An analysis of the driving forces of energy-related carbon dioxide emissions in China's industrial sector

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Abstract

Both energy consumption and the growth of carbon dioxide (CO_2) emissions in China are attributed to the industrial sector. Energy conservation and CO_2 emissions reduction in China's industrial sector is decisive for achieving a low-carbon transition. We analyze the change of energy-related CO_2 emissions in China's industrial sector from 1991 to 2010 based on the Logarithmic Mean Divisia Index (LMDI) method. Results indicate that industrial activity is the major factor that contributes to the increase of industrial CO_2 emissions while energy intensity is the major contributor to the decrease of CO_2 emissions. Industry size shows a varying trend interchanging intervals of growth along the study period. Moreover, both energy mix and carbon intensity of energy use have negative effects on the increase of CO_2 emissions. The cointegration method is adopted to further explore determinants of CO_2 emissions in China's industrial sector. Results show that there exists a long-run relationship between industrial CO_2 emissions and affecting factors such as CO_2 emissions per unit of energy consumption, industrial value added, labor productivity and fossil fuel consumption. China's industrial CO_2 emissions are mainly attributed to the coal-dominated energy structure. Policy suggestions are thus provided to reduce industrial CO_2 emissions in China.

Keywords: CO_2 emissions; China's industrial sector; Cointegration; Decomposition analysis.

Contents

1. Introduction

1.1. Research background

The massive fossil fuel consumption promoted by the rapid process of urbanization and industrialization has led to the serious problem of CO_2 emissions in China. For example, Chinese economy has kept an average annual growth rate of about ten percent since the year 1978. The average annual growth rates of the primary energy consumption and electricity consumption were 6% and 9.2% [1], respectively. Notably, the growth rate of fossil-fuel CO_2 emissions was consistent with the growth rate of the primary energy consumption [2]. Carbon dioxide emissions in China were highly associated with the industrial structure, energy structure and energy efficiency. Apparently, China's economy was dominated by the industrial sector. The average proportion of industrial value added (IVA) in the gross domestic product (GDP) was 40.2% during 1978-2012. Meanwhile, both China's energy structure and electricity structure were dominated by coal, the shares of which were about 70% and 80%, respectively. Although energy intensity in China decreased from 362.60 tons of coal equivalent (tce) per hundred thousand USDs to 94.37 tce per hundred thousand USDs during 1978-2012 (at constant prices in 2000) [3], the efficiency of energy use in China was still relatively low compared to those in other developed economies.

In November 2009, the Chinese government proposed that carbon dioxide emission per unit of GDP (carbon intensity) would be decreased by 40% to 45% in 2020 compared to the year 2005 [4]. In 2010, both energy intensity target and carbon intensity target were included in the12th Five-Year Plan (2011-2015) for National Economic and Social Development, which regulated that in 2015, energy consumption per unit of GDP (energy intensity) would be decreased by 16% and the carbon dioxide emissions per unit of GDP would be decreased by 17% compared to the year 2010. Needless to say, the industrial sector plays an important role in China's energy conservation and emissions reduction. According to the regulation of industrial energy conservation during the 12th Five-Year Plan period (2011-2015), energy consumption per unit of value added in industrial enterprises above designated size (enterprises with the annual sales revenue over 806 thousand USDs) would be decreased by 21% in 2015 compared to the year 2010, and the expected amount of energy conservation would be 670 million tons of coal equivalent (Mtce) during 2011-2015. In addition, the Chinese government also proposed targets of energy consumption per unit of value added in energy-intensive industrial sub-sectors such as iron and steel industry (ISI), nonferrous metals industry (NMI), petroleum processing and coking industry (PPCI), chemical industry (CI), building materials industry (BMI), etc.

Industrialization is currently the major character of economic growth and energy consumption growth in China. During 1985 to 2011, energy consumption in the industrial sector accounted for about 70.3% of the national energy consumption. The proportion has shown an increasing trend over the last few years. On the contrary, the share of industrial value added (IVA) in GDP revealed a decreasing trend. In the year 2011, value added of the industrial sector was 2918.03 billion USDs, accounting for 39.8% of the national GDP; however, industrial energy consumption amounted to 2464.4 Mtce, accounting for 70.8% of China's total energy consumption, and industrial electricity consumption reached 3470.7 billion kWh, accounting for 73.8% of China's total electricity consumption [1]. It can be seen that the industrial sector in China is prominently energy-intensive. Energy conservation and emissions reduction in the industrial sector is the key to China's emissions reduction and the achievement of low-carbon transition.

