricity generation. There are two streams of literature related to our study. The first stream focuses on evaluating the CO_2 index and exploring the energy intensity, energy efficiency and electricity generation technology in China's electricity sector using the framework of low carbon development. Studies within the second stream have tried to identify the driving force(s) behind CO_2 emissions from the demand side.

2.1 Energy intensity, energy efficiency and electricity generation technology

2.1.1 Energy intensity

In terms of electricity generation, carbon intensity denotes the amount of carbon emissions per unit of electricity generation (Peng and Tao, 2018). Zhang (2005) investigated the carbon intensity of electricity generation in three Chinese provinces, Guangdong, Liaoning and Hubei, from 1990 to 2010; he found that the declining trend oincarbon intensity with regard to electricity generation and its provincial variations were mainly due to complex central planning, financial and institutional factors.In order to improve the estimation accuracy of carbon intensity in China's industrial sector (including the electricity sector) and provide a more comprehensive reference for energy policy, Liu (2015) firstly applied the Logarithmic Mean Divisia index (LMDI) to conduct an in-depth study of the factors affecting carbon intensity and divided these into three categories: the emission coefficient effect; the energy intensity effect; and the energy structure effect. The results showed that the energy intensity effect was the main driving force in terms of reducing carbon intensity from 1996 to 2012. Ang (2016) studied the aggregate carbon intensity (ACI) for electricity generation at a national level and found that the ACI in China had fallen from 0.905 in 1990 to 0.6916 in 2013. This reduction could be due to improved energy efficiency rather than fuel switching.

2.1.2 Energy efficiency

With regard to electricity generation, many studies have applied the production efficiency approach, involving methods such as data envelopment analysis (DEA), to investigate the efficiency of thermal electricity generation in China. Yang (2009) established six models based on DEA to assess the performance of each decision unit. Yang (2010) evaluated the energy efficiency of China's thermal electricity production in 2002. In addition, Zhou et al. (2012) also used the DEA model to explore the efficiency of thermal electricity generation. As well as conducting DEA, Zhou (2014) used the LMDI method to investigate the efficiency of China's thermal electricity generation on a regional basis from 2004 to 2010. He found that reducing energy intensity and optimising the energy structure can contribute to CO_2 reduction. Liu (2015) applied the LMDI to decompose China's carbon intensity into three different effects: the emission coefficient effect; the energy intensity effect; and the energy structure effect for the period from 1996 to 2012; he found that energy efficiency improvement plays a key role in reducing energy intensity. In addition to this, Choi and Ang (2012) applied an attribution analysis to quantify the real changes that had occurred in terms of energy intensity. They concluded that the effects of energy intensity mainly contribute to reducing carbon intensity and also found that the effect of the emission coefficient on carbon intensity increased with the expansion of electricity consumption.

2.1.3 Electricity generation technology and energy structure

To provide insights into the effects of technological innovation and structural adjustment that have occurred within China's electricity industry in recent years, Peng and Tao (2018) investigated changes in the carbon intensity of electricity from 1980 to 2014. They found that, since 1980, the impact of technological innovation on the decline in carbon intensity has been greater than that of structural adjustment. However, as electricity generation technology matures, carbon emission reduction in China's electricity industry will come to rely mainly on renewable energy. Researchers have devoted much attention to evaluating the work of decision-making units. Many existing studies attribute the inefficiency in the electricity industry to the ineffective management of decision-making units, as well as the fact that the generally unfavourable operating environment has been neglected. In a departure from other studies, Yang (2009) applied the DEA approach to studying coal-fired electricity plants in China and found that the unfavourable operating environments in some electricity plants resulted in relatively low-efficiency scores. The implementation of appropriate market and regulatory mechanisms could eliminate this inefficiency and bring substantial economic and environmental benefits. In order to identify the dynamic changes in total-factor carbon emission performance that have taken place, Zhang (2013) proposed using the metafrontier non-radial Malmquist CO_2 emission performance index (MCPI) method to estimate these changes in China's thermal electricity plants from 2005 to 2010. The study found that technological advances and changes in energy structure can have a positive influence on reducing CO_2 emissions.

Even though many studies have employed the decomposition method to investigate energy-related emissions, less attention has been paid to the linkages between energy policy and the various drivers. In this study, we apply the IO-SDA method to analyse the factors driving CO_2 emissions in the thermal electricity and heating sector and investigate the historical evolution of each of the drivers that accompanied the implementation of the energy policies. This leads us to a different conclusion from that which has been reached by the existing studies. Related literature has mainly focused on the factors driving carbon emissions from coal-fired electricity plants before 2012. Our research spans a time period covering three five-year plans, which allows us to explore the contradiction between the policy objectives and outcomes. This helps us to explore the causes of this and ascertain what influenced the policy outcomes and the possible deviations from the policy.

Second, some of the related research has applied the DEA model to explore the efficiency of thermal electricity generation to assess its impact on CO_2 emissions. In this study, we introduce the SBM-DEA model and treat CO_2 emissions as an unexpected output in order to assess the energy efficiency of the thermal electricity and heating sector for 30 provinces from 2007 to 2018. By measuring the slack and redundancy of the input and output variables, this study proposes a scheme to optimise the energy structure of the thermal electricity and heating sector, which provides a valuable reference that the government can use to formulate energy structure optimisation strategies in a scientific way. In addition, this study further measures the dynamic technical efficiency within the thermal electricity and heating sector by applying the Adjacent Malmquist model, which is conductive to predicting future trends and formulating appropriate energy policies. Third, most studies have mainly focused on a single CO_2 emissions index and failed to comprehensively reflect the linkages between the different industrial sectors. Therefore, it is hard to assess the impact of sectoral connection and economic structural factors on carbon emissions. This paper further investigates the impact of technological progress, the energy consumption structure and economic scale among different industrial sectors on CO_2 emissions.

2.2 Electricity demand

Demand for electricity has been rising steeply in China during recent years. Increasing fluctuations in electricity demand and insufficient peak shaving (levelling out of peaks in electricity demand) capacity within the electricity supply system constitute two major problems. Analysing changes in demand for electricity within different industrial sectors can provide a reference for electricity demand forecasting, as well as useful guidance for formulating industrial electricity saving and electricity development plans and/or policies. In order to predict China's electricity demand and ensure a stable electricity supply, Paul (2016) applied a decomposition analysis method to assess the effect of changes in various industrial sectors on electricity demand from 1998 to 2002. During the period from 1998 to 2007, China's industrial electricity consumption increased dramatically. In response to this, Wang (2010) applied the LMDI approach to assess the driving forces behind this growing demand for electricity, and found that the production of electricity and heat was one of the biggest contributors. They concluded that these sectors should be given priority in terms of industrial restructuring. Wang et al. (2019) applied a modified SDA model to assess the key factors accounting for the rise in CO_2 emissions from electricity generation in China between 2007 and 2012. He found that the increase in CO_2 emissions resulting from electricity generation was mainly driven by changes in electricity demand.

Some existing studies have investigated the effect of changes in the industrial sector on electricity demand by applying the decomposition analysis method, such as those by Paul (2016) and Wang et al. (2019), described above. However, the demand for electricity from China's industrial sector increased rapidly from 2007 to 2015, accounting for approximately 72 per cent of China's total electricity consumption (National Energy Administration, 2016). It is debatable whether the effects of the demand from the industrial sector for electricity are currently still following the same trajectory outlined by Paul (2016) and Wang (2019), as it may be that some structural adjustment to demand has occurred within the industrial sector. Thus, it is important to study the factors that contribute to demand for electricity and to decompose the drivers of carbon emissions resulting from electricity generation. In addition, this study explores how the consumption trends of various industrial sectors evolved during the period from 2007 to 2015 in order to discover which sectors had a high demand for electricity and heating. These results will help to provide policy suggestions to accelerate the optimisation of the demand structure on the consumption side and achieve the short-term goal of reducing emissions.

3 Data and methodology

3.1 Data sources

The data used for this study are derived from China's Energy Balance tables, and the China Energy Statistical Yearbook and Input-Output (I-O) tables for 2008, 2011, 2013, 2016 and 2019 (The yearbook releases data with a one-year lag, which means the 2008 statistical yearbook contains data for 2007, and so on). The data consists of input and output data for 42 industrial sectors, 20 types of energy input data for the thermal power and heating departments of 30 provinces, and output data on power, heat and CO_2. China is divided into four economic regions, namely the eastern, central, western and northeastern regions. Due to the availability of data, we only studied 30 provinces, which are divided as follows: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan belong to the eastern region; Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan are located in the central region; Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang belong to the western region; and Liaoning, Jilin and Heilongjiang form part of the northeastern region. We adjusted the I-O tables according to the constant price in 2007 and subtracted the imports, because these are produced abroad and therefore do not consume any of China's products and energy in the manufacturing process. The energy balance sheet provides the figures for the usage of each energy source. The conversion standard refers to the conversion coefficient published by the National Bureau of Energy Statistics. The carbon emission coefficients and the average lower heating value of each energy source refers to data published in the 2006 Intergovernmental Panel on Climate Change (IPCC) report. The I-O table gives statistics for the intermediate input, final use, and total output data of each sector. We used the year 2007 as the base period and adjusted the corresponding I-O tables using the constant price in 2010, 2012, 2015 and 2018, respectively. The amount of energy used in thermal electricity generation and the heating sector, for each category of energy, is shown in Table 1. We applied the SBM-DEA model to study the optimisation of the energy structure, and because the model has quantitative requirements regarding the input variables, output variables and the number of decision making units, we combined the 20 input energy sources into 4 types: namely, Total Coal; Total Petroleum Products; Coal Gas; and Gas (the quantity selection criteria used for the variables are explained in subsection 3.2.2).

Table 1

Energy use (unit: 10^4 tce) in thermal electricity generation and heating sector.

Classification of energy	Categories of energy	2007	2010	2012	2015	2018
Total Coal	Raw Coal	101609.9	118482.8	139522.5	142869.8	165963.2
	Cleaned Coal	40.47	13.7	90.95	79.07	0
	Other Washed Coal	1301.99	1395.08	1197.24	1182.43	1871.2
	Briquettes	0	0	0	0	0
	Coke	0	0	0	273.89	20.65
	Other Coking Products	0	0	0	0	0
Total Petroleum Products	Crude Oil	23.59	9.99	17.46	27.36	21.86
	Gasoline	0.19	0.13	0.12	0.35	0.1
	Kerosene	0	0	0	0	0
	Diesel Oil	337.19	171.44	55.38	41.64	45.96
	Fuel Oil	995.83	464.62	329.19	280.93	106.67
	Refinery Gas	256.52	392.52	324.97	286.2	363.12
	Other Petroleum Products	240.74	151.91	29.3	50.34	21.38
Gas	Liquefied Natural Gas (LNG)	8.79	1.51	0.12	5.61	6.87
	Natural Gas	1226.22	2314.83	2897.87	4310.14	6388.16
	Liquefied Petroleum Gas (LPG)	0	310.09	329.69	303.93	364.72
Coal Gas	Coke Oven Gas	5476.95	10573.78	12214.61	13667.46	13638.41
	Blast Furnace Gas	0	14818.96	18469.02	26825.7	37130.04

Converter Gas	0	1793.37	3394.02	3631.54	7294.4
Other Gas	11661	0	0	228.39	86.25

Data source: China Energy Statistics Yearbook 2008–2019. The yearbook releases data with a one-year lag.

The conversion factors for calculating CO_2 emission from different types of energy are shown in Table 2.

Table 2

Conversion factors for calculating CO_2 emissions from different types of energy.

Categories of energy	**CO_2 emissions per heat unit (t /10^3 J)**	**Average lower calorific value (10^{-6}J/t)**	**CO_2 emission factors (t CO_2/t)**	**Conversion coefficient to standard coal (t tec/t)**
Raw Coal	97967	20908	2.4083	0.7143
Cleaned Coal	97967	26344	2.5808	0.9
Other Washed Coal	97967	8363	0.8193	0.357
Briquettes	97500	8363	0.8154	0.6
Coke	107000	28435	3.0425	0.9714
Coke Oven Gas	44400	16726(10^3J/m^3)	7.4263(10^{-4}t/m^3)	5.93
Blast Furnace Gas	260000	5227(10^3J/m^3)	13.5902(10^{-4}t/m^3)	1.286
Converter Gas	260000	5227 (10^3J/m^3)	13.5902(10^{-4}t/m^3)	2.286
Other Gas	260000	5227(10^3J/m^3)	13.5902(10^{-4}t/m^3)	6.9
Other Coking Products	97500	33453	3.2617	1.3
Crude Oil	73300	41816	3.0651	1.4286
Gasoline	70000	43070	3.0149	1.4714
Kerosene	71900	43070	3.0967	1.4714
Diesel Oil	74100	42652	3.1605	1.4571
Fuel Oil	77400	41816	3.2366	1.4286
LPG	63100	50179	3.1663	1.7143
Refinery Gas	57600	46055	2.6528	1.5714
Other Petroleum Products	73300	41816	3.0651	1.2
Natural Gas	56100	38931(10^3J/m^3)	21.8403(10^{-4}t/m^3)	1.22
LNG	56100	54071	3.0334	1.7572

Note: The LNG data was computed using the mass and volume.

The data source, China's Energy Balance Sheet, listed 17 different energy sources for 2007 and 20 energy sources for 2012 and 2015. In order to standardise them, we classified the energy sources into 17 categories. Given the data availability, this study followed the classification used by Wang et al. (2019) and merged the original 42 sectors in the I-O table into 9 sectors. Table 3 shows the descriptive statistics for various data.

Table 3
Descriptive statistics.

