Environmental Science and Pollution Research (2020) 27:23550–23564
https://doi.org/10.1007/s11356-020-08490-0

RESEARCH ARTICLE

Driving forces of China's multisector CO_2 emissions: a Log-Mean Divisia Index decomposition

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Received: 11 December 2019 / Accepted: 17 March 2020 / Published online: 15 April 2020

Abstract

To figure out which factor contributes more on carbon emissions caused by energy consumption, this research took multisector analysis based on the Log-Mean Divisia Index Method (LMDI) and decoupling theory to assess the driving factors of carbon dioxide (CO_2) emissions in China's six sectors from 2003 to 2016. Our empirical results reveal that China's economy can be divided as three decoupling stages and exhibited a distinct tendency toward strong decoupling with a turning point in 2008. Thus, we discuss the impact of 2008 economic crisis on carbon emissions based on decomposition results. The empirical results of our study show the following five conclusions. (1) Most sectors in China are in weak decoupling state due to the inhibition of energy intensity on carbon emissions. (2) Different factors contribute differently to reducing emissions in different sectors, economic output has the most prominent effect, followed by energy intensity and population scale. (3) China's current carbon emission reduction measures benefit more on energy efficiency. (4) The economic crisis has greatly reduced energy efficiency and has no significant impact on other factors. (5) If all industries adjust their energy mix, carbon emissions in China can be reduced by almost 17% every year.

Keywords CO_2 emissions · Multisector · Decoupling theory · LMDI method

Introduction

In 2017, fossil fuel consumption increased in the world, accounting for more than 70% of global energy demand. The atmospheric concentrations of carbon dioxide, methane, and nitrous oxide are currently at their highest levels, and the ocean is warmer and more acidic than any time in human history. On 12 December 2015, nearly 200 states attended the United Nations framework convention on climate change and adopted the Paris agreement on climate change, China proposed its own targets for action: Reaching peak carbon emissions by around 2030 and we will strive to peak as soon as possible; Carbon intensity per unit of GDP will be reduced by 60 to 65% compared with 2005.The proportion of non-fossil energy in primary energy consumption reached about 20%, and the forest stock increased by about 4.5 billion m^3 over 2005. As a major developing country, China has made a solemn commitment to the international community on tackling global climate change. Considering our own national conditions, development stage, and the sustainable development strategy, on 19 December 2017, the national development and reform commission held a teleconference to announce the official launch of the national carbon market, which marks that China has entered a new stage of controlling and reducing carbon emission through market mechanism and economic means (Dong et al. 2019a, b, c). Do China's carbon dioxide emissions have been effectively controlled? Is economic development no longer at the cost of environmental pollution? To deal with those questions, this paper studies whether the economic development has decoupled from environmental pollution and identifies which factors may have the largest influence.

There exist an equilibrium and long-term relationship between economic growth and carbon dioxide emissions (Pan and Xiong 2018). When we have deep study in the relationship between the two prominent factors—economic growth

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and environmental pollution, Kuznets curve hypothesis (Al-Mulali et al. 2016), data envelopment analysis (Vlontzos et al. 2014), and input-output model (Pan and Pan 2018; Wang et al. 2015, 2017; Wen and Zhang 2020) are common methods. Since heterogeneity exists in panel data, the conclusions of Kuznets curve hypothesis are usually controversial. Scholars also use vector autoregressive model (VAR) to study the relationship (Wang and Zhuang 2013; Zhang 2017).

Organization for economic cooperation and development (OECD) proposed the decoupling theory which is used to evaluate whether economic development no longer depends on environmental pollution. The theory has widely been used in decoupling relationship between carbon emission and economic growth at the level of provinces(Sun 2011; Zhao et al. 2016), industries (Wang et al. 2017; Luo et al. 2017), or region (Zhong et al. 2012; Ma et al. 2018a, b). Few scholars apply this theory to other fields like thermoelectric (Zhang et al. 2018). It can also be used in the research of energy consumption and economic growth. Ning et al. (2017) consider the difference of economic development, energy consumption, and carbon dioxide emission from regional aspect. Wu et al. (2018) use Impact-GDP-Technology decoupling model and compare the difference in developed and developing countries. Meng et al. (2018) employ the Tapio Decoupling Index to decompose China's industrial output and fossil energy consumption. Moreau and Vuille (2018) decouple energy using and economic development to verify relationship between economy and environment.

Knowing whether economic development is decoupled from environment, we need to decompose the driving factors. There are many factorization methods, including index decomposition analysis (IDA), structural decomposition analysis (SDA) (Dong et al. 2018a, b), etc. Since SDA can consider both direct and indirect energy consumption, and it is often supported by Input–Output tables (Cansino et al. 2016), in this paper, we choose Log-Mean Divisia Index (LMDI) to decompose carbon emission since we ignore the detail input or output factors and we calculate carbon emission from the aspect of energy consumption. Ang and Liu (2001) firstly present LMDI decomposition method and give two case studies about energy-related CO_2 emissions. After developing for years, LMDI method becomes more mature. Usually, we decompose carbon emission into five effect—energy mix, energy intensity, industry structure, economic output, and population scale effects. But, it usually is not limited by this (Cansino et al. 2015; Liu et al. 2007). Sometimes economic activity, industrial structural shift, and final fuel shift are also considered.

Since there are so many factors, which one has the most significant effect? Results are not usually the same. Xu et al. (2014) hold that the first three driving factors of carbon emissions is economic output effect, population scale, and energy mix effects. Cansino et al. (2015) find that only population drive carbon emission while others are fluctuating, sometimes negative and sometimes positive. Lin and Long (2016) find that in the chemical industry, output per worker, industrial economic scale, energy intensity, and energy mix influence carbon emissions most. Yasmeen et al. (2020) find that in Pakistan, the economic development factor is the main driving force for the increase of per capita carbon emissions in the country and the energy structure and energy efficiency are the restraining factor for per capita carbon emissions.

Why do scholars have different conclusions when using LMDI? We think that it could be caused by that those scholars put all parts together (Zhang et al. 2016) or just discuss one sector (Wang et al. 2015) or one province (Chong et al. 2017). To confirm our assumption, we read more articles that discuss one sector or one region separately. Xu et al. (2012) hold that in Chinese cement industry, the growth of cement output plays most part in driving energy consumption up. Ren et al. (2014) adopt the LMDI method and suggest that the increase in economic output contributes more on the increase of CO_2 emissions in China's manufacturing industry. Minda et al. (2018) apply an extended LMDI model to study the role of different impact factors that affect the public building energy consumption.

Separately discussing one sector can have more clear results, so we consider each independent sector and combine two methods mentioned above—decoupling theory and LMDI method. Wen and Zhang (2019) used the LMDI decompose model to take into account carbon emissions in each energy industry and used the Tapio decoupling model from 2000 to 2015 to seek the decoupling states. There exists some similar study (Wang et al. 2017; Yang et al. 2018; Román et al. 2018); they combine the two methods to carry out a detailed research on environment pollution.