1.2. Overview of China's industrial sector

China's economic growth is dominated by the industrial sector at the industrialization stage. The importance of industrial sector derives from the fact that the sectoral employment accounts for 30 percent of China's total employment, and that industrial value added accounts for nearly 40 percent of GDP, etc. China's industrial sector has developed rapidly over the past three decades, which was mainly driven by the accelerating speed of industrialization and urbanization. The industrial value added (IVA) increased from 92.28 billion USDs in 1985 to 1531.80 billion USDs in 2010 (at constant prices in 1990) [5].

The importance of industrial sector also highlighted by its role in providing raw materials for meeting the massive infrastructure needs during urbanization process. As one of the most energy-intensive sub-sectors of industry, iron and steel industry of China (ISI) produced 683.9 million tons of crude steel in 2011 (about 6.4 times as much as that of Japan, and 7.9 times as much as that of the United States), which ranked first in the world and accounted for 45.1% of the world's total production. Take the cement industry for another example. Cement production of China was 2058 million tons in 2011 (increased by 10.6% compared to the year 2010), and ranked first in the world, which was about 9.3 times as much as that of India, 31 times that of the United States and 37 times that of Japan.

Similar to the rapid growth in value added and output, energy consumption of China's industrial sector also increased significantly, which grew from 714.13 Mtce (million tons of coal equivalent) in 1991 to 2320.2 Mtce in 2011 [1]. Industrial final energy use, a common indicator for tracking industrial energy consumption, grew from 505.29 Mtce to 1478.12Mtce in China during 1991-2011, of which the average annual growth rate was 5.9%. The average annual growth rate of CO_2 emissions from industrial final energy use was 5.4%. Specifically, CO_2 emissions from industrial final energy use increased from 1185.40 Mt to 3134.92 Mt during the same period, which is equivalent for an increase of 164.5%. Industrial processes including cement and limestone manufacture also contribute to CO_2 emissions of China's industrial sector. Due to the massive infrastructure construction, China's cement production increased rapidly from 248.32 Mt in 1991 to 1881.91 Mt in 2010, and the corresponding CO_2 emissions from cement production grew from 130.86 Mt to 991.76 Mt as a result (See Fig. 1).