	Year	n	Min	Max	Mean	SD
Total Coal (unit: 10^4 tce)	2007-2018	150	104.55	20025.72	4749.00	4003.80
Total Petroleum Products (unit: 10^4 tce)	2007-2018	150	0.00	818.35	32.33	77.91
Gas (unit: 10^4 tce)	2007-2018	150	0.00	1634.00	128.60	259.68
Coal Gas (unit: 10^4 tce)	2007-2018	150	0.00	19029.56	1877.33	2650.88
Heat (10^{10} kJ)	2007-2018	150	47.90	133092.95	17569.61	19984.39
Power (10^8 kW•h)	2007-2018	150	83.10	5488.24	1302.24	1083.79
CO_2 (unit: 10^4 tons)	2007-2018	150	779.07	108924.47	25994.67	21832.96

3.2 The Model

The decomposition of factors driving CO_2 emissions in the thermal electricity and heating sector from 2007 to 2018 and the analysis of the internal causes are depicted in Fig. 1. The research flow chart is divided into four steps.

First, we collected relevant data from 30 provinces and 42 industrial sectors for the period 2007-2018. This consisted of the annual consumption figures for 20 types of energy use, heat, power generation and CO_2 emissions from thermal power and heating sector for 30 Chinese provinces, and the I-O data for all 42 industrial sectors from the I-O tables. For modelling purposes, the different types of energy use are regarded as the inputs, while heat, power generation and CO_2 emissions are regarded as the three outputs, of which CO_2 emissions are treated as the undesirable output.

Second, the IO-SDA model was introduced to decompose the factors driving CO_2 emissions into four types, namely: energy structure; energy intensity; input-output structure; and the demand for electricity and heating. Subsequently, the contribution of each driver to the thermal electricity and heating sector, and its evolutionary trend, were examined.

Third, the SBM-DEA model and Adjacent Malmquist model were constructed to evaluate the energy efficiency (to help us assess how the energy structure can be optimised) and technical value (to help us assess the effect of the input-output structure) for each of the provinces, respectively. The slack variables of various provinces, and the possible reasons behind the adynamic change in energy efficiency and technical value were then analysed. Based on the analysis of the slack variables, this study provides energy structure optimisation schemes for the thermal electricity and heating sector. In addition, changes in CO_2 emissions resulting from technological upgrading were also measured using the Adjacent Malmquist model. The study then evaluated the energy intensity in different regions to assess the contribution of the final demand in each sector to CO_2 emissions in order to further analyse the energy intensity effect and the final demand effect.

Finally, this study uncovered the key drivers of CO_2 emissions, as well as analysing the internal causes of changes in each driver and assessing the impact of energy policy on each driver. Some suggestions for optimising the energy structure, improving the energy intensity, increasing technical emissions reduction, and policy implications are then provided based on the experimental results.

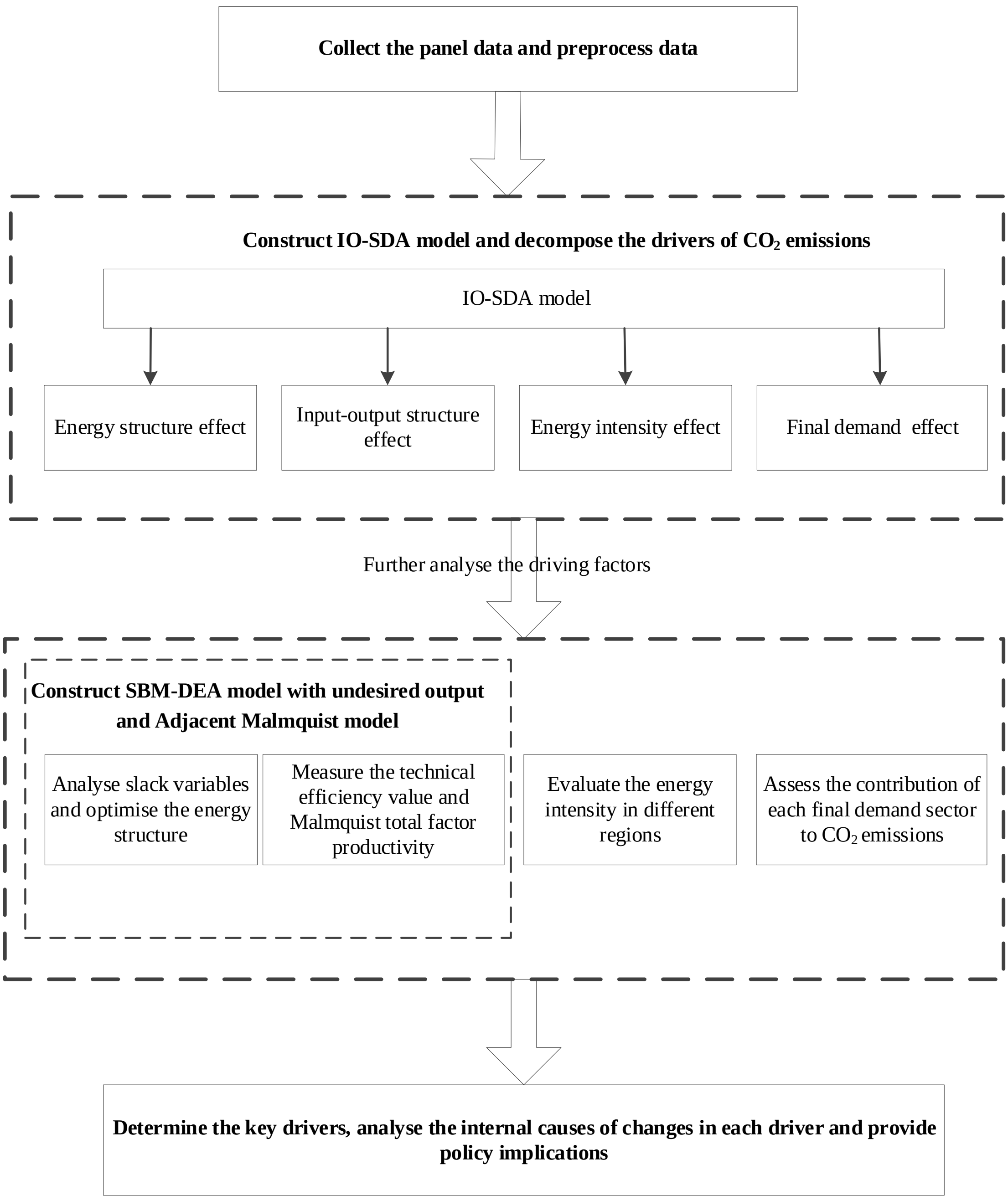


Fig. 1. Flow chart of the research process

3.2.1 I-O SDA model

The I-O tables reveal the complex interdependencies between different economic sectors, as well as showing how commodity production and commodity exchange are linked. I-O tables are therefore widely used to measure direct and indirect CO_2 emissions in various sectors. For the I-O table, the direct consumption coefficient matrix A can be set as:

$$A=[a_{ij}], a_{ij}=\frac{Z_{ij}}{Z_j} \tag{1}$$

where Z_{ij} refers to the intermediate input from sector i to sector j, i=$1,2,\cdots n$, j=$1,2,\cdots n$. $Z=[z_i]$ represents the total output of sector i. $Y=[y_i]$ denotes the final demand from sector i. The total output vector can then be expressed as:

$$\begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{pmatrix} + \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \tag{2}$$

Formula (2) can be transformed into:

$$AZ+Y=Z \tag{3}$$

Then, equation (3) can be simplified as:

$$Z=(I-A)^{-1}Y \tag{4}$$

where I represents the identity matrix and $L=(I-A)^{-1}$ represents Leontief's inverse matrix. In sector i, the CO_2 generated by consuming the energy source k can be calculated as:

$$E_{ik} = f_k \times C_{ik} = \frac{E_{ik}}{C_{ik}} \times C_{ik}, i=1,2,...,n, k=1,2,...,m. \tag{5}$$

where f_k denotes the CO_2 emission coefficient of energy source k and C_{ik} represents the amount of energy combustion of energy source k, $k=1,2,...,m$.

The CO_2 emission coefficient of energy source k is computed as follows:

$$f_k = T_k \times Q_k \tag{6}$$

where T_k is the amount of CO_2 emissions per unit of heat produced by combusting the energy source k ; Q_k is the average lower heating value of energy source k . The values of T_k and Q_k were obtained from the IPCC (2006).In order to explore the impacts of the energy structure, energy intensity, the input-output structure and final demand on CO_2 emissions, we transformed C_{ik} from formula (5) into $C_{ik}=\frac{C_{ik}}{C_i}\times\frac{C_i}{X_i}\times X_i$ and obtained the following:

$$E_{ik}=\frac{E_{ik}}{C_{ik}}\times\frac{C_{ik}}{C_i}\times\frac{C_i}{Z_i}\times\left(I-A\right)^{-1}Y_i, i=1,2,...,n, k=1,2,...,m \qquad (7)$$

where $F=\frac{E_{ik}}{C_{ik}}$ denotes the CO_2 emission coefficient matrix and $F_{n\times m}=\begin{pmatrix} f_1 & f_2 & \cdots & f_m\end{pmatrix}$.

$S_{m\times n}=[s_{ik}], s_{ik}=\frac{C_{ik}}{C_i}$ represents the energy consumption structure matrix. $I_{n\times n}=\frac{C_i}{Z_i}$ is the energy intensity matrix. $L_{n\times n}=(I-A)^{-1}$ represents the effect of the input-output structure on total CO_2 emissions, which reflects the contribution of technological improvements to CO_2 emissions in the production process. $Y=(y_1,y_2,\cdots y_n)^{-1}$ denotes the final demand matrix, reflecting the impact of the demand for the final product on total CO_2 emissions.

The energy consumption structure matrix S and the energy consumption intensity matrix I can be expressed as:

$$S_{m\times n}=\begin{pmatrix} \frac{C_{11}}{\sum_{k=1}^{m}C_{1k}} & \frac{C_{12}}{\sum_{k=1}^{m}C_{1k}} & \cdots & \frac{C_{1n}}{\sum_{k=1}^{m}C_{1k}} \\ \frac{C_{21}}{\sum_{k=1}^{m}C_{2k}} & \frac{C_{22}}{\sum_{k=1}^{m}C_{2k}} & \cdots & \frac{C_{2n}}{\sum_{k=1}^{m}C_{2k}} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{C_{m1}}{\sum_{k=1}^{m}C_{ik}} & \frac{C_{m2}}{\sum_{k=1}^{m}C_{ik}} & \cdots & \frac{C_{mn}}{\sum_{k=1}^{m}C_{ik}} \end{pmatrix}, \quad I_{n\times n}=\begin{pmatrix} \frac{\sum_{k=1}^{m}C_{1k}}{X_1} & 0 & \cdots & 0 \\ 0 & \frac{\sum_{k=1}^{m}C_{2k}}{X_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{\sum_{k=1}^{m}C_{nk}}{X_n} \end{pmatrix} \qquad (8)$$

where C_{ik} denotes sector i's demand for energy source k .

By calculating the sum of the CO_2 emissions produced from the m energy sources consumed by sector i, we can obtain the total amount of CO_2 emitted by sector i:

$$E_i = \sum_{k=1}^{m} E_{ik} \qquad (9)$$

The total amount of CO_2 emissions from the thermal and heating sector can then be established by combining equation (7) and equation (9):

$$E_h = \sum_{k=1}^{m} \frac{E_{hk}}{C_{hk}} \times \frac{C_{hk}}{C_h} \times \frac{C_h}{X_h} \times (I - A)^{-1} Y_h = FSILY \qquad (10)$$

According to equation (10), the changes in CO_2 emissions from the thermal electricity and heating sector in two adjacent periods ΔE_h can be expressed as follows:

$$\Delta E_h = F_t S_t I_t L_t Y_t - F_{t-1} S_{t-1} I_{t-1} L_{t-1} Y_{t-1} \qquad (11)$$

The SDA method can involve many different forms of decomposition. In order to reduce the errors, this study uses bipolar decomposition to decompose the total amount of CO_2 emitted by the thermoelectric and heating sector. More detail about the SDA decomposition method can be found in the following references: Dietzenbacher and Los (1998); Haan (2001); Hoekstra and Bergh (2002); Liang et al. (2013); and Rørmose and Olsen (2005).

$$\begin{aligned}
\Delta E_h = {} & \underbrace{\frac{(F_t + F_{t-1})(I_t + I_{t-1})(L_t + L_{t-1})(Y_t + Y_{t-1})}{2^4} \Delta S}_{\text{energy structure effect}} \\
& + \underbrace{\frac{(F_t + F_{t-1})(S_t + S_{t-1})(L_t + L_{t-1})(Y_t + Y_{t-1})}{2^4} \Delta I}_{\text{energy intensity effect}} \\
& + \underbrace{\frac{(F_t + F_{t-1})(S_t + S_{t-1})(I_t + I_{t-1})(Y_t + Y_{t-1})}{2^4} \Delta L}_{\text{input-output structure effect}} \\
& + \underbrace{\frac{(F_t + F_{t-1})(S_t + S_{t-1})(I_t + I_{t-1})(L_t + L_{t-1})}{2^4} \Delta Y}_{\text{final demand effect}}
\end{aligned} \qquad (12)$$

The formula for calculating changes in the total amount of CO_2 emissions produced by the thermal electricity and heating sector can be rewritten as follows:

$$\Delta E_h = \Delta E_S + \Delta E_I + \Delta E_L + \Delta E_Y \qquad (13)$$

where $\Delta E_S = \frac{(F_t + F_{t-1})(I_t + I_{t-1})(L_t + L_{t-1})(Y_t + Y_{t-1})}{2^4} \Delta S$, $\Delta E_I = \frac{(F_t + F_{t-1})(S_t + S_{t-1})(L_t + L_{t-1})(Y_t + Y_{t-1})}{2^4} \Delta I$

$\Delta E_L = \frac{(F_t + F_{t-1})(S_t + S_{t-1})(I_t + I_{t-1})(Y_t + Y_{t-1})}{2^4} \Delta L$, $\Delta E_Y = \frac{(F_t + F_{t-1})(S_t + S_{t-1})(I_t + I_{t-1})(L_t + L_{t-1})}{2^4} \Delta Y$

ΔE_S denotes the changes in total CO_2 emissions caused by changes in energy structure.