From discussions above, we find two deficiencies in most studies of decoupling theory and LMDI. (1) Most studies consider carbon emissions in one region and there are currently few comparing studies in different sectors. (2) No amount has been given to clarify the volume of carbon emissions that China could reduce. To supplement those omissions, this paper makes four main contributions. (1) We calculate the carbon emissions produced by six economic sectors. (2) With regard to sub-sector decomposition, we study the relationship between economic development and carbon emissions in different sectors and figure out the different effect of different driving factors. (3) Based on these results, we explore the impact of the 2008 economic crisis on China's carbon emissions. (4) Using Japan as an energy mix target, we gain a specific carbon emission amount China can reduce. Figure 1 is the flow chart. We made literature review before, then we are going to introduce data and model, followed by results and comparison, and the last is conclusion.

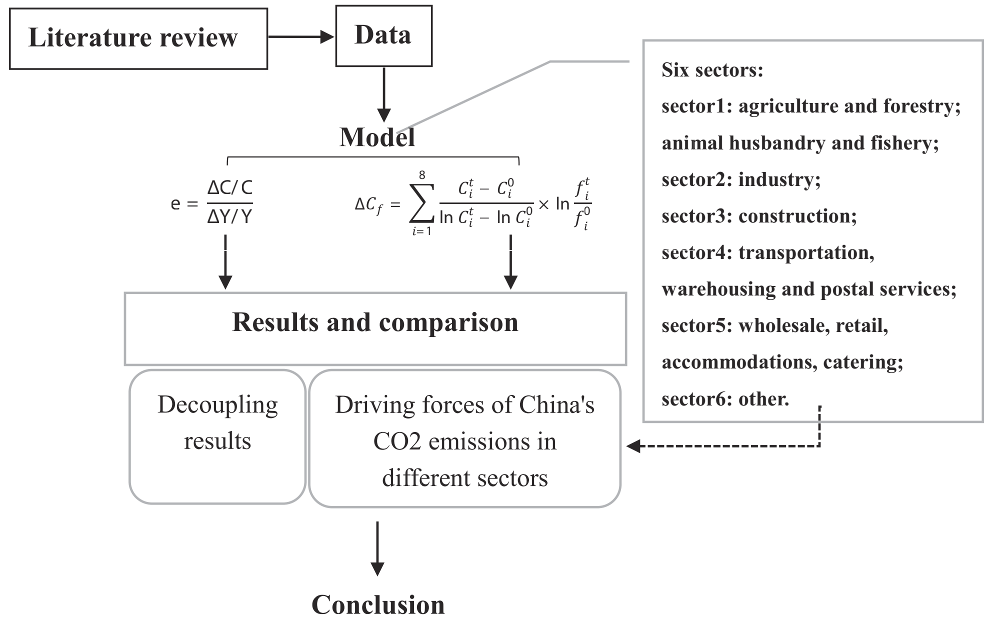


Fig. 1 Flow chart in the paper

Model and database

Decoupling theory and model

In 2002, the OECD (2002) developed the concept of decoupling into an index to define the relationship between economic growth and environmental change, so as to explore how to reduce the correlation between economic growth and environmental pollution (Dong et al. 2019a, b, c). Decoupling theory gradually achieved global recognition as a significant role of successful economy–environment integration. There are different decoupling states presented by Tapio (2005). This article studies carbon emissions and economic growth in China's different sectors, and the formula is as follows:

$$e = (\Delta C/C)/(\Delta Y/Y) \tag{1}$$

where e is the decoupling elasticity coefficient, $\triangle C$ is the carbon emission increment, C is the carbon emissions in the year, ΔY is the gross domestic product (GDP) increment, and Y is the GDP in the year. As the rate of change of carbon emissions and economic growth is different, there should be different values of the decoupling elastic coefficient and different types of decoupling state; these are shown in Table 1 (Li et al. 2016).

Logarithmic Mean Divisia Index method

Based on the Divisia decomposition method proposed by Divisia (1925), Liu and Ang (2001) proposed the LMDI method. This method overcomes the problem that Divisia decomposition failed to pass the statistical test and the new one has no residual item; it was widely accepted. Later, Ang (2004) gave a solution dealing with zero and negative values, solving the only defect in the LMDI processing; the improved LMDI decomposition method has become a relatively mature index decomposition method. The method system is becoming more and more perfect (Ang 2015). This paper establishes a factor decomposition model to study the energy consumption carbon emissions of various industries in China. Formulas are as follows:

$$C_j = \sum_{i=1}^{8} C_{ij} = \sum_{i=1}^{8} \left(\frac{C_{ij}}{E_{ij}} \times \frac{E_{ij}}{E_j} \times \frac{E_j}{Y_j} \times \frac{Y_j}{P_j} \times P_j \right) = \sum_{i=1}^{8} (f_i \times s_i \times m_i \times g_i \times p_i) \tag{2}$$

$$\Delta C = C^t - C^0 = \Delta C_f + \Delta C_f + \Delta C_s + \Delta C_m + \Delta C_g + \Delta C_p \tag{3}$$

$$\Delta C_f = \sum_{i=1}^{8} \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{f_i^t}{f_i^0} \tag{4}$$

$$\Delta C_s = \sum_{i=1}^{8} \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{s_i^t}{s_i^0} \tag{5}$$

$$\Delta C_m = \sum_{i=1}^{8} \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{m_i^t}{m_i^0} \tag{6}$$

$$\Delta C_g = \sum_{i=1}^{8} \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{g_i^t}{g_i^0} \tag{7}$$

$$\Delta C_p = \sum_{i=1}^{8} \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{p_i^t}{p_i^0} \tag{8}$$

where C_j is the total carbon emissions in sector j ($j = 1, 2, ..., 6$, representing 6 different sectors), C_{ij} is the carbon emissions generated by the consumption of i energy in the j sector ($i = 1, 2, ..., 8$, representing 8 different energy), C^t and C^0 are the amount of carbon emission in year t and the beginning year. E_{ij} is the consumption of i energy in the j department

Table 1 Decoupling elasticity coefficient and its type

$\Delta Y/Y>0$		$\Delta Y/Y<0$	
$\Delta C/C>0$			
$e>1.2$	Expansive negative decoupling	$e<0$	Strong negative decoupling
$0\le e<0.8$	Weak decoupling		
$0.8\le e\le 1.2$	Expansive coupling		
$\Delta C/C<0$			
$e<0$	Strong decoupling	$0\le e<0.8$	Weak negative decoupling
		$e>1.2$	Recessive decoupling
		$0.8\le e\le 1.2$	Recessive coupling

(equivalent to the standard coal equivalent), E_j is the total amount of energy consumed in the j sector (equivalent to the standard coal equivalent), Y_j indicates the output of sector j in the current year and is calculated as GDP. P_j indicates the number of employees in the j department that year. f_i indicates the intensity of carbon emissions (carbon emission coefficient), s_i represents the energy consumption structure (energy mix (energy structure (ES0), m_i represents energy intensity (EI) (also can be seen as energy efficiency (Choi et al. 2017)), g_i represents the GDP per capital (economic output per capital (EO)), and p_i represents the size of working people in this sector (population scale (PS)). $\triangle C_f$, $\triangle C_s$, $\triangle C_m$, $\triangle C_g$, and $\triangle C_p$ represent the effects of carbon emission changes due to the above five factors, respectively. Since the carbon intensity effect is essentially the carbon emission factor of i energy, the change in carbon emissions caused by the carbon intensity effect is zero, so we do not consider the carbon emissions caused by carbon intensity in the calculation, that is:

$$\Delta C_f=\sum_{i=1}^{8}\frac{C_i^t-C_i^0}{\ln C_i^t-\ln C_i^0}\times\ln\frac{f_i^t}{f_i^0}=0 \tag{9}$$

By combining the two methods of LMDI and decoupling theory, we can first find out the linkage between China's economic development and carbon emissions, and then, according to the LMDI decomposition method, reasonably control carbon emissions by adjusting the decomposed factors without affecting economic development (Dong et al. 2019a, b, c).