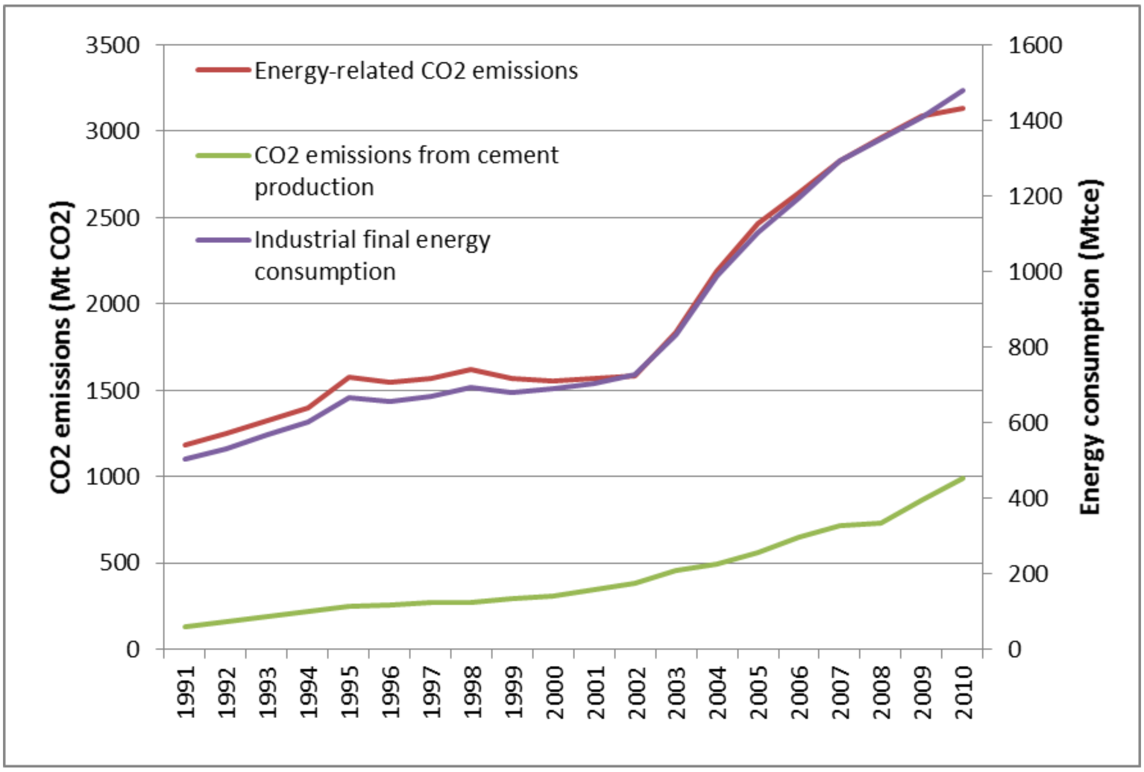


Fig. 1. Energy consumption and CO_2 emissions trends in China's industrial sector during 1991-2010.

Source: CEIC China Database [1]; China Energy Statistical Yearbook [3]

From the perspective of carbon dioxide emissions from industrial final energy use, CO_2 emissions was driven up by 5.4% when industrial final energy consumption increased by 4.9%. However, a decrease in industrial final energy use occurred during the "stagnancy" period of 1998-2001 and consequently there was a subsequent reduction in the corresponding CO_2 emissions. The phenomenon was mainly because of the ownership restructuring in Chinese state industry. Numerous small-and medium-sized state-owned enterprises were converted into shareholding companies with mixed public and private ownership, which were sold, leased, merged or just allowed to go bankrupt. The growth of industrial value added thereby dropped sharply from about 20% to 8% during 1998-2001.

Coal has dominated the energy consumption structure in China's industrial sector for a long time. During the study period, energy consumption related with coal increased by 4.5% annually. In the meantime, the sectoral demand for electricity and natural gas grew by 9.5% and 6.3%, respectively. Notably, the proportion of energy consumption related with coal decreased continuously from 87% in 1991 to 79% in 2010. Based on the final energy consumption of China's industrial sector, we calculate the corresponding CO_2 emissions from different energy sources. Results demonstrate that raw coal and coke are the major contributors to carbon dioxide emissions of China's industrial sector. Although the share of CO_2 emissions from raw coal showed a decreasing trend from 57.5% to 37.6% during 1990-2010, the share of CO_2 emissions from coke increased from 17.9% in 1990 to 32.5% in 2010 (Fig.2). Particularly, carbon dioxide emissions from raw coal and coke accounted for 70% of industrial CO_2 emissions in 2010.