ΔE_I represents the changes in total CO_2 emissions due to changes in energy intensity. ΔE_L represents the changes in total CO_2 emissions caused by changes in the intermediate input-output structure. Lastly, ΔE_Y denotes the changes in total CO_2 emissions caused by changes in the final demand. In order to further evaluate the impact of energy structure adjustment and changes in final demand on CO_2 emissions reduction, we decomposed the energy structure effect and final demand effect, as follows:

$$SE_k = \frac{(F_t + F_{t-1})\Delta S_k (I_t + I_{t-1})(L_t + L_{t-1})(Y_t + Y_{t-1})}{2^4} \tag{14}$$

$$FDE_i = \frac{(F_t + F_{t-1})(S_t + S_{t-1})(I_t + I_{t-1})(L_t + L_{t-1})}{2^4}\Delta Y_i \tag{15}$$

where ΔS_k represents the changes in the consumption of energy source k between two periods, and ΔY_i denotes the output changes in sector j between two periods. SE_k is the contribution made to reducing emissions by each energy source in terms of the energy structure effect and $\sum_{k=1}^{m} SE_k = \Delta E_S$. FDE_j represents the impact of changes in the demand scale of industry *i* on the final demand. $\sum_{i=1}^{n} FDE_i = \Delta E_Y$ denotes the final demand effect.

3.2.2 SBM-DEA model with undesirable output

In order to further evaluate the energy structure optimisation approach and measure the energy efficiency of the thermal electricity and heating sector, the SBM-DEA model was innovatively applied to estimate the slack variables and technical efficiency. DEA is suitable for dealing with production activities with multi-inputs and multi-outputs of Decision Making Units (DMU), and has been widely used to evaluate the relative efficiency of DMU (Cong et al., 2021; Zhang et al., 2021). The principle that DEA works on is to determine the relatively effective frontier of DMU by using linear programming and convex analysis methods on the basis of keeping the input or output unchanged, and then projecting each DMU onto the production frontier. The relatively effective frontier of DMU represents the top surface of a convex polyhedron which composed of productive effective points in all DUMs. Efficient point falls on the frontier and its efficiency value is 1; invalid points are surrounded by the frontier, and the efficiency value is between 0 and 1. The relative effectiveness of DMU was evaluated by comparing the degree of deviation from the DEA frontier.

However, traditionally DEA uses either the radial or angular measurement method.

The radial method often ignores the slack problem and thus the efficiency value of the production unit may be overestimated (Han et al., 2020; Cong et al., 2021). The angular method tends to bias the efficiency measurement results of the production units. In order to avoid any measurement errors caused by the shortcomings of the aforementioned two methods, Tone (2001) proposed a non-angular and non-radial SBM model. Both the SBM and CCR model are based on the constant return to scale principle. Unlike traditional DEA, the SBM-DEA can evaluate the efficiency values from both the input and output perspectives (Sun and Huang, 2021).

Based on Tone's (2001) method, we assumed that there are k DMUs. Each DMU has m input factors and n output factors, $X=\left(x_{ij}\right)\in\mathbf{R}^{m\times k}$ denotes the input matrix and $Y=\left(y_{ij}\right)\in\mathbf{R}^{n\times k}$ represents the output matrix. The possible production set can be defined as $P=\left\{(x,y)\middle|x\geq X\boldsymbol{\lambda},y\leq Y\boldsymbol{\lambda},\boldsymbol{\lambda}\geq\mathbf{0}\right\}$, where $\boldsymbol{\lambda}$ is the non-negative weight vector on the real set $\mathbf{R}^{k}$, $X\boldsymbol{\lambda}$ and $Y\boldsymbol{\lambda}$ denotes the input and output values on the frontier. For a particular $\mathrm{DMU}_0(x_0,y_0)$, the efficiency value of $\mathrm{DMU}_0(x_0,y_0)$ can be evaluated by using the following SBM-DEA model:

$$\rho^{*}=\min\frac{1-\dfrac{1}{m}\sum_{i=1}^{m}\dfrac{s_i^{-}}{x_{i0}}}{1+\dfrac{1}{n}\sum_{r=1}^{n}\dfrac{s_r^{+}}{y_{r0}}}$$
$$s.t.\begin{cases}\boldsymbol{x}_0=X\boldsymbol{\lambda}+\mathbf{s}^{-}\\ \boldsymbol{y}_0=Y\boldsymbol{\lambda}-\mathbf{s}^{+}\\ \boldsymbol{\lambda},\mathbf{s}^{-},\mathbf{s}^{+}\geq\mathbf{0}\end{cases}\tag{16}$$

where ρ^{*} denotes the efficiency value of $\mathrm{DMU}_0(x_0,y_0)$ and $\sum\boldsymbol{\lambda}=1$. $\mathbf{s}^{-}\in\mathbf{R}^{m}$ represents the slack variable for m desirable inputs, and s_i^{-} denotes the redundancy of the ith input. $\mathbf{s}^{+}\in\mathbf{R}^{n}$ represents the slack variable for n outputs, and s_r^{+} denotes the deficiency of the rth output.

Thermal power plants produce not only desired electricity and heat, but also undesired outputs such as CO_2. In order to measure the energy efficiency and technical efficiency more accurately, the undesirable outputs are taken into consideration. Based on the above model, the updated SBM-DEA model with undesirable outputs can be shown as follows:

$$\min \rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1+\frac{1}{n_1+n_2}\left(\sum_{r=1}^{n_1}\frac{s_r^{e+}}{y_{r0}^e}+\sum_{j=1}^{n_2}\frac{s_j^{u+}}{y_{j0}^u}\right)}$$

$$s.t.\begin{cases} \boldsymbol{x}_0 = X\boldsymbol{\lambda}+\mathbf{s}^- \\ \boldsymbol{y}_0^e = Y^e\boldsymbol{\lambda}-\mathbf{s}^{e+} \\ \boldsymbol{y}_0^u = Y^u\boldsymbol{\lambda}+\mathbf{s}^{u+} \\ \boldsymbol{\lambda},\mathbf{s}^-,\mathbf{s}^{e+},\mathbf{s}^{u+} \geq 0 \end{cases} \tag{17}$$

where $\rho,\mathbf{s}^-,\mathbf{s}^{e+},\mathbf{s}^{u+}$ represents the efficiency value, input redundancy, desirable output deficiency and undesirable output redundancy, respectively. $\mathrm{DMU}_0(x_0, y_0)$ is valid only when ρ is equal to 1. At this point, $\mathbf{s}^-=0,\mathbf{s}^{e+}=0$ and $\mathbf{s}^{u+}=0$. If $\rho<1$, the $\mathrm{DMU}_0(x_0, y_0)$ is invalid and the input and output need to be further optimised.

Although the non-parametric analysis method requires a smaller quantity of DMU than the parametric method, if the number of DMU is less than that of the input-output index ($k<m+n$),the results are likely to indicate that most or even all the DMUs are effective, and thus the model's evaluative ability will be compromised. Generally speaking, the number of DMU should not be less than the product of the number of input and output indicators, and not less than 3 times the number of input and output indicators (Cooper et al., 2007) (see formula (18)). In terms of the model's practical application, the data availability and DEA analysis results should be taken into consideration when deciding how many DMUs to select. If the model has insufficient ability to differentiate, the input or output indicators should be reduced according to the actual situation to improve the degree of differentiation.

$$k \geq \max\left\{m\times n, 3\times\left(m+n\right)\right\} \tag{18}$$

3.2.3 Adjacent Malmquist model

Since Tone (2001) proposed an improved SBM model which included an undesirable output, this model has been widely applied in the evaluation of economic development efficiency and energy efficiency, etc., for example: sustainability efficiency evaluation (Jiang et al., 2021), and energy efficiency (Rao et al., 2012), energy structure optimisation (Sun and Huang, 2021), energy supply efficiency (Cong et al., 2021). Traditional DEA models, such as the Constant Return to Scale (CRS) model, Variable Return to Scale (VRS) model, and SBM model, only evaluate the technical efficiency at a specific time based on sectional data.

However, technical efficiency is a long-term process which changes continually over time. When the evaluated DMU data is panel data that includes multiple points in time, the results obtained using the traditional DEA evaluation method would be unrealistic, because they are likely to ignore the time effect and the changes in the common frontier. In order to solve the problems associated with analysing panel data and evaluate the dynamic changes in productivity, the Malmquist total factor productivity index analysis method can be used. In our study, the Adjacent Malmquist model is introduced to calculate the dynamic technical value for the thermal electricity and heating sector from 2007 to 2018. To demonstrate the principle behind the Malmquist total factor productivity index, we take the input-oriented CRS model as an example (see Fig. 2).

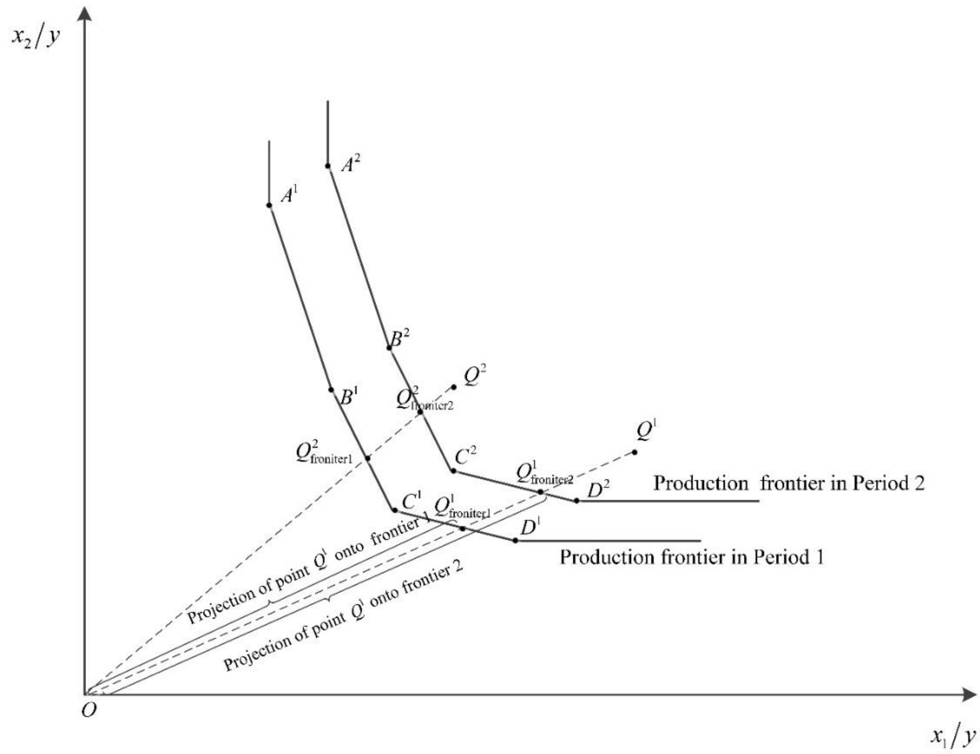


Fig. 2 Malmquist productivity index diagram (input-oriented CRS)

We assumed that subscript 1 and subscript 2 represent the data for Q in period 1 and period 2, respectively. The frontier of period 1 is composed of $A^1B^1C^1D^1$, and the frontier of period 2 is composed of $A^2B^2C^2D^2$. For a particular $\mathrm{DMU}_0(x_0, y_0)$, the productivity changes in the two periods depend on and vary with the production frontier. Taking production frontier 1 as the benchmark, the Malmquist productivity index of Q is:

$$M^1(Q^2, Q^1) = \frac{E^1(Q^2)}{E^1(Q^1)} = \frac{OQ^2_{\text{froniter1}} / OQ^2}{OQ^1_{\text{froniter1}} / OQ^1} \tag{19}$$

Taking production frontier 2 as the benchmark, the Malmquist productivity index of Q is:

$$M^2(Q^2, Q^1) = \frac{E^2(Q^2)}{E^2(Q^1)} = \frac{OQ^2_{\text{froniter2}} / OQ^2}{OQ^1_{\text{froniter2}} / OQ^1} \quad (20)$$

Thus, two different Malmquist productivity indices of Q are produced by referring to frontier 1 and frontier 2, respectively. Based on the method proposed by Caves et al. (1982), Fare et al. (1992) used the geometric average of the two Malmquist indices as the Malmquist productivity index of the evaluated DMU, i.e.:

$$M(Q^2, Q^1) = \sqrt{\frac{E^1(Q^2)}{E^1(Q^1)} \frac{E^2(Q^2)}{E^2(Q^1)}} = \sqrt{\frac{OQ^2_{\text{froniter1}} / OQ^2}{OQ^1_{\text{froniter1}} / OQ^1} \frac{OQ^2_{\text{froniter2}} / OQ^2}{OQ^1_{\text{froniter2}} / OQ^1}} \quad (21)$$

So, the Malmquist productivity index of $\text{DMU}_0(x_0, y_0)$ from period t to $t+1$ can be expressed as:

$$M(x_0^{t+1}, y_0^{t+1}, x_0^t, y_0^t) = \sqrt{\frac{E^t(x_0^{t+1}, y_0^{t+1})}{E^t(x_0^t, y_0^t)} \frac{E^{t+1}(x_0^{t+1}, y_0^{t+1})}{E^{t+1}(x_0^t, y_0^t)}} \quad (22)$$

4 Results

4.1 Decomposition analysis of CO_2 emissions from thermal electricity and heating sector

Fig. 3 shows the impact of the four factors on CO_2 emissions in China's thermal electricity and heating sector from 2007 to 2018. These four factors have different effects on CO_2 emissions at different stages. Overall, the final demand effect was responsible for the majority of the growth in CO_2 emissions; the figure increased by 6.835 billion tons from 2007 to 2018. The energy intensity effect increased CO_2 emissions by 115 million tons, accounting for 3.64 per cent of the total effect. However, the energy structure effect and the input-output structure effect helped to reduce emissions, with the input-output structure effect making the greatest contribution to reducing carbon emissions resulting from energy production in China. It reduced CO_2 emissions from energy production by 3.834 billion tons, which accounts for 107.14 per cent of the total effect. Meanwhile, the energy structure effect had a weaker impact on reducing emissions, with a reduction of 452 million tons, accounting for 14.3 per cent of the total.