Database

According to the current China's State Statistics Bureau's industry classification standards, we refer to Ning et al. (2017) and divide China's industries into six sectors, shown in Table 2 (Chai et al 2012). Based on research demand and statistical caliber, scholars divide all Chinese sectors into different categories, some 39 sectors (Dong et al. 2018a, b), or 30 sectors (Deng et al. 2018), some 4 big sectors (Yu et al. 2018). For research convenience and data acquisition, we simplified the division.

At the same time, this paper lists eight types of energy: coal (10^4 tons), coke (10^4 tons), crude oil (10^4 tons), gasoline (10^4 tons), kerosene (10^4 tons), diesel (10^4 tons), fuel oil (10^4 tons), and natural gas (10^8 cum). Due to the integrity of the data, some irreplaceable data-like employment data in different sectors is missing before 2003, our research period is from 2003 to 2016. Our GDP figures have been deflated, taking 2003 as the base year. We refer to Shao et al. (2016), Zhao et al. (2009), and Porter et al. (2017), adopt Intergovernmental Panel on Climate Change (IPCC) Carbon Emission Calculation Guideline for data selection and carbon emission accounting method selection (IPCC). Data comes from China Statistics Yearbook. Carbon emission coefficients are shown in Table 3.

Here, we need to do some comparison about Provincial Guidelines for National Greenhouse Gas Inventories that is published by the National Development and Reform Commission and IPCC list. The 2006 IPCC Guidelines for National Greenhouse Gas Inventories are based on the previous revisions in1996, incorporating new energy and new gases, and updating previously published methods based on advances in scientific and technical knowledge. The new guidelines can assist countries in developing a complete national greenhouse gas inventory. Moreover, all countries, regardless of their experience or resources, are able to make reliable estimates of emissions and removals of these gases in accordance with the new guidelines. The new guide provides all departments with the required default values for each parameter and emission factor, so the easiest way is to provide only a

Table 2 Sectors dividing

Sector	Sector component
Sector 1	Agriculture and forestry, animal husbandry, and fishery
Sector 2	Industry
Sector 3	Construction
Sector 4	Transportation, warehousing, and postal services
Sector 5	Wholesale, retail, accommodations, catering
Sector 6	Other sectors

Table 3 Carbon emission coefficient of various energy sources

Energy	Carbon emission coefficient	Energy	Carbon emission coefficient
Coal	0.7559	Kerosene	0.5714
Coke	0.8550	Diesel	0.5921
Crude oil	0.5857	Fuel oil	0.6185
Gasoline	0.5538	Natural gas	0.4483

Note: Carbon emission = energy consumption volume (equivalent to the standard coal equivalent) × carbon emission coefficient

country's own activity data. This approach maintains compatibility, comparability, and consistency across countries, and the final estimate is neither higher nor lower than the actual estimate, which can minimize uncertainty.

According to the requirements of the United Nations Framework Convention on Climate Change, all Parties should prepare national greenhouse gas inventories in accordance with the IPCC Guidelines for National Greenhouse Gas Inventories. Provincial Greenhouse Gas (GHG) inventory preparation in China generally follows the basic approach of the IPCC Guidelines for National Greenhouse Gas Inventories, and draws on the good practices of GHG inventory preparation for energy activities in China in 1994 and 2005.When people calculate carbon emission in China, they can use carbon emission coefficient or method provided by both IPCC list and Provincial GHG inventory. (Information above comes from IPCC and National Development and Reform Commission).

Decoupling results analyze

Generally, it can be seen from Table 4 that the situation in all sectors are slowly getting better and we divide different results into three situations. First is stable state—sectors 3, 4 and 6. Sector 3 is nearly in weak decoupling state while sectors 4 and 6 are in expansive coupling. Second is semi-stable state—sectors 2 and 5. Sector 2 is in expansive coupling state in early times and then in weak decoupling state and last in strong decoupling state. Instead, sector 5 is in weak decoupling state first and then in expansive coupling state. The last one is unstable state—sector 1. Sector 1 is in a cycle of weak decoupling–expensive decoupling–weak decoupling with higher frequency, with a big energy consumption fluctuation during the research period. Also, we can divide China's economy decoupling state into three stages, with a turning point in 2008. The first stage occurred during the years from 2004 to 2008; during this period, China was in either weak decoupling state or expansive coupling state. Weak decoupling state means that carbon emission decreases and GDP increase slightly while expansive coupling means that energy consumption increases and GDP increases too. The second stage was from 2008 to 2009, with a turning point caused by the economic crisis. The third stage was from 2009 to 2016 and included a distinct tendency toward weak to strong decoupling.

The year 2009 was unusual; most sectors were in expansive negative decoupling state. In other words, output released more carbon dioxide in that year for some reason like energy waste. We believe that Chinese economy hit bottom in 2009 because the financial crisis in 2008. However, due to the impact of the crisis, the domestic economic situation became unstable, resulting in excessive energy consumption. Another unusual year was 2014, China's overall economy entered strong decoupling state due to the strong decoupling of industrial carbon emissions, which led directly to the decoupling of the overall economy. This point is in line with the fact that China has had negative energy consumption growth during 2015, showing that under the current new normal economic development, our effort in environment protection makes sense; there is no obvious correlation between economic growth and energy consumption.

We can also see that there is high similarity between the decoupling of industry and the decoupling of the overall economy. They have almost the same decoupling state. The strong decoupling of industry leads directly to the decoupling of the overall economy of industry, indicating that (1) industry does account for most of China's energy consumption and (2) our carbon emission reduction policy should call on industry to rectify their emission policies. From 2011 to 2015, the "Twelfth Five-Year Plan" period, our overall situation was better than it was during the "Eleventh Five-Year Plan" period, mainly due to industrial decoupling. This indicates that the emission reduction policy makes sense in national emission reduction. For example, the carbon trading system launched in 2011 covers electricity generation, steel production, and cement manufacturing in seven provinces and cities and has performed well in suppressing industry carbon emissions. Prior to this measure, relation between Chinese economic growth and energy consumption was weak decoupling state. During the Eleventh Five-Year and Twelfth Five-Year Plan periods, China adopted a variety of energy-saving and emission-reduction measures, significantly slowing the energy consumption growth. The decoupling state of economic growth and energy consumption means that the dependence of economic growth on energy consumption has gradually