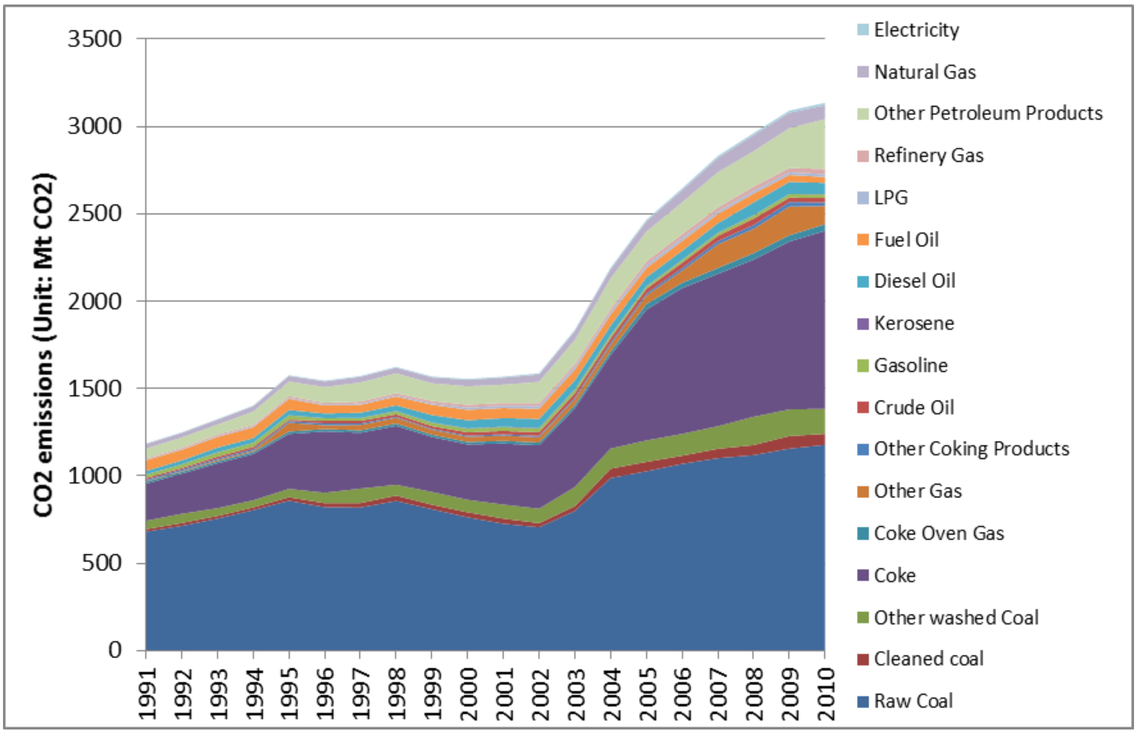


Fig. 2. Carbon dioxide emissions from industrial final energy consumption.

Source: China Energy Statistical Yearbook [3]

It can be seen from Fig. 2 that carbon dioxide emissions of China's industrial sector during the study period (1991-2010) were attributed to the rapid growth of energy demand as well as the coal-dominated energy structure. The key factors contributing to the decrease in carbon dioxide emissions of China's industrial sector during 1998-2001 included the industrial restructuring caused by ownership change with a decrease in the growth of industrial value added of 20.76 percent, a decrease in the sectoral energy intensity of 15.23 percent. Energy diversification also helped reduce the share of coal in China's industrial final energy consumption. The predominant share of carbon dioxide emissions of China's industrial sector comes from the manufacturing industry (90 percent), with smaller shares from mining and quarrying industry (7 percent) and industry of electric power, gas and water production supply (3 percent). Therefore, trends in China's industrial sector emissions are closely tied to economic output in energy-intensive manufacturing. The energy-related CO_2 emissions of manufacturing industry increased from 1090.38 Mt in 1991 to 2604.91 Mt in 2010, which is equivalent to an increase of 139%.

It is necessary to analyze the changes as well as determinant factors of China's industrial CO_2 emissions. The major contributions of our study are summarized as follows: first, this paper provides a reference for the targets of industrial CO_2 emissions reduction by decomposing factors that affect CO_2 emissions in China's industrial sector and quantifying the impacts of each factor on industrial CO_2 emissions change; second, this article offers a scientific basis for China's future strategies of sustainable development of the industrial sector by establishing a long-run equilibrium relationship between China's industrial CO_2 emissions and factors such as carbon dioxide emissions per unit of energy consumption, industrial value added, sectoral labor productivity and sectoral fossil fuel consumption; third, policy suggestions are provided to reduce industrial CO_2 emissions in China.

The remainder of this paper is structured as follows. Section 2 presents a brief literature review. Section 3 describes the methodologies and data source. Section 4 presents the empirical results. Section 5 summarizes findings and attempts to draw some policy implications.

2. Literature

2.1. Decomposition method

Index decomposition analysis, which has been developed since the late 1970s [6], is widely used to explore the driving forces that underlie the increase of CO_2 emissions. Generally, the index decomposition method is used to measure the contributions of each factor based on the CO_2 emission identity. Using the Logarithmic Mean Divisa Index (LMDI) proposed by Ang [7], numerous studies analyzed China's CO_2 emissions change such as Wang et al. [8], Zhang et al. [9], Zha et al. [10], Tan et al. [11]. The above-mentioned studies pointed out that energy intensity was the determinant factor contributing to the decline in China's CO_2 emissions over different periods. Using the newly proposed three-level "perfect decomposition" method and provincially aggregated data, Wu et al. [12] investigated the evolution of energy-related CO_2 emissions in China during 1985-1999 and found that the industry-related sector provides the strongest negative influence on the energy intensity effect. Using adaptive weighting divisia index, Fan et al. [13] measured the final energy-related carbon intensity of material production sectors and pointed out that greater emphasis should be given to the secondary industry.

China's total carbon dioxide emissions are dominated by the industrial sector. For the change of industrial CO_2 emissions, Zhang [14] and Liu et al. [15] showed different research results for the role of energy intensity. By using decomposition analysis, several studies including Kim and Worrell [16], Steenhof [17], Xu et al. [18], Lin and Moubarak [19], Wang et al. [20], Tian et al. [21] explored energy related GHG emission trajectories, features, and driving forces of industrial sub-sectors in China. Table 1 summarizes a collection of the highly cited decomposition studies that focused on the main factors affecting CO_2 emissions change of industrial sectors in

China.

Table 1 Studies of contributors to the changes of industrial CO_2 emissions in China.