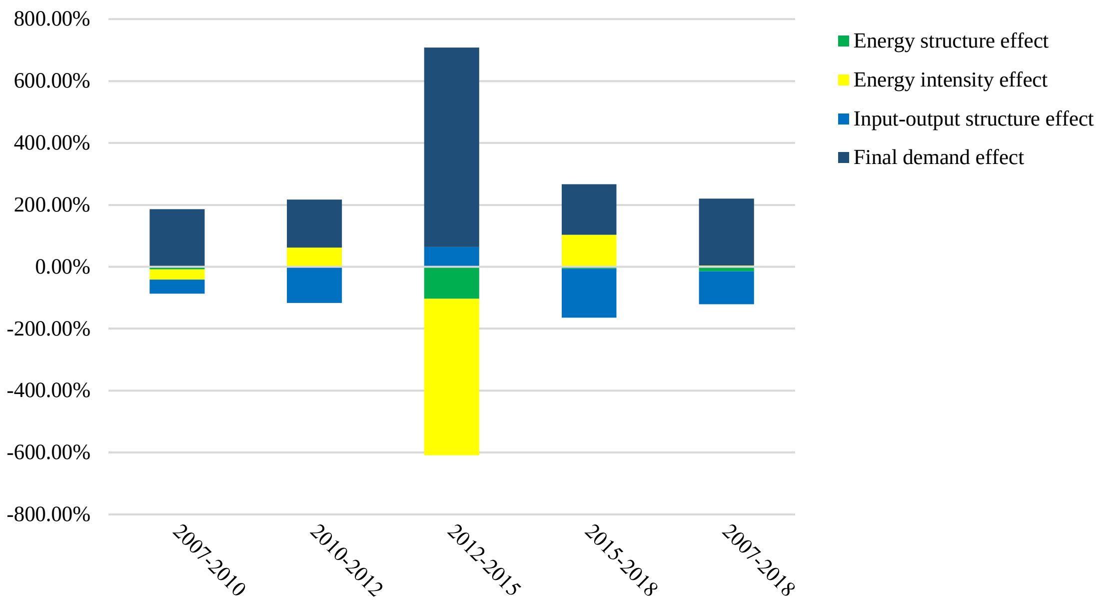


Fig. 3. Contribution of four factors to changes in CO_2 emissions during the period 2007-2018

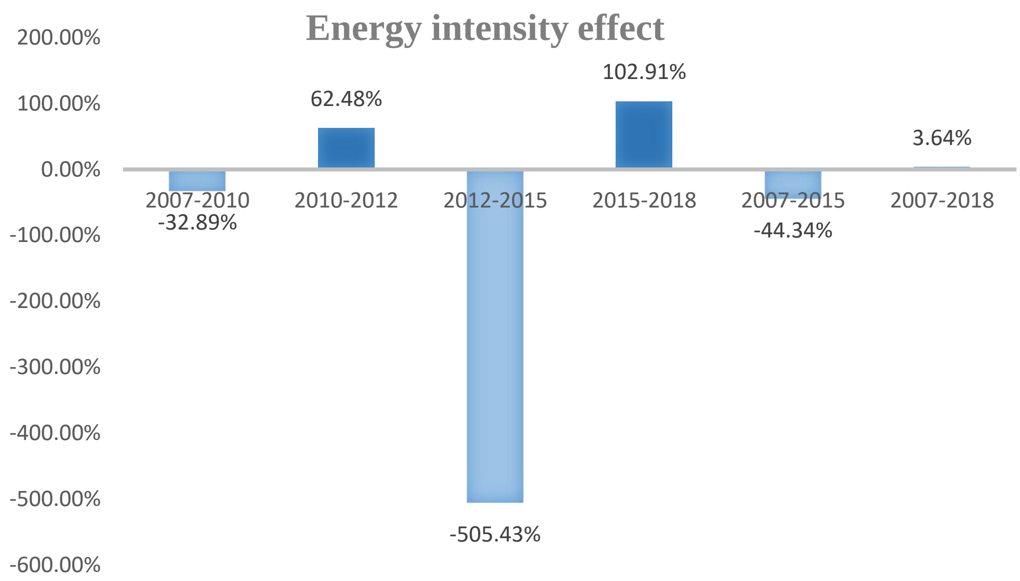
The energy intensity effect can be optimised by improving the efficiency of energy utilisation, which involves adapting the industrial structure and introducing technological innovation. The input-output structure effect is a reflection of technological progress. In terms of the long-term reduction in emissions, reducing the intensity of energy consumption, and optimising the input-output structure both play an important part. In the short term, controlling the final demand and optimising the energy structure are effective ways of achieving a reduction in emissions. In the next sections, we further analyse the mechanisms through which the energy intensity effect and the final demand effect operate to reduce carbon emissions.

4.2 Analysis of the mechanisms by which the four factors reduce emissions

In this subsection, we analyse the emission reduction mechanisms used by the four drivers of change in relation to the thermal power and heating sector. Based on the research findings, we put forward corresponding policy recommendations.

4.2.1 Analysis of the emission reduction mechanism of the energy intensity effect

Our results show that, overall, the energy intensity effect increased CO_2 emissions from 2007 to 2018. However, the energy intensity effect declined from 2007 to 2015, although there was an increase between 2010 and 2012 (see Fig. 4). This implies that the energy policy applied to the thermal power and heating sector during the 12th period of the five-year plan (2011-2015) had a generally positive effect on reducing emissions, but in specific years, the energy intensity deviated from the policy target, which is also proved by the energy intensity coefficient shown in Fig. 5.



Note: The dark blue represents increments in emissions, the light blue represents reductions in emissions (similarly hereafter).

Fig. 4. Energy intensity effect during the period 2007-2018

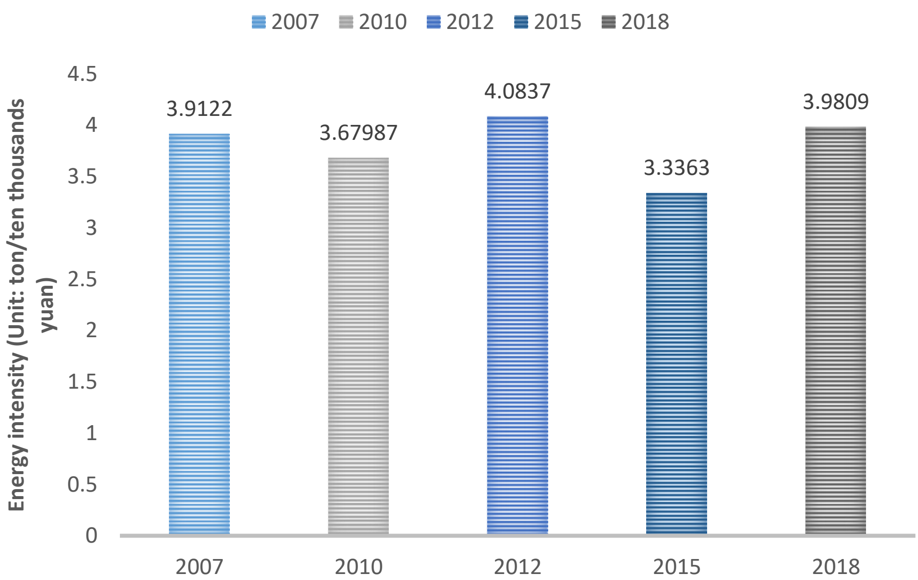


Fig. 5. Energy intensity coefficient of thermal electricity and heating sector during the period 2007-2018

During the 11th period of the five-year plan (2006-2010), the Chinese government set a mandatory target of reducing energy intensity by 20%. Both the decline in carbon intensity and the reduction in emissions confirmed the effectiveness of the energy policies. During the 12th period of the five-year plan, the government introduced a more stringent mechanism for controlling the total energy consumption, and set carbon intensity targets for each province. Overall, these policies achieved their goals; however, it is worth considering why the period from 2010 to 2012 witnessed a deviation from the generally positive trend. Moreover, Fig. 4 and Fig. 5 show that the energy intensity coefficient and its effect on emissions increased significantly during the 13th period of the five-year plan (2016-2020), which implies that the energy intensity of the thermal power sector did not fulfil the policy expectations.

As mentioned above, it is noteworthy that the energy intensity of China's thermal electricity and heating sector increased between 2010 and 2012, thereby offsetting most of the beneficial effects of the policy. Identifying the causes of this reversal can help to provide guidance for formulating more effective energy policies in the future. From the analysis of relevant data, we found the following possible explanations: First, consumption of raw coal during the three periods under study was 16.87, 21.04 and 3.35 million tons, respectively. Compared to the period from 2007 to 2010, the amount of low-carbon energy used, such as natural gas, fell by half, while the amount of liquefied natural gas dropped by 93.5 per cent during the period from 2010 to 2012. Therefore, the dramatic increase in the use of raw coal and the sharp decline in low-carbon energy use were the major factors that led to the significant increase in energy intensity between 2010 and 2012. From 2012 to 2015, the country began to vigorously promote the policy of clean energy substitution, and the use of raw coal was significantly reduced to only 16 per cent of the total for the preceding period, while the use of low-carbon energy increased threefold compared with that of the period from 2010 to 2012. Second, during the 11th period of the five-year plan (2006-2010), the Chinese government set a mandatory target of reducing energy intensity by 20 percent from the 2005 level. During this period, inefficient and technologically backward small thermal electricity units were forced to close. This policy improved the energy efficiency of the thermal electricity sector, which saw a reduction in carbon emissions of 1.74 billion tons from 2005 to 2010. Moreover, as a result of the global financial crisis in 2008, China's economic growth slowed down from 2008 to 2009, and the growth rate of primary energy consumption dropped sharply. This also reduced the energy intensity in the thermal electricity sector to a certain extent.

In order to analyse the causes of changes in energy intensity in more detail, we calculated the energy intensity values of the thermal electricity and heating sector for 30 provinces from 2007 to 2018. As the annual output values of the thermal electricity and heating sector for some of the provinces are not released in the Statistical Yearbook, we used the measure of CO_2 emissions per unit of power generation to approximate the energy intensity values. The results are shown in Fig. 6 and Table 4.

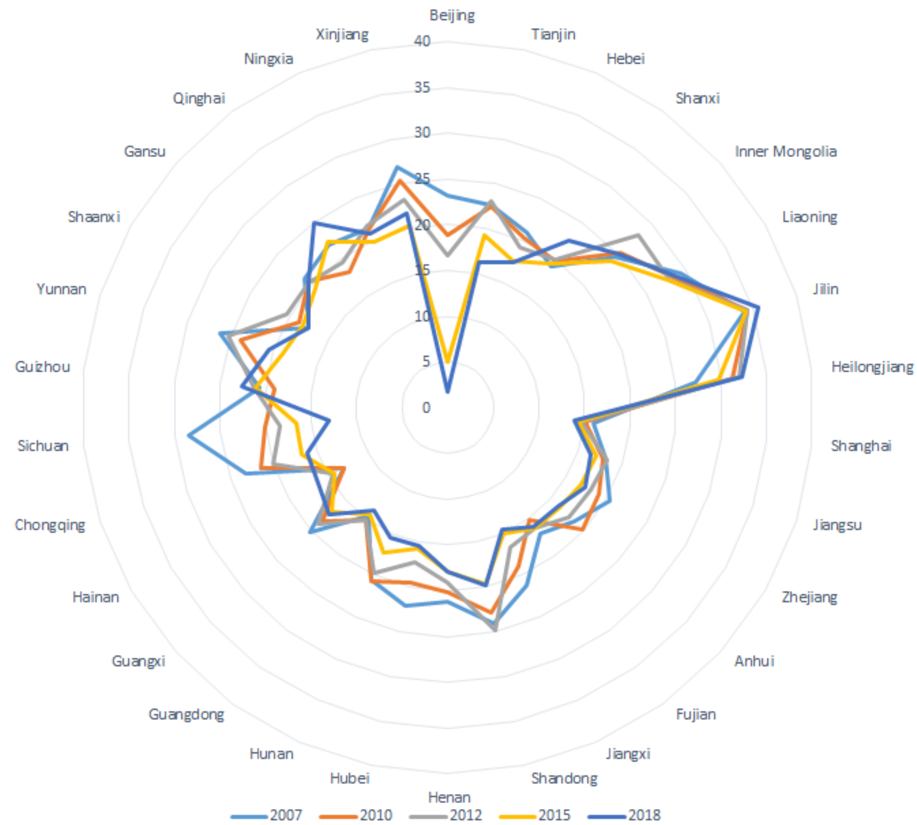


Fig. 6. CO_2 emissions per unit of electricity generated in the thermal electricity and heating sector for 30 provinces during the period 2007-2018 (unit: 10^4t / 10^8 kW•h)

Fig. 6 shows that, apart from Hainan province, the CO_2 emissions per unit of electricity generated by the thermal electricity and heating sector in Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong (most of the eastern region) followed a downward trend from 2007 to 2018, and the average rate of decline for these provinces was 22.8 percent. In the eastern region, Beijing experienced the biggest drop of 92.24 percent. In the central region, Shanxi's CO2 emissions per unit of electricity rose by 17.6 percent from 2007 to 2018. In the northeastern region, the CO_2 emissions per unit of electricity generated by Liaoning, Jilin and Heilongjiang were much higher than those of the other provinces. More specifically, Jilin and Heilongjiang's emissions increased from 34.16 and 27.19 to 35.65 and 32.39, respectively. The CO_2 emissions per unit of electricity of these two provinces increased by 4.36 percent and 19.15 percent, respectively, between 2007 and 2018. In terms of the western region, Inner Mongolia, Guizhou, Shanxi and Qinghai showed an upward trend, while the other provinces saw an average decline of 18.78 percent, and Sichuan experienced the most dramatic decline of 54 percent.