Table 4 Results of multisector decoupling results

Year	Sector 1		Sector2		Sector 3		Sector 4		Sector 5		Sector 6		The whole industry	
2004	2.34794	Expansive negative decoupling	1.48431	Expansive negative decoupling	1.61034	Expansive negative decoupling	1.16501	Expansive coupling	1.70455	Expansive negative decoupling	1.154526	Expansive coupling	1.64967	Expansive negative decoupling
2005	0.78394	Weak decoupling	1.04681	Expansive coupling	0.44527	Weak decoupling	0.93363	Expansive coupling	0.41290	Weak decoupling	0.868245	Expansive coupling	1.03469	Expansive coupling
2006	1.08194	Expansive coupling	0.95802	Expansive coupling	0.49081	Weak decoupling	1.14909	Expansive coupling	0.53875	Weak decoupling	0.632427	Weak decoupling	0.94313	Expansive coupling
2007	0.01788	Strong decoupling	0.65118	Weak decoupling	0.36900	Weak decoupling	0.98824	Expansive coupling	0.50129	Weak decoupling	0.142397	Weak decoupling	0.65929	Weak decoupling
2008	7.86141	Strong decoupling	0.60346	Weak decoupling	0.63203	Weak decoupling	1.06154	Expansive coupling	0.05252	Weak decoupling	2.386917	Expansive negative decoupling	0.59504	Weak decoupling
2009	2.71641	Expansive negative decoupling	1.35332	Expansive negative decoupling	0.69790	Weak decoupling	0.94461	Expansive coupling	2.73766	Expansive negative decoupling	1.691295	Expansive negative decoupling	1.30117	Expansive negative decoupling
2010	0.98838	Expansive coupling	0.77922	Weak decoupling	1.02274	Expansive coupling	1.13023	Expansive coupling	0.57321	Weak decoupling	1.277398	Expansive negative decoupling	0.90449	Expansive coupling
2011	0.99753	Expansive coupling	0.93597	Expansive coupling	1.15314	Expansive coupling	0.85468	Expansive coupling	1.19592	Expansive coupling	1.059159	Expansive coupling	1.03134	Expansive coupling
2012	0.51763	Weak decoupling	0.72987	Weak decoupling	0.20895	Weak decoupling	1.53590	Expansive negative decoupling	0.94853	Expansive coupling	1.150761	Expansive coupling	0.77186	Weak decoupling
2013	1.35349	Expansive negative decoupling	0.53171	Weak decoupling	1.11353	Expansive coupling	0.94158	Expansive coupling	1.03047	Expansive coupling	1.127068	Expansive coupling	0.57172	Weak decoupling

declined. Although China's economic growth and energy consumption have not yet achieved strong decoupling, an essential contribution to economic growth has undergone significant structural changes. The contribution rate of technological progress is continuously rising, and the proportion of low-energy-consuming services in China's GDP is increasing. It is precisely because of the weak decoupling between economic growth and carbon emission that China has ability to promise that greenhouse gas emissions will peak before 2030 or even earlier. Going forward, China can contribute more to reducing global climate risks.

Multisector LMDI decomposition of carbon emission

Through LMDI decomposition and Eqs. (2)–(8), we can separately decompose the carbon emission of six sectors and study the effects of energy mix, energy intensity, economic output per capita, and population on energy consumption carbon emissions. For comparability, all calculation results are shown in increments. The contributions of the four drivers are represented by bar graphs, and changes in carbon emission increments are represented by line charts. The data in the figure below indicates that how much a certain factor add the increment of carbon emissions. The positive and negative values represent respectively the promoting and suppressive effects on increment of energy consumption carbon emissions.

Agriculture, forestry, animal husbandry, and fishery sector

It can be seen from Fig. 2 that the energy mix effect on carbon emission is not obvious. Usually, it promotes carbon emission a little, but in 2009 and 2013, it suppresses a lot. The energy intensity effect has been suppressive for long; we can say that the energy efficiency of sector 1 is higher, so it has a significant suppressive effect on carbon emissions. The economic output per capita has always been a catalyst for carbon emissions. Especially after 2013, while the number of employed people in agriculture has been declining year by year, the economic output per capita has still played a catalytic role. The population size effect has always suppressed agricultural carbon emissions. Since 2013, the number of employed people has shown a downward trend, causing the inhibition of the population-scale effect to be more pronounced. During the study period, whether the number of people employed in sector 1 increased or not, the population scale still suppressed carbon emissions. Considering only carbon emissions, we may posit that China's employment population in sector 1 has large space for growth.

From 2003 to 2016, only the economic output per capita contributed to promoting carbon emissions. Under the circumstances that the energy mix, energy intensity, and population scale all inhibit carbon emissions, we find that carbon emissions from sector 1 are increasing year-on-year, indicating that economic output per capita has dominant impact on agricultural carbon emissions.

Industry sector

It can be seen from Fig. 3 that the energy structural effect plays uncertain but small role in promoting carbon emissions, sometimes it promotes carbon emission when consuming more coal while sometimes not when consuming less coal. Sector 2 has special requirements for raw materials and somewhat fixed demand for energy types. Figure 4 shows that sector 2 has the highest consumption of coal, crude oil, and coke with an unbalanced energy mix. We calculated the makeup of the cumulative industrial energy consumption from 2003 to 2016, and coal accounted for 68.52%, crude oil accounted for 18.19%, and coke accounted for 10.65%. The remaining energy accounted for only 2.64%. It can be said that this structure is in long-term fixed state. On the other hand, from Table 3, we can see that coal, coke, and crude oil occupy the first three places in the energy carbon emission coefficient. It is obvious that sector 2 will generate more carbon emissions when it consumes same amount of standard coal equivalent.

Energy intensity has long-term suppressive effect on carbon emissions, indicating that China's industrial energy usage efficiency is relatively high. Only in 2008 was the effect of the energy intensity effect reversed—in that year, this factor promoted carbon emissions. In 2008, affected by the global economic crisis, economic output fell sharply. The positive market atmosphere of previous years led to optimistic overestimation. The economic crisis caused a series of problems—such as capital chain breakage, factory bankruptcies, and so on, which led to poor efficiency in industrial energy usage. Carbon emission intensity rate rose in 2009.

Most time, the economic output effect make largest contribution on promoting carbon emissions, this is in line with Lin and Long's (2016) findings in the chemical industry. However, in 2012–2013, the economic output effect suppressed carbon emissions. According to our analysis, there only exist 2 years when China's industrial output per capita decreased, in 2011 it decreased by 0.625% and in 2013 by 10.43%. Does this indicate the decrease in economic output per capita does not necessarily suppress carbon emissions until it reaches a limited value?

Since 2014, industrial carbon emissions have been in a downward trend, with only the economic output contributing to carbon emissions, while the other three are in concert with suppressing carbon emissions. In 2013, carbon emissions reached a peak of $3009.23 \cdot 10^4$ tons, but in 2014 fell to

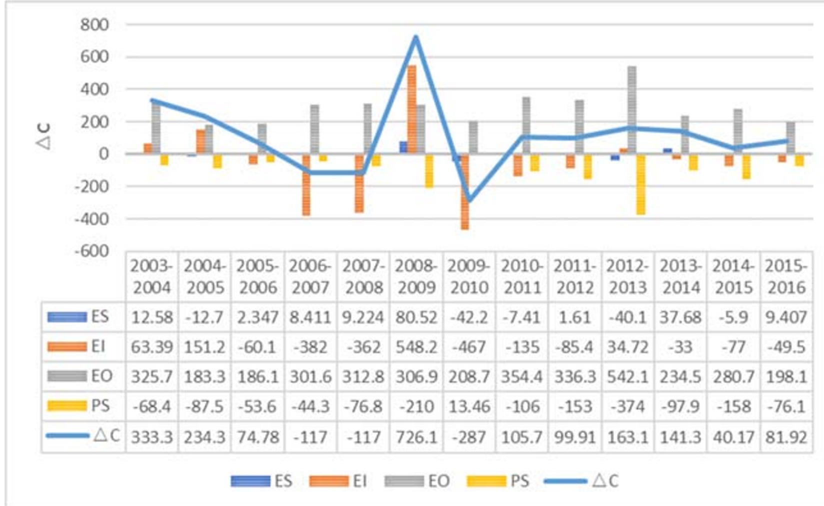


Fig. 2 Decomposition of carbon emissions in agriculture, forestry, animal husbandry, and fishery sector

2989.05·10^4 tons, and in 2016, it continues to drop down to 2867.06·10^4 tons. An important reason for this decline is that population size has inhibited the growth of carbon emissions in recent years, while energy intensity contributes a lot in curbing it.