Reference	Period	Sector	Contributors to the increase of emissions	Contributors to the decline of emissions
Kim and Worrell [16]	1981-1996	Iron and steel industry	Activity effect, Structural change in the product mix, Final fuel mix, Utility mix	energy-efficiency
Zhang [14]	1990-1997	Industrial sector	Output effect	Energy intensity, Production structure
Steenhof [17]	1980-2002	Electricity sector	Fossil fuel effect	Efficiency effect
Liu et al. [15]	1998-2005	Industrial sector	Energy intensity, Final fuel shift	Energy intensity change during 1998-2002
Xu et al. [18]	1990–2009	Cement industry	Efficiency policies, Industrial standards	Growth of cement output
Lin and Moubarak [19]	1986 - 2010	Textile industry	Industrial activity, Industrial scale	Energy mix, Carbon intensity
Tian et al. [21]	2001-2010	Iron and steel industry	Product scale effect	Energy intensity effect, Emission factor change
Wang et.al [20]	2005-2009	Cement industry	Cement production activity, Clinker production activity	Energy intensity

2.2. The cointegration model

The cointegration approach has been widely adopted in energy economic studies because of its unique advantages [22-23]: first, it can overcome the problem of spurious correlation of time series; second, because of its ability to capture the long-term relationship among the economic variables, it has been frequently used to analyze the impacts of economic indicators on energy demand, CO_2 emissions, the macroeconomy and so on. In the literature, a large number of studies over the last few years have discussed energy demand or carbon dioxide emissions in different countries using the cointegration method, such as India [24], Tunisia [25], South Africa [26], Greece [27], Bangladesh [28], Pakistan [29], Australia [30], Malaysia [31] and so on. For the case of China, several studies proved the relationship between energy demand and economic growth [32-34] as well as the relationship between carbon dioxide emissions and economic growth [35-37]. In the literature, many studies focus on the major factors influencing energy demand or CO_2 emission in the industrial sector in China because of its important role and China's current development stage [38-39]). Table 2 lists a series of the most highly cited studies that shed light on influencing factors of CO_2 emissions in China based on the cointegration method.

Table 2 Studies of energy consumption and CO_2 emissions in China based on the Cointegration method.

Reference	**Dependent variable**	**Main influencing factors**
Jalil and Mahmud [32]	CO_2 emissions in China	Energy consumption, economic growth, Foreign trade

Jalil and Feridun [33]	CO_2 emissions in China	Economic growth, financial development and energy consumption
Zhao et al. [39]	CO_2 emissions in Power industry	The standard coal consumption rate for generating power (SCC), the average thermal power equipment utilization hour (EUH), the industrial added value of the power sector (IVA)
Lin and Ouyang [40]	Electricity intensity in nonmetallic mineral products industry	R&D intensity, Industrial electricity price, Enterprise scale, Labor productivity

In light of the above discussion, studies on CO_2 emissions of China's industrial sector are relatively few. The purpose of this paper is to analyze the contributors to CO_2 emissions change of China's industrial sector during 1991-2010 based on the decomposition analysis. Besides, in order to further explore the influencing factors of China's industrial CO_2 emissions, we establish the long-term relationship between industrial CO_2 emissions and factors such as carbon dioxide emissions per unit of energy consumption, industrial value added, sectoral fossil-fuel use and sectoral labor productivity using the cointegration method.

3. Methodology and data source

3.1. Decomposition analysis

The decomposition of fossil fuel CO_2 emissions into related factors dates back to a series of studies undertaken in the 1980s, mainly at the industry level for a single industrialized country. Kaya [41] proposed the Kaya Identity and decomposed the CO_2 emissions into several affecting variables:

$$GHG = \frac{GHG}{TOE} * \frac{TOE}{GDP} * \frac{GDP}{POP} * POP \qquad (1)$$

where, GHG stands for greenhouse gas emissions; TOE is the total energy consumption; GDP is the gross domestic product, and POP is the population. Eq. (1) establishes the relationship between greenhouse gas emissions and influencing factors such as greenhouse gas emissions per unit of energy consumption, energy consumption per unit of GDP, GDP per capita and population.

Considering the importance of energy structure, we expand Eq. (1) as:

$$GHG = \frac{GHG}{EFF} * \frac{EFF}{TOE} * \frac{TOE}{GDP} * \frac{GDP}{POP} * POP \qquad (2)$$

where, EFF is the fossil fuel energy consumption. The identity in Eq. (2) focuses on CO_2 emissions from the combustion of fossil fuels (coal, oil and natural gas). Ang [42-43], Ang and Lee [44-45] discussed several methodological and application issues related to the technique of the decomposition of industrial energy consumption.