From an overall regional perspective, the CO_2 emissions per unit of electricity generated by the thermal electricity and heating sector in the northeastern region were much higher than those of the other regions during the period 2007-2018 (see Table 4). The western region produced the second highest level of CO_2 emissions per unit of electricity, which was higher than the national average level during the same period.

The central and eastern regions ranked third and fourth, respectively, meaning that hey produced less than the national average level during the same period..

Table 4

CO_2 emissions per unit of electricity generated in the thermal electricity and heating sector during the period 2007-2018 (unit: 10^4t / 10^8 kW•h)

Region	2007	2010	2012	2015	2018
Eastern region	19.41	18.66	18.85	16.95	16.69
Central region	20.31	19.94	18.81	17.48	17.94
Western region	22.95	21.96	23.19	20.66	21.46
Northeastern region	29.64	30.58	30.53	29.79	31.27
Whole country	21.22	20.60	20.76	18.87	19.14

From 2010 to 2012, due to the relative backwardness of the western region and a reliance on the enrichment of resources, the GDP growth of the northwestern provinces increasingly came to depend on the development of coal-related industries. With the introduction of a series of national stimulus policies after the financial crisis, economic growth began to recover, accompanied by an increase in demand for electricity. Coupled with the relatively moderate energy intensity reduction targets set for the western provinces, these provinces were unable to suppress the increase in energy supply. From 2010 to 2012, the construction of coal bases within the western provinces accelerated. These coal bases comprised 10 large-scale coal enterprises with a capacity of 100 million tons and 10 smaller coal enterprises with a capacity of 50 million tons, and they produced more than 90 percent of the country's total coal output. In fact, during the 11th period of the five-year plan, some of these coal bases had already started operating, and were producing a considerable yield. The unprecedented scale of coal mining has been accompanied by large-scale coal-fired electricity generation and coal-chemical projects involving high levels of energy consumption. These industrial clusters have developed rapidly in the western provinces and regions, thereby forming a so-called 'energy base'. This is also the main reason for the substantial increase in the coal consumption of thermal electricity from 2010 to 2012. Table 4 shows that the CO_2 emissions per unit of electricity rose from 21.96 in 2010 to 23.19 in 2012, which also confirms this conclusion.

In 2012, the energy development plan for the 12th period of the five-year plan was finally proposed. During this period (2011-2015), the government gradually established an effective and reasonable mechanism to control the total amount of energy used. It was planned that China's total energy consumption should stabilise at about 4.1 billion standard tons in 2015. In the future, the government would levy a tax on fossil energy consumption. The plan also set a target for each province to reduce its energy intensity, with the western regions including Ningxia, Inner Mongolia and Gansu aiming for a 15 per cent reduction, and the eastern regions of Jiangsu, Zhejiang and Guangdong trying to achieve an 18 per cent reduction. These measures have significantly reduced coal consumption and carbon intensity in the thermal electricity and heating sector. In addition, the average price of thermal coal at the end of 2011 had nearly tripled to in excess of 850 yuan/ton, compared with 227 yuan/ton in 2000. Soaring coal prices have caused huge losses in the downstream thermal electricity industry, and the demand for coal has also been greatly reduced. It also clearly shows that there was a significant decline in the CO_2 emissions per unit of electricity from 2012 to 2015.

On 18th June 2019, the People's Daily announced that China's energy intensity had dropped by 11.35 per cent since the implementation of the 13th five-year plan (2016-2020), and the dual control target for energy consumption and energy intensity met the scheduled requirements of the 13th five-year plan. However, the energy intensity of the thermal electricity and heating sector did not show a downward trend from 2015 to 2018. Table 4 shows that, except for the eastern region, CO_2 emissions per unit of electricity in other regions increased, especially in the northeastern and western regions. Shanxi province in the western region experienced the largest increment, with an increase of 3.03. This may be due to the significant increase in the installed capacity of thermal power, resulting in a significant increase in fossil energy consumption. Since 2016, the installed capacity of thermal power has maintained a rapid growth rate. By the end of September 2017, the installed capacity of thermal electricity in China had reached 1.08 billion kilowatts, which is close to the red line set in the Thirteenth Five-Year Plan. Table 1 shows that the energy use of raw coal in the thermal electricity and heating sector rose from 1.43 billion tons of standard coal in 2015 to 1.66 billion tons of standard coal in 2018. In November 2017, Polaris power grid reported that the supply of thermal electricity had greatly increased, and there was an obvious imbalance between supply and demand. In the future, the energy policy aims to achieve a balance between stock adjustment and incremental optimisation in the thermal electricity sector on a regional basis. Striking a balance between clean energy development and fossil energy utilisation may help to reduce energy intensity.

4.2.2 Analysis of the emission reduction mechanism of the energy structure effect

As shown in Figure 7, the energy structure effect has continuously reduced emissions by 8.49%, 0.98% , 103.18% and 5.18%, respectively, during the four periods studied. Between 2010 and 2012, the emission reduction effect was relatively small. However, it then significantly improved during the period from 2012 to 2015. To reveal the reasons behind this phenomenon, we further analysed the energy use in the thermal power sector between 2007 and 2018 and measured the carbon emission factors after the conversion of various energies into standard coal. Based on the energy use in the thermal electricity generation and heating sector shown in Table 1, we obtained the incremental consumption of each energy combustion unit in the thermal electricity and heating sector from 2007 to 2018, which is shown in Table 5 (unit: 10,000 tons).

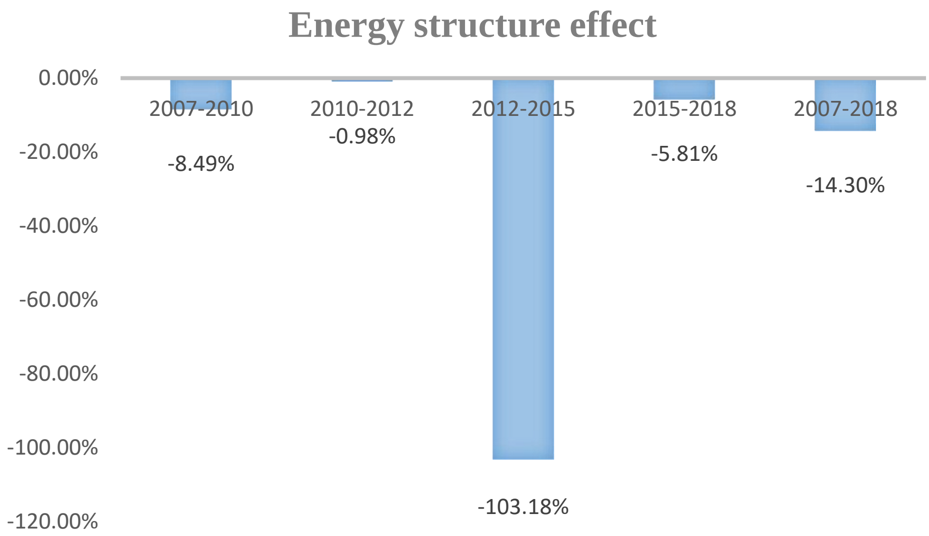


Fig. 7. Energy structure effect during the period 2007-2018

Table 5 shows that, compared with the period 2007-2010, there was a dramatic increase in the consumption of high-carbon energy, such as raw coal, between 2010 and 2012; while the consumption of low-carbon energy such as blast furnace gas markedly declined. This may explain the relatively weak reduction in the contribution of the energy structure effect. During the period from 2012 to 2015, the consumption of raw coal dramatically declined, while the consumption of blast furnace gas and natural gas grew markedly, which could help to explain the significant reduction in emissions caused by the energy structure effect. From 2015 to 2018, the increase in the consumption of raw coal slowed down, while increments in the consumption of blast furnace gas and natural gas remained low. During the period from 2015- 2018, the consumption of raw coal was relatively higher than the period from 2007-2010 and the consumption of low-carbon energy is smaller. Therefore, the effect of the energy structure on reducing emissions during the period 2015 to 2018 was weaker than for the period from 2007 to 2010. The results shown in Table 5 also imply that the consumption of raw coal has a big impact on carbon emissions. The large swings in raw coal consumption between 2007 and 2015 may be due to the fact that the construction of coal bases in the western provinces accelerated during the period from 2010 to 2012, thereby greatly increasing the supply of coal. In 2012, the 12th period's five-year energy development plan imposed mandatory controls on coal consumption. At the same time, coal prices rose, and low-carbon energy was increasingly used to replace raw coal. These developments led to a significant reduction in the energy structure effect between

2012 and 2015. In addition, the consumption of high-carbon energy such as washed coal, diesel oil, and fuel oil, declined relatively slowly; while the consumption of low-carbon energy such as blast furnace gas grew steadily, which also helps to explain the effect of changes in the energy structure. It can therefore be concluded that the energy structure effect has succeeded in reducing the emissions generated by China's thermal electricity and heating sector, perhaps due to the continual optimisation of the energy consumption structure.

Table 5

Increments in energy consumption (unit: 10^4 tce) from 2007 to 2018.

Categories of energy	**Adjusted CO_2 emission factors (t CO_2/t tec)**	**2007-2010**	**2010-2012**	**2012-2015**	**2015-2018**
Raw Coal	3.37	16872.88	21039.71	3347.37	23093.35
Cleaned Coal	2.87	-26.78	77.25	-11.88	-79.07
Other WashedCoal	2.29	93.08	-197.84	-14.81	688.77
Coke	1.36	0.00	0.00	273.89	0.00
Coke Oven Gas	3.13	5096.84	1640.83	1452.85	-253.23
Blast Furnace Gas	0.13	14818.96	3650.05	8356.69	-29.06
Converter Gas	1.06	1793.37	1600.66	237.52	10304.33
Other Gas	0.59	-11661.00	0.00	228.39	3662.86
Crude Oil	0.20	-13.60	7.47	9.90	-142.14
Gasoline	2.51	-0.06	-0.01	0.24	0.00
Kerosene	2.15	0.00	0.00	0.00	-5.50
Diesel Oil	2.05	-165.75	-116.06	-13.74	-0.25
Fuel Oil	2.10	-531.21	-135.43	-48.26	0.00
LPG	2.17	-7.29	-1.39	5.49	4.31
Refinery Gas	2.27	136.00	-67.55	-38.77	-174.26
Other Petroleum Products	1.85	-88.84	-122.60	21.04	1.27
Natural Gas	1.69	1088.61	583.04	1412.27	76.92
LNG	2.55	310.09	19.59	-25.76	-28.96

Next, we further analysed the impacts of the changes in energy structure on CO_2

reduction between 2007 and 2018 and disclosed the contribution of each energy source to carbon reduction. On the basis of the SDA decomposition, we continued to decompose the contribution of each energy source to reducing carbon emissions. The emissions reduction for each type of energy is shown in Table 6 (unit: 10,000 tons).

Table 6

Emissions reduction for each type of energy (unit: 10^4 t) from 2007 to 2018.

Categories of energy	2007-2010	2010-2012	2012-2015	2015-2018	2007-2018
Raw Coal	-20739.51	-3256.77	-31186.26	-20358.96	-87841.19
Cleaned Coal	-113.01	238.36	-65.40	-303.07	-231.12
Other Washed Coal	-1020.48	-2361.13	-630.04	2323.54	-2907.74
Coke	0.00	0.00	860.07	0.00	0.00
Coke Oven Gas	5372.58	-450.20	611.70	-926.23	58.60
Blast Furnace Gas	8213.76	506.70	3985.14	-3931.67	4343.37
Converter Gas	7519.44	5386.38	-225.40	2736.61	19698.05
Other Gas	-5989.46	0.00	101.43	12427.92	29273.82
Crude Oil	-33.57	10.10	15.83	-79.94	-8829.70
Gasoline	-0.14	-0.06	0.34	0.00	0.00
Kerosene	0.00	0.00	0.00	-19.82	-38.77
Diesel Oil	-415.75	-257.71	-33.62	-0.46	-0.35
Fuel Oil	-1447.52	-430.19	-154.72	0.00	0.00
LPG	-8.70	-1.59	5.45	-7.16	-976.22
Refinery Gas	80.20	-145.63	-72.01	-448.32	-3264.51
Other Petroleum Products	-302.28	-322.84	41.53	0.13	-8.79
Natural Gas	1278.88	245.23	1943.67	19.73	-120.37
LNG	376.85	-46.66	-69.20	-83.77	-879.37
Total reduction effect	-7228.72	-886.01	-24871.51	-6731.17	-45176.8

Table 6 clearly shows that different energy sources had differing impacts on reducing emissions from China's electricity and heating industries between 2007 and 2018. Changes in energy structure, involving a reduction in the use of raw coal, cleaned coal, other washed coal, crude oil, kerosene, diesel oil, LPG, refinery gas and other petroleum products, natural gas and LNG had significant effects on emissions reduction in China's thermal electricity and heating sector during this period. Between 2007 and 2010, increments in the use of coke oven gas, blast furnace gas, converter gas, refinery gas, natural gas and LNG increased CO_2 emissions. From 2010 to 2012, the increase in cleaned coal, blast furnace gas, converter gas, crude oil, and natural gas had a positive effect on CO_2 emissions. From 2012 to 2015, the increases in coke, coke oven gas, blast furnace gas, other gas, crude oil, LPG, other petroleum products and natural gas had the effect of raising CO_2 emissions. From 2015 to 2018, the increase in other washed coal, converter gas, other gas, other petroleum products and natural gascaused a corresponding increase in CO_2 emissions. These results further confirm that increasing the consumption of low-carbon energy, such asblast furnace gas and converter gas , and cutting down the use of raw coal, contributes to emissions reduction.