What is more, since 2014, the increase in industrial carbon emissions has been negative, indicating that China's industrial carbon emission reduction strategy has achieved good results. However, this effect does not come from adjustment in energy mix and energy intensity but the suppression of population-scale effects. The effect of the energy mix effect on the increase in carbon emissions in the past 2 years is still unstable. It may be because that the adjustment of the energy mix strategies is still in adaptive period. The industrial energy mix is fixed for so long that the mitigation strategy has not been integrated with the industrial production process. But there are some improvements in the energy mix of industry. Figure 4 shows that since 2014, the amount of coal used for industrial energy consumption in China has begun to decrease, which has significant negative impact on overall industrial carbon emissions.

Construction sector

Figure 5 shows that the effect of the energy mixes on carbon emissions is relatively weak and generally has deterrent effect. Like sector 2, energy consumption structure of sector 3 is also somewhat fixed. In accumulated amount of energy consumption from 2003 to 2016, sector 3 mainly consumes diesel, coal, and gasoline and accounted for 41.1, 31.3, and 23.2%, respectively. The remaining energy only accounted for 4.4%. The carbon emission coefficient of the three main energy is relatively low, especially the diesel, of 0.5921, and the construction sector consumes less coal. Compared with sector 2, sector

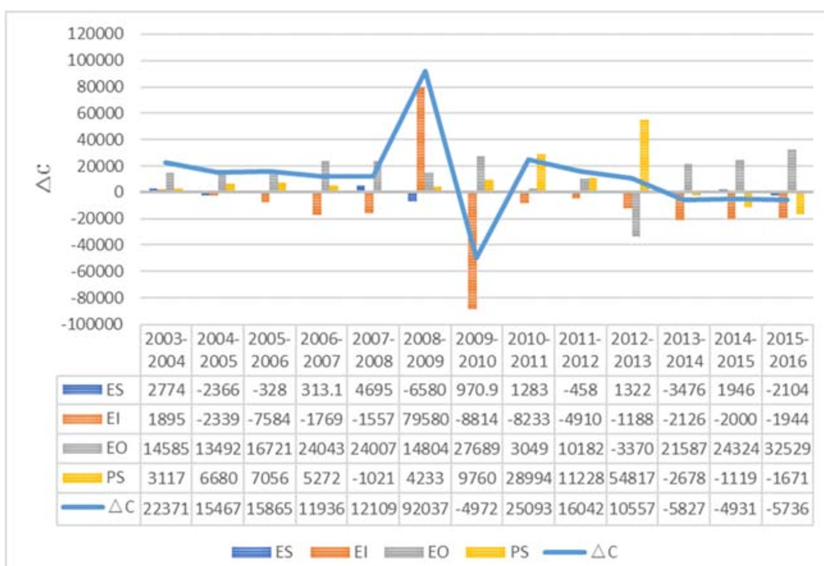


Fig. 3 Decomposition of carbon emissions in industry sector

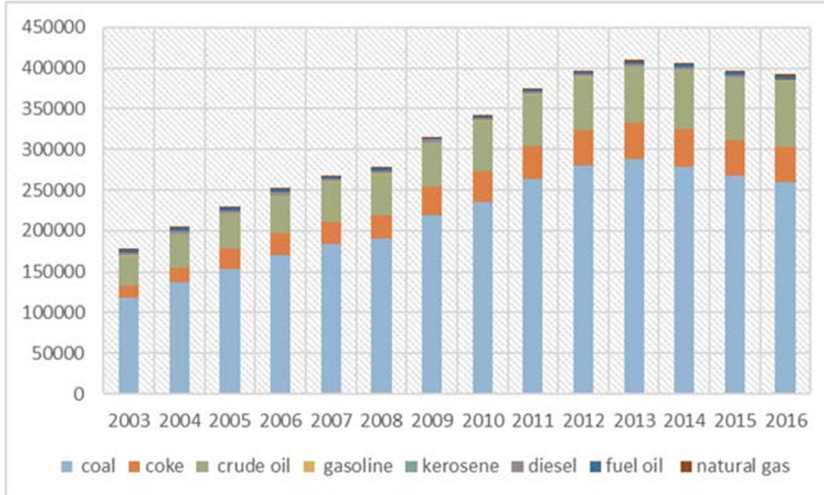
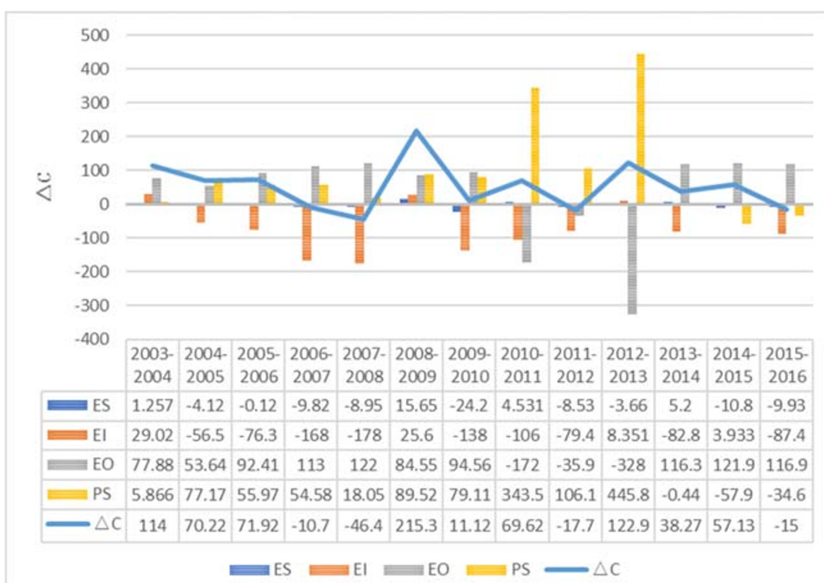


Fig. 4 Industrial energy consumption

3 had less carbon emissions, and energy mix had negative effect on carbon emissions. Only the years from 2008 to 2009 showed bigger positive promotion.

Energy intensity inhibits carbon emission in the long term and sometimes has such small positive effect that we can omit it. So, we can say that energy intensity has long-term suppressive effect on construction carbon emissions, and sector 3 has higher energy usage efficiency.