In this paper, we use the decomposition approach to identify factors influencing energy consumption and energy-related CO_2 emissions of China's industrial sector:

$$GHG_i = \frac{GHG_i}{EFF_i} * \frac{EFF_i}{TOE_i} * \frac{TOE_i}{IVA} * \frac{IVA}{EPT_i} * EPT_i = CIE_i * EM_i * EI_i * IA_i * IS_i \qquad (3)$$

where, the subscript i denotes the industrial sector of China; CIE is CO_2 emissions per unit of energy consumption (carbon intensity of energy use); EM is the share of fossil fuel use in the total energy consumption (energy mix, which represents the level of energy diversification); EI is energy consumption per unit of industrial value added (sectoral energy intensity); IA is industrial value added per capita (industrial activity), and EPT is the employment of China's industrial sector. Generally, an increase in employment implies the expansion of an economic sector. Therefore, we use this indicator to represent the industry size. Table 3 summarizes the definitions of variables in this paper:

Table 3 Determinants of energy-related CO_2 emissions change in China's industrial sector.

Variable	Determinant	Description	Item
CIE_i	GHG_i / EFF_i	Carbon Intensity of Energy Use	GHG_i : carbon dioxide emitted from energy consumption
EM_i	EFF_i / TOE_i	Energy Mix	TOE_i : total energy consumption
EI_i	TOE_i / IVA	Energy Intensity	EFF_i : fossil fuel energy consumption
IA_i	IVA / EPT_i	Industrial Activity	IVA : industrial value added
IS_i	EPT_i	Industry Size	EPT_i : employment in China's industrial sector

The change in CO_2 emissions of China's industrial sector (ΔGHG_i) between a base year 0 and an end year T can be decomposed into the effects of the change in CIE_i (ΔGHG_{CIE_i}), the change in EM_i (ΔGHG_{EM_i}), the change in EI_i (ΔGHG_{EI_i}), the change in IA_i (ΔGHG_{IA_i}) and the change in IS_i (ΔGHG_{IS_i}):

$$\begin{aligned} \Delta GHG_i &= GHG_i(T) - GHG_i(0) \\ &= \Delta GHG_{CIE_i} + \Delta GHG_{EM_i} + \Delta GHG_{EI_i} + \Delta GHG_{IA_i} + \Delta GHG_{IS_i} \end{aligned} \tag{4}$$

The effects, in turn, can be calculated with the following formula by using the LMDI method:

$$\Delta GHG_{CIE_i} = \frac{GHG_i(T) - GHG_i(0)}{\ln\left[GHG_i(T) - GHG_i(0)\right]} * \ln\left[CIE_i(T) - CIE_i(0)\right] \tag{5}$$

$$\Delta GHG_{EM_i} = \frac{GHG_i(T) - GHG_i(0)}{\ln\left[GHG_i(T) - GHG_i(0)\right]} * \ln\left[EM_i(T) - EM_i(0)\right] \tag{6}$$

$$\Delta GHG_{EI_i} = \frac{GHG_i(T) - GHG_i(0)}{\ln\left[GHG_i(T) - GHG_i(0)\right]} * \ln\left[EI_i(T) - EI_i(0)\right] \tag{7}$$

$$\Delta GHG_{IA_i} = \frac{GHG_i(T) - GHG_i(0)}{\ln\left[GHG_i(T) - GHG_i(0)\right]} * \ln\left[IA_i(T) - IA_i(0)\right] \tag{8}$$

$$\Delta GHG_{IS_i} = \frac{GHG_i(T) - GHG_i(0)}{\ln\left[GHG_i(T) - GHG_i(0)\right]} * \ln\left[IS_i(T) - IS_i(0)\right] \tag{9}$$

The decomposition of the changes in CO_2 emissions of China's industrial sector can be calculated according to the equations above. We use relevant data during the 1991-2010 period and separate the time into four time intervals for easier data management.

3.2. The cointegration analysis

The cointegration method, introduced by Engle and Granger [46], has been widely adopted to analyze influencing factors of carbon dioxide emissions, i.e., Narayan and Narayan [47], Jahangir Alam, et al. [48], Saboori and Sulaiman [49], Al-mulali et al., [50].