The following conclusions can be drawn. First, from 2012 to 2015, energy structure optimisation had the most significant effects on reducing emissions, while the period from 2007 to 2010 and the period from 2015 to 2018 saw a smaller reduction. Changes in the energy structure during the period from 2010 to 2012 had the least effect on reducing emissions. Second, increasing the consumption share of low-carbon energy is conducive to reducing emissions. In addition to reducing raw coal, cleaned coal, other washed coal, crude oil and refinery gas, decreasing the proportion of high-carbon energy sources, such as diesel oil, kerosene and other petroleum products, had limited effects on emissions reduction. Therefore, the reduction in emissions from China's thermal electricity and heating sector as a result of adjusting the energy structure was mainly caused by the increased share of low-carbon energy, while the emissions reduction effect was relatively small in the case of high-carbon energy, such as diesel oil, kerosene and other petroleum products.

This study then further explored how the energy structure in China's thermal electricity and heating sector could be optimised. Based on Sun and Huang's (2021) study, the SBM-DEA model that treats CO_2 as an unexpected output was introduced to estimate the slack variables for the 30 provinces from 2007 to 2018. Studying the slack variables is helpful in terms of discovering the causes of energy efficiency loss and can thus provide a scientific reference for adjusting the energy structure. Table 7 presents the results of the energy efficiency and the slack variables in relation to China's thermal electricity and heating sector from 2007 to 2018. The average energy efficiency values for all 30 provinces in each period are all less than 1, which means the energy structure needs to be further optimised.

Table 7

Energy efficiency and slack variables from 2007 to 2018.

Year	Score	Slack variables (unit: 10^4 tec)				
		Total Coal	**Petroleum Products**	**Gas**	**Coal gas**	**CO_2 (10^4 tons)**
2007	0.924	-23.98	-4.30	-1.00	-86.93	-119.69
2010	0.921	-16.19	-6.75	-4.87	-121.25	-116.03
2012	0.955	-22.36	-5.71	-2.85	-37.58	-133.44
2015	0.947	-31.78	-3.90	-1.81	-67.17	-140.18
2018	0.933	-19.74	-3.88	-2.63	-102.83	-312.79

Note: The 20 energy sources are divided into four major categories and converted into standard coal.

In 2007, the total coal, petroleum products, gas and coal gas had a redundancy of 239,776 tec, 42,977 tec, 10,035 tec and 869,267 tec, respectively. Meanwhile, CO_2 emissions had a redundancy of 0.12 million tons. To achieve the energy efficiency target for 2010, the thermal electricity and heating sector needed to reduce its consumption of total coal, petroleum products, gas and coal gas by 161,875 tec, 67,507 tec, 48,719 tec and 1,212,539 tec, respectively. In the same year, CO_2 emissions had a redundancy of 0.116 million tons. In 2012, the consumption of total coal, petroleum products, gas and coal gas had a redundancy of 2,336,063 tec, 57,081 tec, 28,504 tec and 375,772 tec, respectively. CO_2 emissions can be reduced by 0.133 million tons when the energy efficiency reaches the optimal value. For 2015, the total coal, petroleum products, gas and coal gas had a redundancy of 239,776 tec, 42,977 tec, 10,035 tec and 869,267 tec, respectively, while CO_2 emissions had a redundancy of 0.12 million tons. Similarly, the input redundancy values of various energy sources and the CO_2 emissions reduction in 2015 and 2018 can be obtained from the data shown in Table 7. In summary, the value of energy efficiency was at its highest in 2012, out of all the five periods, and the energy efficiency value is consistent with the effect of the energy structure on emissions reduction to a certain extent from 2007 to 2018. In addition, the redundancy values of coal-related products were relatively large in each of the periods studied, which implies that the input of coal-related products should be reduced.

4.2.3 Analysis of the contribution of the input-output structure effect

The input-output structure effect was derived by changing the Leontief inverse. The elements of the Leontief inverse indicate the impact of a unit change in the exogenous final demand on the output of the industry. In addition, each element in the Leontief inverse reflects the direct and indirect effects arising from the interdependence of sectors or industries in the production of goods and services to meet the final demand. The traditional view usually treats the Leontief inverse matrix as the final form of the direct consumption coefficient matrix in order to capture the linkages between sectors or industries and measure technological progress and changes in production structure. For policy and planning purposes, Stone and Brown (1962) suggest that the direct consumption coefficient can be further decomposed using the RAS method into the substitution effect and fabrication effect to reflect the change in the production substitution rate and the technical level, respectively. Dietzenbacher and Los (1998) combined the RAS method and the SDA model to decompose the direct consumption coefficient matrix and calculated the production substitution rate and technical level in specific units. To improve the efficiency and scope of the RAS method, Tho (1998) directly applied the RAS procedure to the Leontief inverse and decomposed the substitution and fabrication factors.

The Leontief inverse is a powerful tool in I-O analysis. It plays an important role in economic impact studies, structural change analysis and the identification of key sectors for development planning. In our study, the input-output structure effect comprehensively reflects the efficiency of the production technology and production structure used in thermal electricity production. Fig. 8 shows that, in the first two periods and the fourth period, the input-output structure had the effect of reducing emissions. This indicates that the country's determination to push forward the upgrading of thermal electricity generation technology has made substantial progress. However, during the period from 2012 to 2015, the input-output structure effect became a driver for increasing carbon emissions.

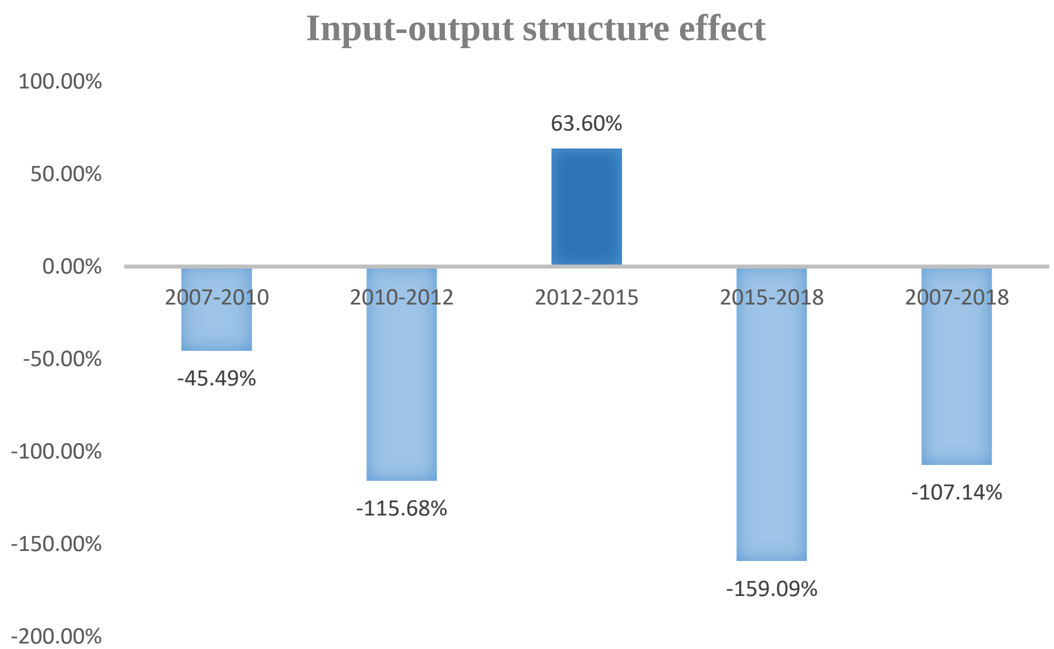


Fig. 8. Input-output structure effect during the period 2007-2018

Due to the lag in the market reform of the industrial development mechanism and the rise in coal prices, electricity generation enterprises have suffered continuous losses since 2011. Electricity generation companies are not optimistic about the prospect of being able to make a profit from thermal electricity and there have been no significant breakthroughs in the reform of the national electricity system. Therefore, thermal electricity enterprises started to significantly reduce both investment and electricity generation, leading to a reduction in the utilisation rate of thermal electricity equipment and a significant weakening of the effect of technological upgrading and the scale effect. According to data released by the China electricity council, in the first quarter of 2012, the country produced an additional 6.49 million kilowatts of thermal electricity, which is 3.52 million kilowatts less than in the preceding year. In 2014, investment in thermal electricity was significantly lower than that of wind-powered electricity and hydroelectricity. Furthermore, given the slow growth rate of the national installation capacity in 2015 and the decline in the growth rate of electricity consumption under the "New Normal"[2], the utilisation hours of equipment for the industry as a whole did not improve significantly until 2015. The Malmquist total factor production index for the adjacent base period shown in Table 8 indicates that the productivity of the thermal electricity sector decreased during the period 2012-2015,which proves that the effect of upgrading technology in the thermal electricity sector was not very effective.

[2] 'New Normal' refers to a sustainable medium to high growth stage. The economic growth rate in 2015 was relatively low, and it suppressed the demand and consumption.

Table 8

Malmquist total factor production index for adjacent base period.

Time span	Malmquist total factor production index	Technical efficiency change	Technological change
2007-2010	1.1551	1.0387	1.1039
2010-2012	1.0564	1.0854	0.9661
2012-2015	0.9998	1.0081	0.9997
2015-2018	1.1630	1.0075	1.1579

Note: A Malmquist index greater than 1 indicates an increase in productivity, while an index less than 1 indicates a decrease in productivity.

4.2.4 Analysis of the contribution of the final demand effect

Figure 9 shows that the final demand effect is one of the main driving forces behind the increase in CO_2 emissions in China's thermal electricity and heating sector, and that it continues to increase.

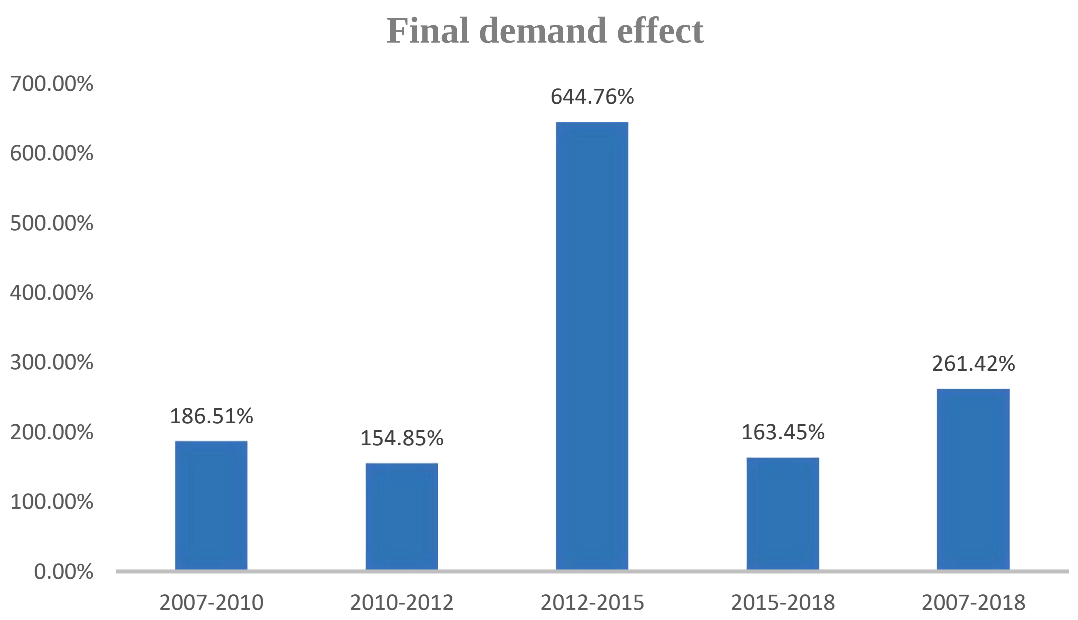


Fig. 9. Final demand structure effect between 2007 and 2018

Next, the study specifically analysed the contribution of the scale change in each industry to the growth in carbon emissions generated by the thermal electricity and heating sector from 2007 to 2018. The impacts of changes in the scale of various industries on CO_2 emissions in China from 2007 to 2018 are shown in Table 5 (unit: 10,000 tons) and Figure 6.

Table 9

Impact of changes in final demand of various industries on carbon emissions.