Economic output plays major role in promoting carbon emissions, followed by population-scale effects. The economic output effect only appeared to be suppressive during the year 2010–2013, as economic output per capita continued to decline from 2011 to 2013, decreasing 19.34, 5.81, and 24.55%, respectively. On the one hand, during 2011 to 2013, the construction sector had an annually GDP growth rate of 9.7%. On the other hand, from 2011 to 2013, employment in the construction sector in China increased sharply. The effect of population size on carbon emissions has become particularly apparent. Both GDP and the size of the working population have played a role in economic output per capita, leading to a situation in which economic production per capita suppressed carbon emissions. However, the population-scale effect began to suppress carbon emissions after 2013. Because the number of people employed in the construction industry became flat in 2014 as compared with 2013 and declined in 2015 and 2016. This may help explain why the effect of economic output per capita began to promote carbon emissions after 2013. Overall, in the sector 3, the number of employed people has decreased, but economic output has maintained a positive growing trend. In addition, we believe that the increase in the number of employed people does not mean that the population scale has catalytic effect on carbon emissions. Only when population reaches a limit value will the population-scale effect promote carbon emission. This



	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016
ES	1.257	-4.12	-0.12	-9.82	-8.95	15.65	-24.2	4.531	-8.53	-3.66	5.2	-10.8	-9.93
EI	29.02	-56.5	-76.3	-168	-178	25.6	-138	-106	-79.4	8.351	-82.8	3.933	-87.4
EO	77.88	53.64	92.41	113	122	84.55	94.56	-172	-35.9	-328	116.3	121.9	116.9
PS	5.866	77.17	55.97	54.58	18.05	89.52	79.11	343.5	106.1	445.8	-0.44	-57.9	-34.6
△C	114	70.22	71.92	-10.7	-46.4	215.3	11.12	69.62	-17.7	122.9	38.27	57.13	-15

Fig. 5 Decomposition of carbon emissions in construction sector

situation is understandable due to the gradual maturity of sector 3, even though the increase in the population size means more inputs and outputs and suggests that the suppression of carbon emissions by technological progress can effectively counteract the promotion of the population scale effect.

Transportation, warehousing, and postal sector

The energy mix effect suppresses carbon emissions for a long period of time in sector 4, and energy consumption stay in fixed energy mix consisting mainly of diesel and gasoline. The two types of energy have lower carbon emission coefficients and lower carbon emissions. The energy intensity effect inhibits carbon emissions, meaning that energy efficiency is high. The effect of economic output per capita, along with the population size effect, has been a promoting factor in the long term. Larger inputs and larger outputs have promoted the increase of carbon emissions.

However, around 2013, due to the large increase in the employed population and the small increase in GDP in 2013, the per capita output decreased, and this has inhibited carbon emissions. The population size effect promotes carbon emissions over a long period of time, because sector 4 requires a lot of manpower input. At the same time, a large amount of output occurs, and expected output and unexpected output increase substantially as well. The number of employees increased from 2003 to 2016 year by year, and dramatically increased in 2013, when online shopping was widely popularized.

From Fig. 6, we can see that the carbon emissions of sector 4 were greatly affected by the economic output per capita effect, and the ΔC trend is almost in line with economic output per capita. Carbon emissions have been increasing for years. Only in 2008, affected by the economic crisis, the contribution of each effect became weak, resulting in small increase in carbon emissions for that year.

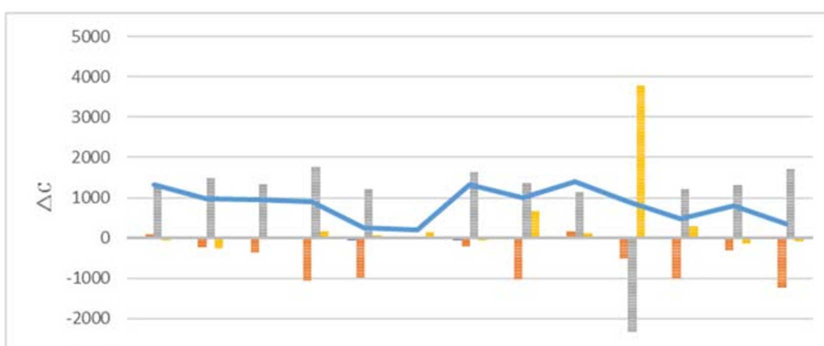
Wholesale, retail, accommodation, and catering sector

Figure 7 shows that the sector's carbon emissions increased, and in some years, there was a decline due to the significant suppression of energy intensity during 2003–2016. Unlike other sectors, although energy mix effects contribute little to carbon emissions, the promotion and suppression effects were parallel in sector 5. When coal consumption increased, carbon emissions were often promoted. Especially from 2008 to 2009, coal consumption increased 143% ($12.8 \cdot 10^4$ tons in 2008 and $31.1 \cdot 10^4$ tons in 2009). This situation has also happened in the sector 3, we can conclude that coal consumption can directly affect the energy mix of the sector, and thus affect the direction of the role of energy mix on carbon emissions.

Energy intensity has higher suppressive effect on carbon emissions for a long time, since the sector has achieved higher energy efficiency. Only in the 2008 economic crisis did energy efficiency decrease, which caused energy intensity to promote $11.7 \cdot 10^4$ tons of carbon emissions.

The economic output per capita has obvious promotion effect on carbon emissions. During the research period, the sector had an annual GDP increase rate of 11.3%, while only 2.79% of the employed population. Under this situation, economic output per capita increased 8.65% annually. But in 2013, the economic output per capita effect inhibited carbon emissions and this factor's economic output per capita decreased for the first time to 10.5%, this was mainly caused by a lower rate of employed population.

Fig. 6 Decomposition of carbon emissions in transportation, warehousing, and postal sector



	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016
ES	-32.8	-3.02	-6.27	16.16	-61.7	39.03	-52.1	-11.7	-5.89	-32.4	-26.9	-45	-24.7
EI	91.17	-234	-353	-1049	-972	49.94	-205	-1041	155.4	-513	-997	-319	-1221
EO	1326	1483	1331	1753	1220	-10.6	1649	1367	1133	-2328	1206	1304	1701
PS	-62.1	-261	-16.3	174.8	73.59	130.5	-59.3	676.9	111.7	3787	293.9	-142	-94.8
△C	1322	984.3	955.5	894.8	260.4	208.9	1333	990.4	1395	914	475.3	798.3	360.8

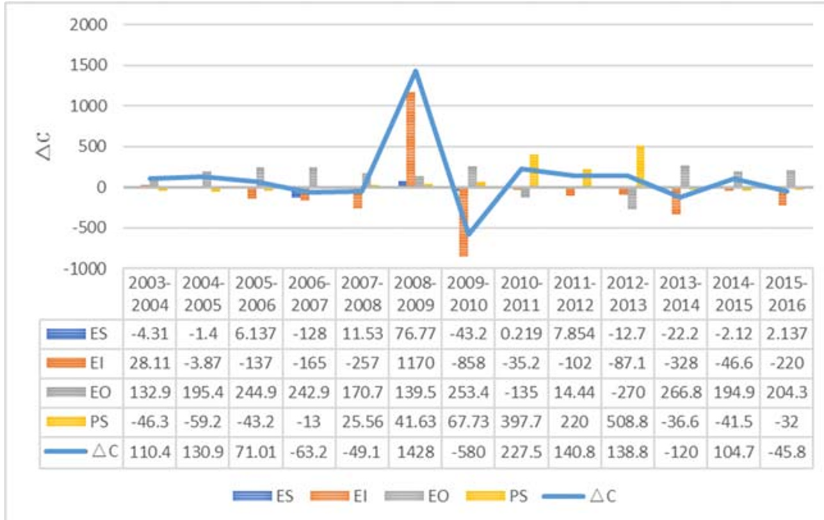


Fig. 7 Decomposition of carbon emissions in wholesale, retail, accommodation, and catering sector

The inhibition and promotion effects on carbon emission coexist at the population scale, but we still believe that the factor promoting carbon emissions is small. For the period from 2008 to 2013, the rates of employment had significant effect on emissions. Over the period from 2008 to 2013, employment population show increasing trend. Reducing industry employment can restrain carbon emissions and will not affect GDP significantly. Is this a symbol that the employment in sector 5 has become saturated?