3.2.1. Definition of variables

Variables in this article are defined as follows:

Carbon dioxide emissions per unit of energy consumption (CIE): Carbon dioxide emissions per unit of energy consumption (carbon intensity of energy use), which are mainly influenced by energy structure, reflect the quality of energy because of different coefficients of CO_2 emissions. If the share of clean energy in energy structure were higher, greenhouse gas emissions per unit of energy consumption would be lower. However, energy consumption of China's industrial sector is dominated by coal, which has the highest coefficient of CO_2 emissions among fossil fuels. Therefore, in order to reduce CIE, China must improve energy structures of consumption as well as production. Moreover, CIE is also influenced by the efficiency of energy use.

Industrial value added (IVA): Rapid economic growth is a major factor affecting China's energy demand. Likewise, energy consumption of China's industrial sector is mainly driven by the growth of industrial value added (IVA). From the historical data of this paper, there was a decline in energy demand when the growth of industrial value added slowed down during the period of China's industrial restructuring from 1998 to 2000. Over the last two decades, the industrial value added of China's industrial sector grew rapidly from 143.38 billion USDs in 1990 to 1531.78 billion USDs in 2010 (both are at constant prices in 1990), which was equivalent to a growth of 834% [1]. To summarize, during 1991-2000, the average annual growth rate of IVA of China's industrial sector was about 12.6%, and the average annual growth rate of industrial total energy consumption was about 6.5%, which was nearly half of the growth rate of IVA.

Labor productivity (LP): The improvement of labor productivity helps reduce energy intensity, and thereby contributes to the reduction of carbon dioxide emissions of China's industrial sector. Reasons for the decline in carbon dioxide emissions include: first, the improvement of labor productivity helps reduce energy intensity [51], thereby helps decrease energy consumption and energy-related CO_2 emissions; second, skilled workers might have greater knowledge in energy utilization [52], so that can reduce energy consumption in the production process; third, the improvement of labor productivity can be seen as the process of mechanization and computerization, which help improve efficiency of energy utilization. During 1991-2010, the average annual growth rate of labor productivity of China's industrial sector was about 11%.

Fossil fuel consumption (EFF): The main source of carbon dioxide emissions is the combustion of fossil fuels, followed by certain industrial processes, land-use changes and renewable electricity generation from biomass. New energy and other renewable energy including solar power, wind power and hydropower have no emissions footprints [53]. Therefore, increasing the supply of renewable energy is good way to replace carbon-intensive energy sources. However, clean energy use only accounted a small share in China's industrial sector, and the increased fossil fuel consumption led to the increasing sectoral CO_2 emissions.

3.2.2. The cointegration model

Based on the discussion above, we construct the function of carbon dioxide emissions of China's industrial sector as follows:

$$TCO_{2_t} = f(CIE_t, IVA_t, LP_t, EFF_t) \tag{10}$$

where, TCO_{2_t} is the total amount of carbon dioxide emissions from energy consumption; CIE_t is carbon dioxide emissions per unit of energy consumption (carbon intensity of energy use); IVA_t is the value added of China's industrial sector;

LP_t is the labor productivity (industrial value added per worker); EFF_t is the fossil fuel consumption. All data from 1991 to 2010 are collected from CEIC China database [1] and China Energy Statistical Yearbook [3]. All data are calculated at constant prices in 1990. All variables are taken the logarithm to avoid the heteroscedasticity.

The function of carbon dioxide emissions of China's industrial sector is as follows:

$$LnTCO_{2_t} = \alpha_1 LnCIE_t + \alpha_2 LnIVA_t + \alpha_3 LnLP_t + \alpha_4 LnEFF_t + c \qquad (11)$$

Before conducting the cointegration analysis, stationary tests are essential for identifying the stationarity of time series. A stationary linear combination of economic variables indicates the existence of cointegration relationship, which is a long-run equilibrium. The most popular testing procedures are the augmented Dickey-Fuller (ADF) test [54], and the Phillips-Perron (PP) test [55].

In order to avoid impacts of higher-order serial correlation, the ADF test includes the lagged difference of dependent variable y_t in the right side of regression equation:

$$\Delta y_t = \beta_0 + \alpha_0 t + \alpha_1 y_{t-1} + \sum_{i=1}^{m} \beta_i \Delta y_{t-i} + \varepsilon_t \qquad t = 1, 2, 3 T. \qquad (12)$$

where, β_0 is a constant; $a_0 t$ is the linear trend; y_t is the tested variable in period t ; Δy_{t-1} is $y_{t-1} - y_{t-2}$; $\varepsilon_t \sim i.i.d.N(0, \sigma^2)$ (independently and identically distributed).