Sector	2007-2010	2010-2012	2012-2015	2015-2018	2007-2018
Service sector	38120.12	28569.87	41800.38	42750.01	181793.88
Heavy industry	62106.87	22890.26	30260.16	9139.25	115215.89
Light industry	17666.58	11259.78	17489.58	1273.01	46383.23
Construction industry	51032.65	34320.07	89889.03	48256.74	234792.06
Chemical industry	664.97	5494.67	1213.90	4075.51	11898.61
Agriculture	-78.53	4971.74	-1490.38	2955.11	6499.13
Transportation industry	-2782.98	7023.59	-978.22	7850.94	12905.97
Fossil energy sector	-7622.42	-2068.26	9919.88	-8417.06	-8532.81
Electricity sector	-353.21	27939.34	-32684.84	81628.54	82567.38
Total	158754.05	140401.05	155419.49	189512.04	683523.33

Table 9 and Figure 9 show the impact of changes in China's industrial demand on the growth of CO_2 emissions from 2007 to 2018. It can be seen that the scale of industrial expansion within the service sector played a dominant role in promoting the growth of CO_2 emissions in the thermal electric and heating sector during the period from 2007 to 2018. Regarding the final demand effect, the fossil energy, transport, agriculture and electricity sectors all experienced a reduction in emissions between 2007 and 2010. During the periods 2010-2012 and 2015-2018, fossil energy continued to play a role in reducing CO_2 emissions, but the other sectors all contributed to an increase in CO_2 emissions. From 2012 to 2015, the growth of demand in the service industry, the construction industry, heavy industry and light industry played a major part in the increase in CO_2 emissions, while the transport industry, agriculture and the electric power industry contributed to a reduction in emissions. In terms of the industrial structure, within the secondary industries sector, heavy industry and the construction industry were the major contributors to CO_2 emissions from the thermal electricity and heating sector. However, the contribution of the service industry and agriculture were relatively low. If expansion continues on the same scale, the effect of the primary and tertiary industries (agriculture and services) on increasing CO_2 emissions from electric heating energy will be less than that of the secondary industries (manufacturing). Although the increase in the scale of industrial expansion will lead to an increase in carbon emissions from the electricity and heating sector, increasing the ratio of the primary and tertiary industrial structures is conducive to slowing down the growth rate of carbon emissions from electricity and heating energy.

5. Discussion and policy implications

With the continuous growth of China's economy, thermal electricity and heating supply have become one of the most important material foundations of economic development. At the same time, the carbon emissions produced by electricity generation not only have adverse effects on the environment, but also restrict the development of China's economy. In 2015, the electricity industry in China released 48.6 percent of the country's CO_2, of which coal-fired CO_2 emissions accounted for the largest share. During the 11^{th} and 12^{th} periods of the five-year plans, China pursued carbon emission reduction policies aimed at the thermal electricity and heating sector, such as accelerating the upgrading of technology, reducing energy consumption and optimising the energy structure in the thermal and heating sector. Some scholars such as Paul (2016) and Wang (2019) have also focused on thermal electricity and applied the decomposition method to investigating the drivers behind the rise in CO_2 emissions during the period 2002-2012 using aggregated five-yearly data, in an attempt to provide guidance for energy policy. They maintained that the increase in CO_2 emissions from electricity generation during the period 2002-2012 was mainly driven by changes in electricity demand.

However, in the decomposition process, they only specified the total effect of energy structure optimisation and final demand, and ignored the specific amount of reduction in carbon emissions produced by each energy source and each industrial sector. Moreover, data that is based on a five-year cycle tends to obscure the mechanism behind energy policy, and thus may produce misleading results. With the launch of subsequent economic stimulus policies, China's energy demand underwent a rapid increase from 2007 to 2018. In order to trade off between economic development and reducing carbon emissions, and to formulate appropriate future energy policies, it is crucial to investigate the contribution made by each of the industrial sectors to CO_2 emissions, and assess whether the energy policy is having the desired effect. Based on our aggregated data decomposition for the three-yearly data, we argue that the formulation of energy policies should take into consideration the contextual factors affecting each province and adapt measures to local conditions. The purpose of our research is to provide policy guidance for formulating a more effective energy policy that is better suited to the reality of the situation.

From 2007 to 2018, CO_2 emissions from the thermal electricity and heating sector initially rose and then fell and then increased again, reaching a local peak in 2012. In general terms, the study shows that the energy structure effect, and the input-output structure effect are the main factors which account for the overall reduction in CO_2 emissions between 2007 and 2018. In particular, advances in electricity generation technology have played a prominent role in reducing CO_2 emissions. The demand effect caused by the expansion in the scale of the economy was the main factor driving the increase in CO_2 emissions from 2007 to 2018. The energy intensity effect had a weak effect on increasing CO_2 emissions from 2007 to 2018.

In addition, we also found that the ongoing upgrading of technology used in thermal power generation has not played a very important role in reducing emissions. In other words, in order to be effective, the technology upgrading effect needs to be accompanied by the market reform of thermal power prices. For example, between 2007 and 2015, the input-output structure effect had the largest impact on emissions reduction in the thermal electricity and heating sector. This shows that China's long-term policy of encouraging technological innovation in electricity production has had significant positive effects. The implementation of new technologies not only reduces energy consumption, but also curbs the rise in carbon emissions. Moreover, technological innovation affects the input-output structure of each sector of the national economy. Changes in the input-output structure will reduce the input of products that generate high carbon emissions, thus helping to achieve the goal of reducing carbon emissions. However, the effect of technology on emissions transformed from a positive to a negative one during the period between 2012 and 2015. The explanation for this lies in the fact that the market reform of thermal power prices lags behind that of coal prices, resulting in a conflict between the marketised coal system and the nationally planned electricity system, which has worsened in recent years. With the rise in coal prices, thermal electricity enterprises suffered serious losses, which led to a substantial reduction in investment and electricity generation. This in turn resulted in a significant reduction in the utilisation rate of thermal electricity equipment and a significant reduction in the scale effect and the effect of technological upgrading. This finding indicates that policymakers should accelerate the market-oriented reform of electricity prices, otherwise efforts to vigorously promote the upgrading of technology may be counterproductive. In addition, technological innovation requires substantial and sustained capital investment. The government could provide this through tax collection to reduce the research and development (R&D) costs of enterprises and stimulate further R&D.

Under China's strict energy intensity reduction target policy, the energy intensity rebounded significantly in 2012. Although the energy intensity effect was the second most important factor accounting for emissions reduction during the period from 2007 to 2015, it nonetheless became a driver of emissions growth between 2010 and 2012. In addition, according to the overall decomposition results for the period from 2007 to 2018, energy intensity had a weak effect on increasing CO_2 emissions. During the 11th period of the five-year plan (2006-2010), the Chinese government set a mandatory target of reducing energy intensity by 20%. During the 12th period of the five-year plan (2011-2015), the government set targets for individual provinces to reduce their energy intensity. However, a breakdown of the results shows that energy intensity increased significantly between 2010 and 2012, becoming the main driver of carbon emissions. This is probably due to the large coal reserves and backward economy in the western region of China, and the fact that GDP growth in the northwestern provinces became increasingly dependent on the development of coal-related industries. In the face of surging coal consumption and industrial electricity consumption, these western provinces have been unable to resist the temptation of rising demand and have greatly increased their mining activity. This implies that the government should focus on accelerating energy substitution and the upgrading of technology in the western region; however, in fact this could have a negative impact if the policy objectives are inconsistent with the reality of the situation. During the 13th period of the five-year plan (2016-2020), the increase in energy intensity may have been due to the significant increase in the installed capacity of thermal power, resulting in a significant increase in fossil energy consumption. To resolve this problem, the energy policy aims to achieve a balance between stock adjustment and incremental optimisation in the thermal electricity sector on a regional basis, which may prove to be more effective.

The energy structure effect in the thermal electricity and heating sector produced a sustained reduction in emissions; however, the reduction effect was relatively small. This confirms that the energy consumption structure in the electricity sector has been continually optimised, which is due to the strong support for the development of clean energy provided by the Chinese government. From the numerical value of the energy consumption structure effect, it can be seen that the utilisation ratio of clean energy in China is not very high, and its contribution to reducing carbon emissions remainssmall. In the future, the Chinese government should continue to support and encourage enterprises to use clean energy, for example by offering subsidies or tax reductions.

The final demand effect was the main driving force behind CO_2 emissions from the thermal electricity and heating sector during the period from 2007 to 2018. The decomposition of the final demand effect suggests that, among secondary industries, the construction industry was the main contributor. Overall, the amount of electricity and heating energy used in the secondary industries was generally higher than that in the primary and tertiary industries. It is vital to maintain a balance between CO_2 emissions and economic development in these sectors. Reducing the demand for electricity and heating energy from the secondary industries is conducive to decelerating the growth in carbon emissions from electric and heating energy sources, which is also in line with China's industrial restructuring policy. In order to adjust the economic structureand growth pattern, it appears that a circular, energy-saving economy may be the way forward. By adapting the industrial structure and, as far as possible, achieving low carbonisation of the final product, the energy demand structure and energy efficiency can be improved.

In terms of practical implications, first, efforts to develop energy restructuring and clean energy substitution have become particularly important in order to reduce carbon emissions in various countries such as China and EU member countries. Due to the idiosyncracies of the existing electricity supply structure and layout in China's electricity sector, measuring the impact of energy structure adjustment is of particular significance for formulating energy policy. Second, this paper investigated the impact of the energy intensity effect on CO_2 emissions reduction in the thermal electricity and heating sector. In addition, we also identified the causes of the contradiction between the energy intensity policy and the reality of the situation. Reducing energy intensity within the production process has become the core goal of environmental policy. As China was the largest consumer of fossil fuels in the world in 2011 (BP, 2012), studying the changes in energy intensity in the thermal electricity and heating sector can provide guidance for a carbon emissions reduction policy that is able to cope with the increasingly stringent energy constraints on economic development as well as the increasingly serious environmental problems. Third, the input-output structure reflects the production technology used. Thus, investigating the input-output structure effect in the thermal electricity and heating sector is conducive to measuring the contribution of the technological mitigation effect, as well as its evolutionary trend, and providing guidance for the government to tailor its energy policy accordingly. In addition, China's demand for electricity has continually increased, and the country is now facing huge fluctuations in electricity demand and a system with insufficient peak regulation capacity to cope with these. Investigating the demand structure and its impact on CO_2 emissions reduction can help to predict demand for thermal electricity and heating. Doing so can inform policies designed to optimise the demand structure, improve the efficiency of electricity utilisation, and formulate electricity development plans to ensure stable electricity generation and a stable supply.

6. Conclusions

In this study, we determined the key drivers of CO_2 emissions China's thermal electricity and heating sector by applying the IO-SDA method from 2007 to 2018. We also studied the evolutionary trends of these drivers, analysed the internal causes of the changes in each driver and assessed the impacts of the country's energy policy on the drivers of CO_2 emissions in the thermal electricity and heating sector. This produced four main findings:

First, the growth in final demand was the main driving force behind the rise in CO_2 emissions, which indicates that the swift expansion in the scale of the economy is largely responsible for increasing CO_2 emissions. Increased demand for electricity and heating in the service, and construction industries, and in heavy industries, was the main factor that explains the sharp increase in CO_2 emissions from the thermal electricity and heating sector. Moreover, the contribution of the construction industry to the final demand effect increased to a greater extent than that of heavy industry, because the country has stepped up its efforts to phase out energy-intensive, heavily polluting industries, such as steelmaking, so the demand for electricity from heavy industry has fallen. The construction industry is closely related to economic development, and infrastructure investment is also a key measure through which China is attempting to stabilise economic growth. Therefore, further reductions in energy-intensive heavy industry and increased optimisation of energy demand and electricity utilisation in the construction industry can effectively reduce carbon emissions from thermal electricity generation.

Second, the emissions reduction seen in the thermal electricity and heating sector can mainly be attributed to improvements in the input-output structure. However, ongoing technological upgrading in the thermal power sector has not resulted in the desired reduction in emissions. This is because the market reform of the industrial development mechanism lags far behind the pace of technological development, and the conflict between the use of coal and the use of electricity has worsened. With the rise in coal prices, thermal electricity enterprises suffered serious losses, which led to a substantial reduction in investment and electricity generation. This led to a significant reduction in the utilisation rate of thermal electricity equipment as well as in the scale effect and the effect of technological upgrading. This implies that China needs to speed up its reform of electricity price marketisation.

Third, the decrease in energy intensity was the second driving force behind the reduction in emissions during the period from 2007 to 2015. However, the overall decomposition results from 2007 to 2018 indicate that the change in energy intensity had a weak effect on increasing CO_2 emissions. In addition, we also found that the mandatory reduction in energy intensity proposed in the 11th period of the five-year plan actually had the opposite effect between 2010 and 2012. This can be largely attributed to the long-term dependence of the western region's economy on coal-based resources. The increased demand for electricity, brought about by economic growth, prompted the western region to expand its coal production and form a nascent energy base. This finding suggests that the government should have given priority to accelerating energy substitution and upgrading technology in the western region, because focusing only on reducing energy intensity could backfire. The eastern region could focus on enhancing the technological advantages and improving the technological efficiency of thermal power generation. With regard to the central region, efforts should be directed at improving thermal power generation technology, gradually phasing out small coal power enterprises, making full use of its resource advantages and improving the efficiency of its energy utilisation. Finally, the northeastern region of the country should continue to close down and/or improve small thermal power plants that are associated with high energy consumption and heavy pollution. The increment in energy intensity in 2018 implies that, during the 13th period of the five-year plan (2016-2020), it may be prove more effective to try to achieve a balance between stock adjustment and incremental optimisation in the thermal electricity sector on a regional basis.

Finally, but importantly, optimising the energy structure to replace high carbon fossil energy with low carbon energy, such as blast furnace gas and converter gas in the thermal electricity and heating sector has had a sustained reduction effect, which is consistent with the policy objectives and the mainstream literature. However, the effect on reducing carbon emissions remains small, and progress still needs to be made in terms of low carbon energy and clean energy alternatives. Overall, in the process of implementing emissions reduction measures at the production end of the electricity and heating sector, it is important to strike a balance between economic development and energy consumption. In addition, when formulating energy policies, policymakers need to take full account of the reality of the situation in each province and adapt measures to local conditions.

In terms of policy implications, we suggest that energy policies should be more flexible and adaptive to the varying socio-economic conditions in different cities and provinces in China. The eastern region could focus on enhancing the technological advantages and improving the technological efficiency of thermal power generation. More specifically, Tianjin, Hebei and Fujian should proactively adjust their energy consumption structure in order to reduce energy consumption and increase the proportion of new energy development and utilisation. The central region should focus more on improving thermal power generation technology, gradually phasing out small coal power enterprises, making full use of resource advantages and improving the efficiency of its energy utilisation. In addition, energy policies should guide the technological transformation and upgrade the manufacturing industry in the central region, and encourage a shift from more traditional industries to greener development.