Other sectors

Other sectors include real estate, finance, education, etc. This sector has more to do with our daily necessities. From Fig. 8, the overall carbon emissions are in an increasing state, and only in the past 2 years has there been a downward trend due to the suppression of energy intensity effects. The impact of energy mixes on carbon emissions is the same as sector 3.

When coal consumption doubled in 2009, the energy mix effect drastically stimulated carbon emissions. The energy intensity has suppression impact on carbon emissions for a long time. Particularly in the past 2 years, the suppressive effect has become more prominent, while in 2008 alone, it promoted $4.2 \cdot 10^4$ tons of carbon emissions, indicating that the economic crisis has large impact on China's industry. The economic output per capita effect has the largest and most stable impact on promoting carbon emissions. The highest contribution was in 2006 with $5.25 \cdot 10^4$ tons and the lowest was in 2013 with $1.64 \cdot 10^4$ tons. The population-scale effect promotes carbon emissions and becomes stronger as time goes by.

In 2008, four factors promoted carbon emissions at the same time, causing an increase of $14.7 \cdot 10^4$ tons of carbon emissions—mainly resulting from the increase of energy

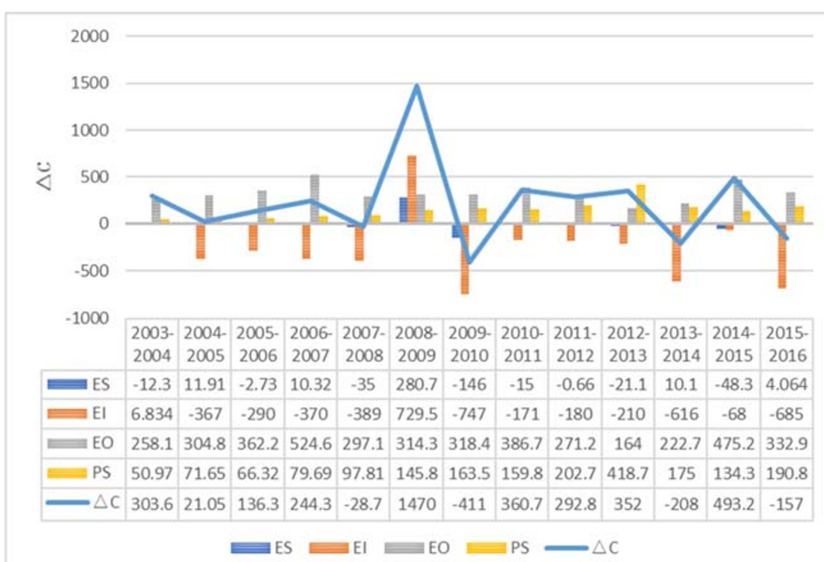


Fig. 8 Decomposition of carbon emissions in other sectors

Table 5 Comparison of decomposition results of energy consumption

Industry	Energy mix		Energy intensity		Economic output		Population scale	
	Uncertain	1	–	2	+	4	+	3
Construction	–	1	–	2	+	4	+	3
Agriculture, forestry, animal husbandry, and fishery	–	1	–	3	+	4	–	2
Transportation, warehousing, and postal services	–	1	–	3	+	4	+	2
Wholesale, retail, accommodation, and catering	–	1	–	3	+	4	+	2
Other sectors	–	1	+	3	+	4	+	2
Overall sector	Uncertain	1	–	3	+	4	+	2

Note: The sign indicates the promotion or inhibition effect of the factor, and uncertain means the influence is not clear, sometimes positive and sometimes negative. The number represents the degree of contribution, 4 is the largest and 1 is the smallest

intensity. This illustrates that an economic crisis impacts energy intensity more than energy mix.

Summaries

From analysis above, we can see four effects of the influence of energy carbon emissions in various sectors in Table 5 and Fig. 9. Figure 9 shows that China's energy consumption carbon emissions have not declined until 2014. There are two main reasons for this. First, in 2014, the population-scale effect began to curb carbon emissions. Then, the suppressive role of the energy intensity also increased year by year, mainly due to the suppression of carbon emissions caused by the industrial energy mix. The energy mix has large but unclearly contribution to the emissions. This shows that China's carbon emission reduction measures recently are conducive to improving energy efficiency, but have not reached the level of changing energy mix.

We posit the following conclusions. (1) The energy mix of various sectors is so stable and unchanged that its contribution to each sector is not significant. The energy mix effect restrains the carbon emissions of each sector but promotes carbon emissions in sector 2, because sector 2 uses too much coal. (2) The energy intensity effect inhibits the carbon emissions of various sectors. In other sectors, the energy intensity effect promotes carbon emissions, indicating that other sectors have lower energy efficiency. (3) The economic output effect is the main driving force for carbon emissions and contributes greatly to adding carbon emissions in various sectors. We can say that China's economic growth is still occurring at the cost of environmental pollution. (4) The population scale effect is promoting carbon emissions in various sectors also plays a significant role, especially for industrial and construction sectors, second only to the pulling effect of economic output effects. However, in sector 1, the number of people employed has been relatively low, so the population scale effect inhibits industrial carbon emissions.