With regard to the agriculture-oriented areas in central China, the government should encourage the development of more modern forms of agriculture geared towards producing scarce, higher value products, which can then be sold for higher prices. The western region contains large provinces such as Guizhou, Shaanxi and Inner Mongolia, whose industries are largely based on coal production and fossil energy consumption, which means that it will take a longer for energy saving measures to make progress. These regions need to achieve low-carbon development through internal integration and the optimisation of coal-power-related industries. Therefore, it is necessary to concentrate equally on structural adjustment and technological progress, and in particular to improve the technological capabilities of the coal and coal-chemical industries that are associated with high energy consumption. At the same time, the promotion of energy saving technology and 'clean coal' technology in these areas is also essential. In the case of provinces with abundant wind and solar energy resources, such as Inner Mongolia, Gansu and Xinjiang, the local governments should encourage the proactive development of clean energy. Liaoning, Jilin and Heilongjiang provinces in northeastern China should continue to close down and/or improve small thermal power plants, particularly those associated with high energy consumption and heavy pollution. At the same time, they should also shut down small steel and cement enterprises. In addition, accelerating market-oriented reform in relation to electricity pricing is also important in order to realise the benefits of technology upgrading and innovation, because the moderate liberalisation of energy prices could relieve the cost pressure of thermal power enterprises, resolve the contradiction between coal and electricity to some extent, and reduce the scale effect and technology effect of thermal power enterprises. The market-oriented reform of electricity pricing should not only focus on the price per se, but should also be accompanied by adjustments in the industrial structure and the adoption of a new development pattern involving different pricing levels. For example, industries and enterprises that consume a lot of electricity and generate a high level of emissions should be forced to reduce their energy consumption by having to pay higher prices.

This research has some limitations. Thermal electricity generation contributes to over a third of China's energy-related CO_2 emissions. Therefore, it is worthwhile evaluating the efficiency of thermal electricity generation and estimating its potential for reducing CO_2 emissions. Although we attempted to assess the efficiency of the production technology in our study, the findings remain sketchy. Therefore, future research could focus on constructing more comprehensive indicators with which to evalute the efficiency of thermal electricity generation.

References

Ang, B. W. (1999). Is the energy intensity a less useful indicator than the carbon factor in the study of climate change?. *Energy Policy*, 27(15), 943-946.

Ang, B. W., & Su, B. (2016). Carbon emission intensity in electricity production: A global analysis. *Energy Policy*, 94, 56-63.

Ang, B. W., & Tian, G. (2016). Carbon intensity of electricity in asean: Drivers, performance and outlook. *Energy Policy*, 98, 170-179.

Ang, B. W., Zhou, P., & Tay, L. P. (2011). Potential for reducing global carbon emissions from electricity production- A benchmarking analysis. *Energy Policy*, 39(5), 2482-2489.

BP (2013) Statistical Review of World Energy. (Online). Available at: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html (accessed 10 August 2021).

Caves, D., Christensen, L., & Diewert, W. (1982). The economic -theory of index numbers and the measurement of input, output, and productivity. *Econometrica*, 50, 1393-1414.

Choi, K. H., & Ang, B. W. (2012). Attribution of changes in divisia real energy intensity index – An extension to index decomposition analysis. *Energy Economics*, 34(1), 171-176.

Cong, D., Liang L., & Jing, S., et al. (2021). Energy supply efficiency evaluation of integrated energy systems using novel SBM-DEA integrating Monte Carlo. *Energy*, 2021, 231, 120834.

Cooper, W., Seiford, L., & Tone, K. (2007). *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-solver Software (2nd eds.).* New York: Springer Science and Business Media.

Dietzenbacher, E., & Los, B. (1998). Structural decomposition techniques: Sense and sensitivity. *Economic Systems Research*, 10(4), 307-324.

Fan, Y., Liu, L. C., Wu, G., Tsai H. T., & Wei,Y. M.. (2007). Changes in car bon intensity in China: Empirical findings from 1980–2003. *Ecological Economics*, 62(3), 683-691.

Fare, R., Grosskopf, S., Lindgren, B., & Roos, P. (1992). Productivity changes in Swedish pharamacies 1980-1989: A non-parametric Malmquist approach. *Journal of Productivity Analysis*, 3, 85-101.

Fu B., Wu M., Che Y., Wang, M., Huang, Y. and Bai, Y. (2015). The strategy of a low-carbon economy based on the STIRPAT and SD models. *Acta Ecologica Sinica*, 35 (4), 76-82.

Graus, W., & Worrell, E. (2009). Trend in efficiency and capacity of fossil electricity generation in the EU. *Energy Policy*, 37(6), 2147-2160.

Hoekstra, R., & Van den Bergh, J.C. (2002). Structural decomposition analysis of physical flows in the economy. *Environmental and Resource Economics*, 23(3), 357-378.

Han, Y., Zhou, R., & Geng, Z., et al. (2020). A novel data envelopment analysis cross-model integrating interpretative structural model and analytic hierarchy process for energy efficiency evaluation and optimization modeling: Application to ethylene industries. *Journal of Cleaner Production*, 245, 118965.

IEA (2016) World Energy Outlook. (Online). Available at: https://www.iea.org/reports/world-energy-outlook-2016 (accessed 15 August 2021).

IPCC (2006) IPCC Guidelines for National Greenhouse Gas Inventories. (Online). Available at: https://www.ipcc.ch/report/2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/ (accessed 15 August 2021).

Jiang, T., Zhang, Y., & Jin, Q. (2021). Sustainability efficiency assessment of listed companies in China: a super-efficiency SBM-DEA model considering undesirable output. *Environmental Science and Pollution Research*, 1-17.

Jobert T., Karanfil F., & Tykhonenko A.. (2010). Convergence of per capita CO2 emission in the EU: Legend or reality?. *Energy Economics*, 32(6), 1364-1373. Leontief, W. (1974). Environmental repercussions and the economic structure: An input-output approach: A reply. *Review of Economics and Statistics*, 56(1), 109-110.

Karmellos, M., Kopidou, D., & Diakoulaki, D. (2016). A decomposition analysis of the driving factors of co2 (carbon dioxide) emissions from the power sector in the european union countries. *Energy*, 94(9), 680-692.

Lin, B., & Xuan, X. (2015). CO_2 emissions of China's food industry: an input-output approach. *Journal of Cleaner Production*, 112(2), 1410-1421.

Liu, N., Ma, Z., & Kang, J. (2015). Changes in carbon intensity in china's industrial sector: Decomposition and attribution analysis. *Energy Policy*, 87, 28-38.

Maruyama, N., & Eckelman, M. J. (2009). Long-term trends of electric efficiencies in electricity generation in developing countries. *Energy Policy*, 37(5), 1678-1686.

Mi, Z., Meng, J., Guan, D., Shan, Y., Liu, Z., & Wang, Y., et al. (2017). Pattern changes in determinants of Chinese emissions. *Environmental Research Letters*, 12(7), 074003.

Mi, Z., Zheng, J., Meng, J., Ou, J., & Wei, Y. M.. (2020). Economic development and converging household carbon footprints in China. *Nature Sustainability*, 3, 529-537.

National Bureau of Statistics (2016) China Statistical Yearbook. (Online). Available at: http://www.stats.gov.cn/tjsj/ndsj/2016/indexch.htm (accessed 15 August 2021).

National Energy Administration (2013) Notice of The State Council on the issuance of the 12th Five-Year Plan for energy Development . (Online). Available at: http://www.nea.gov.cn/2013-01/28/c_132132808.htm (accessed 1 January 2013).

National Energy Administration (2016) The total electricity consumption in 2015. (Online). Available at: http://www.nea.gov.cn/2016-01/15/c_135013789.htm (accessed 15 January 2016).

Ouyang, X., & Lin, B. (2015). An analysis of the driving forces of energy-related carbon dioxide emissions in China's industrial sector. *Renewable and Sustainable Energy Reviews*, 45, 838-849.

Paul A.S. (2007). Decomposition for emission baseline setting in china's electricity sector. *Energy Policy*, 35(1), 280-294.

Peng, X., & Tao, X. (2018). Decomposition of carbon intensity in electricity production: Technological innovation and structural adjustment in china's electricity sector. *Journal of Cleaner Production*, 172, 805-818.

Peters, G. P., Weber, C. L., Dabo, G., & Klaus, H. (2007). China's growing CO_2 emissions - A race between increasing consumption and efficiency gains. *Environmental Science and Technology*, 41(17), 5939-5944.

Rao, X., Wu, J., Zhang, Z., & Liu, B. (2012). Energy efficiency and energy saving potential in China: An analysis based on slacks-based measure model. *Computers and Industrial Engineering*, 63(3), 578–584.

Su, B., & Ang, B.W. (2012). Structural decomposition analysis applied to energy and emissions:

some methodological developments. *Energy Economics*, 34, 177-188.

Su, B., Ang, B.W., & Low, M. (2013). Inputeoutput analysis of CO2 emissions embodied in trade and the driving forces: processing and normal exports. *Ecological Economics*, 88, 119-125.

Sun, S., & Huang, C., (2021). Energy structure evaluation and optimization in BRICS: A dynamic analysis based on a slack based measurement DEA with undesirable outputs. *Energy*, 216:119251.

Sun. J.W. (2005). The decrease of CO_2 emission intensity is decarbonization at national and global levels. *Energy Policy*, 33(8), 975-978.

Stone, R., Brown, A. (1962). A Computable Model of Economic Growth. A Program for Growth Series. London: Chapmar and Hall.

Tian, X., Chang, M., Lin, C., & Hiroki, T. (2014). China's carbon footprint: A regional perspective on the effect of transitions in consumption and production patterns. *Applied Energy*, 123(1), 19-28.Wang, X., Huang, K., Yu, Y., Hu, T., & Xu, Y. (2016). An input-output structural decomposition analysis of changes in sectoral water footprint in china. *Ecological Indicators*, 69, 26-34.

Toh, M. (1998). The ras approach in updating input–output matrices: an instrumental variable interpretation and analysis of structural change. *Economic Systems Research*, 10(1) , 63-78.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, 130(3), 498-509.

Wei, J., Huang K., Yang, S., Li, Y., Hu, T., & Zhang, Y. (2017). Driving forces analysis of energy-related carbon dioxide (CO_2) emissions in Beijing: An input-output structural decomposition analysis. *Journal of Cleaner Production*, 163, 58-68.

Wang, X. (2010). Decomposition analysis of electricity intensity over 1998–2007 in China. International Conference on Advances in Energy Engineering, Beijing, 2010, 85-88, doi: 10.1109/ICAEE.2010.5557607.

Wang S., Zhu X., Song, D., We, Z., Chen, B., & Feng, K.(2019). Drivers of CO_2 emissions from electricity generation in china based on modified structural decomposition analysis. *Journal of Cleaner Production*, 220, 1143-1155.

Yamakawa, A., & Peters, G.P. (2011). Structural decomposition analysis of greenhouse gas emissions in norway 1990–2002. *Economic Systems Research*, 23(3), 303-318.

Yang, H. (2009). Incorporating both undesirable outputs and uncontrollable variables into dea: The performance of chinese coal-fired electricity plants. *European Journal of Operational Research*, 197(3), 1095-1105.

Yang, H., & Pollitt, M. (2010). The necessity of distinguishing weak and strong disposability among undesirable outputs in DEA: Environmental performance of chinese coal-fired electricity plants. *Energy Policy*, 38(8), 4440-4444.

Yang, L., & Lin, B. (2016). Carbon dioxide-emission in china's electricity industry: Evidence and policy implications. *Renewable and Sustainable Energy Reviews*, 60, 258-267.

Zhang, C., Heller, T. C., & May, M. M. (2005). Carbon intensity of electricity generation and CDM baseline: case studies of three Chinese provinces. *Energy Policy*, 33(4), 451-465.

Zhang K., Li W., Han Y.,et al., (2021). Production capacity identification and analysis using novel multivariate nonlinear regression: Application to resource optimization of industrial processes. *Journal of Cleaner Production*, 282, 124469.

Zhang, M., Liu, X., Wang, W. & Zhou, M. (2013). Decomposition analysis of CO_2 emissions from electricity generation in China. *Energy Policy*, 52, 159-165.

Zhang, N., & Choi, Y. (2013). Total-factor carbon emission performance of fossil fuel electricity plants in china: A metafrontier non-radial malmquist index analysis. *Energy Economics*, 40(2), 549-559.

Zhang, Z.Q., Qu, J. S., & Zeng, J.J. (2008). A Quantitative comparison and analysis on the assessment indicators of greenhouse gases emission. *Journal of Geographical Sciences*, 18(4), 387-399.

Zhao, X., Xi, Z., & Shuai, S. (2016). Decoupling CO_2 emissions and industrial growth in china over 1993-2013: The role of investment. *Energy Economics*, 60, 275-292.

Zhao, X., Zhang, X., Li, N., Shao, S., & Geng, Y. (2016). Decoupling economic growth from carbon dioxide emissions in china: A sectoral factor decomposition analysis. *Journal of Cleaner Production*, 142, 3500-3516.

Zheng, J., Mi, Z., Coffman, D., et al. (2019). Regional development and carbon emissions in China. *Energy Economics*, 81, 25-36.

Zhou, G., Chung, W., & Zhang, Y. (2014). Carbon dioxide emissions and energy efficiency analysis of china's regional thermal electricity generation. *Journal of Cleaner Production*, 83, 173-184.

Zhou, P., & Wang, H. (2012). Energy and CO_2 emission performance in electricity generation: A non-radial directional distance function approach. *European Journal of Operational Research*, 221(3), 625-635.

Zhou, P., Ang, B. W., & Han, J. Y. (2010). Total factor carbon emission performance: A malmquist index analysis. *Energy Economics*, 32(1), 194-201.