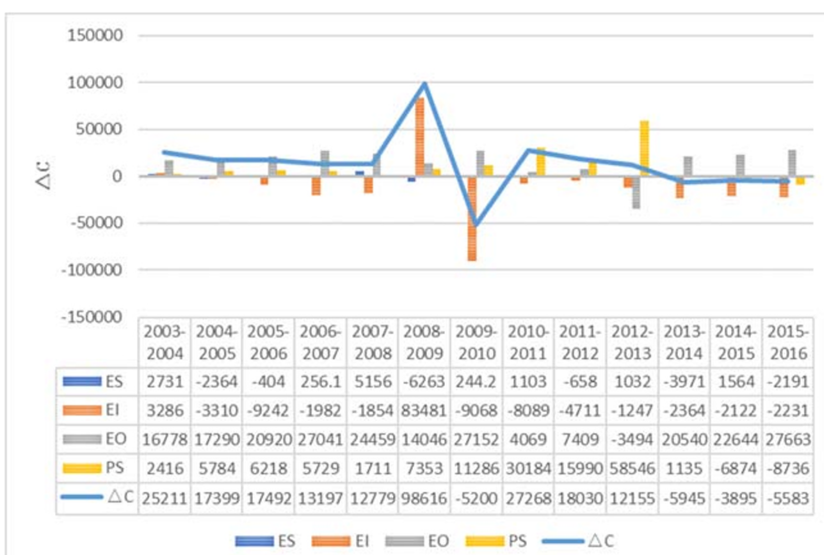


Fig. 9 Decomposition of carbon emissions in the whole sector

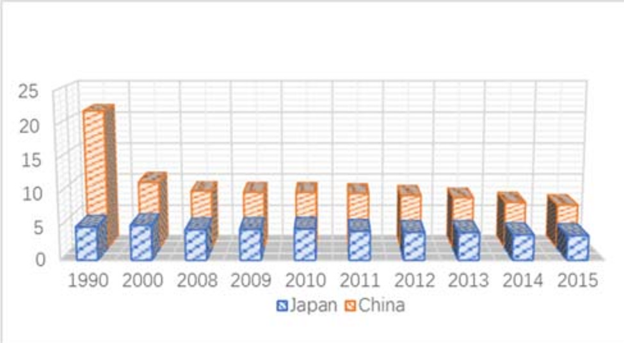


Fig. 10 Energy intensity in China and Japan

We need to address the impact of energy intensity on various sectors during the economic crisis of 2008. During the economic crisis in 2008, there was serious impact between the United States and some Asian countries and regions such as China and Hong Kong, and the time of the crisis lasted for a long time (Ye et al. 2016). After 2008, China's GDP growth rate did not continue its rapid growth (Mi et al. 2017). From 2008 to 2009, China's GDP growth rate was 9%, while the country's total energy consumption increased by 44.74% (calculated according to method in "Database," which is $3169.12 \cdot 10^4$ tons in 2008 and $4587 \cdot 10^4$ tons in 2009), and the energy intensity increased by 32.26%. In 2009, the carbon emission reaches a peak of $3362.17 \cdot 10^4$ tons and an increment in carbon emissions of $986.17 \cdot 10^4$ tons. Among the increment, energy intensity promotes $834.8 \cdot 10^4$ tons (of which $795.8 \cdot 10^4$ tons were due to the industrial energy intensity effect). In 2008, the suppression of energy intensity was turned into the promotion of energy intensity. We have full reason to believe that the economic crisis greatly reduced energy efficiency. This can also explain the negative decoupling phenomenon in the industrial sector in 2008.

Energy mix optimization

To have a clear understanding of how much Chinese carbon emissions can be reduced, we begin to optimize Chinese energy mix, and aim at Japan. Results are shown in Fig. 10. Japan has more mature experience in environmental governance. Figure 10 shows that Japan performs better than China in energy intensity (energy consumption per unit of gross domestic product. The less, the better. Data comes from the World Bank). Japan's figures are from 5.03 in 1990 to 3.74 in 2015 while China was at 21.18 in 1990 to 6.69 in 2015. Chang et al. (2018) conducted a comparative study in the two countries based on LMDI results and found that China achieved only relative decoupling and while Japan successfully continued the real decoupling state of economic growth from air-pollutant emissions. We therefore believe it is advisable to aim at Japan and optimize our energy mixes to reduce carbon emissions.

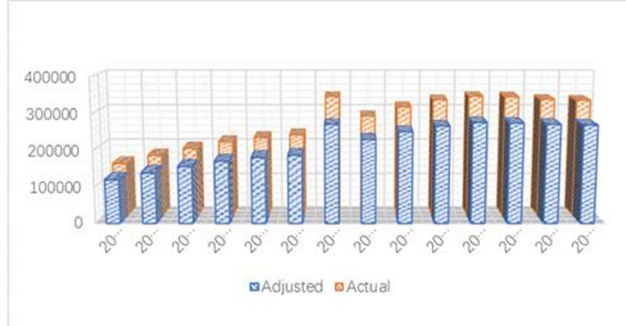


Fig. 11 Carbon emission comparison

In 1973, fossil energy accounted for 94% of Japan's total energy, and it slightly decreased to 89% in 2016 (data comes from the Web page) (SOHU 2018). However, China's energy mix has undergone major changes. In 1973, 16.9% was coal, 75.5% was petroleum, and in 2016, only 39% was oil, while 25% was coal and 24.7% was gas. This means that coal accounted for almost 28% (25/89) of fossil energy, 28% (24.7/89) of gas, and 44% (39/89) of oil. Note that oil here includes oil, petrol and so on. We consider the three ratios in comparison with the optimal Chinese energy mix, and results are revealed in Fig. 11.

Figure 11 suggest that by adjusting the energy mix while maintaining the same total energy consumption, carbon emissions can be significantly reduced. Real carbon emissions and adjusted carbon emissions show the same trends, with significant difference—almost 0.5 billion kg CO_2 per year. This means that by adjusting the energy mix, we can reduce approximately of 17% carbon emissions every year.

Conclusion

Combining the decoupling status of various sectors and their carbon emissions, we find that most of the weak decoupling states achieved in China are due to the inhibition of energy intensity on carbon emissions, meaning that China has relatively high energy efficiency. The strong decoupling state in the industrial sector in the past 2 years is mainly due to the reduction of coal consumption since 2013, which has directly led to the emergence of an overall strong decoupling phenomenon. This article also has some drawbacks. For example, whether there is more suitable carbon emission accounting method, the optimization of energy structure must ensure the production demand and so on. Generally, we have the following conclusions:

1. China's economic growth is still occurring at the cost of environmental pollution. Economic output per capita drives China's carbon emissions a lot, followed by the suppression of the energy intensity and the promotion of

population scale, and the effect of energy mix effects is not obvious.

2. China's carbon emission reduction measures in the past 2 years are conducive to improving energy efficiency but fail to change the energy mix. However, energy mix changes in the industrial sector are relatively obvious. If we adjust energy mix based on Japan's energy mix, Chinese carbon emission will reduce approximately 17% every year.
3. The economic crisis has greater impact on energy efficiency but influenced other factors little. When facing the same crisis in the future, to control carbon emissions, we must pay attention to the rational use of energy and maintain or even increase usage efficiency.
4. Industrial carbon emission plays an irreplaceable role in the overall national emission reduction. Carbon emission reduction must begin in industry from reducing the usage of coal to improve energy mix.

According to the 13th Five-Year Plan for the development of the coal industry published by China National Development and Reform Commission and National Energy Administration, China's industrial coal usage will be controlled at 58% by 2020 (68.52% of the cumulative industrial energy consumption from 2003 to 2016, as mentioned in the "Industry sector"). This confirms that our conclusions are conducive to the implementation of green economy, as well as serves as references for policy formulation. From the above conclusions, we have the following policy suggestions: first, different factors have diverse impacts on the 6 sectors and we cannot generalize them when making policies. For example, the population size effect significantly inhibits carbon emissions in sector 1 but promotes emissions in several other sectors. Therefore, we should combine the characteristics of various industries and formulate corresponding measures to reduce emissions. Second, when facing the crisis in the future, to control carbon emissions, we must pay attention to the rational use of energy and maintain or even increase usage efficiency. Finally, energy mix plays an obvious role in increasing China's carbon emissions. We should take optimizing energy structure as the key and take improving other factors as the principle to gradually reduce China's carbon emissions.

Funding information This study is supported by the National Natural Science Foundation of China (NSFC) (Grant No. 71871169, U1933120, 71373188, and U1333115).

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