In order to test the null hypothesis of the presence of a unit root in y_t, we conduct the hypothesis testing that $\alpha_1 = 0$ in Eq. (12). If α_1 is significantly less than zero, then the null hypothesis of a unit root is rejected:

$$\begin{cases} H_0 : \alpha_1 = 0 \\ H_1 : \alpha_1 \prec 0 \end{cases} \quad (13)$$

The PP test uses the same model as the ADF test, but it is remarkably insensitive to the heteroscedasticity and the autocorrelation of the residuals. Therefore, both the ADF test and the PP test are applied in this paper for a comprehensive assessment of the stationary time series.

If the integration of each series is of the same order, then we can continue to test the existence of the cointegration relationship over the sample period. The Engle-Granger two-step procedure and Johansen-Juselius method [56-57] are the most commonly used methods for the cointegration test. The Engle-Granger two-step method is applied to the cointegration test in a single equation, while the Johansen-Juselius method not only can detect the existence of cointegration among economic variables but also can accurately determine the number of cointegration vectors. Therefore, we use the Johansen-Juselius trace test and the maximum eigenvalue test to determine the number of cointegrating vectors in our model.

Two test statistics are included in the Johansen-Juselius test: the maximum eigenvalue and trace test statistics. The maximum eigenvalue statistic tests the assumption of the existence of r cointegration vectors by calculating the maximum likelihood test statistic $LR_{\max}$:

$$LR_{\max} = -T \ln(1 - K_{r+1}) \quad (14)$$

where, T is the number of samples; K_{r+1} is the eigenvalue. Trace statistic tests the assumption that there are less than r co-integrating vectors by calculating the likelihood test statistic LR_{trace}:

$$LR_{trace} = -T \sum_{i=r+1}^{n} \ln(1-K_r) \qquad r = 0, 1, 2, n \div . \tag{15}$$

where, T is the number of samples; $K_{r+1},...,K_n$ is the $(n-r)$ smallest eigenvalues for estimation. The distribution of the test statistics is shown in the study by Osterwald-Lenum [58].

3.3. Data source

This study is based on the annual data covering the period from 1991 to 2010. Data of industrial value added, sectoral energy consumption (standard unit of Mtce) and sectoral employment are collected from the China Statistical Yearbook [9]. In order to avoid the problem of double counting, we collect the final consumption of different energy sources in China's industrial sector (the physical units such as million tons and cubic meters) from the China Energy Statistical Yearbook [3].

Carbon dioxide emissions of China's industrial sector from fossil fuel consumption are calculated by:

$$CO_2 = \sum_{i=1}^{16} CO_2 = \sum_{i=1}^{16} E_i * CF_i * CC_i * COF_i * (44/12) \tag{16}$$

In which, CO_2 stands for the energy-related carbon dioxide emissions; i represents the different energy sources including raw coal, cleaned coal, other washed coal, coke, coke oven gas, other gas, other coking products, crude oil, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas (LPG), refinery gas, other petroleum products and natural gas; CF_i is the conversion factor from the physical unit to kjoule (in this paper, we take Appendix Ⅳ in China Energy Statistical Yearbook [3] as a reference for calculation); CC_i is the coefficient of carbon content, which is collected from the Intergovernmental Panel on Climate Change [59]; COF_i is the carbon oxidation factor, which is usually assumed to be one for the convenience of calculation, and $44/12$ is the conversion factor from carbon to carbon dioxide. In summary, $CF_i * CC_i * COF_i * 44/12$, which is the coefficient of carbon dioxide emissions from different energy sources, is assumed to be constant over time. Since China's power structure is dominated by coal (80 percent), we also include the energy-related CO_2 emissions for electricity generation using the method adopted by Lin and Jiang [60]. Data of China's power structure are collected from the CEIC China Database [1], and data of average annual coal consumption for power generation are collected from the China Electric Power Yearbook [61].

However, the limitations of decomposition methodology for analyzing time-series include the use of current values for calculating the energy content, the conversion rates of different energy sources from the physical unit to the unit of kjoule, and emissions factors in defining energy and CO_2 emissions performance should also be noted. Although different scholars use different time intervals [62] in the analyses of energy use, energy intensity and energy-related CO_2 emissions in China, in order to maintain a consistency with the time intervals in China's Economic and Social Development Plan, we prefer the five-year intervals in this paper.

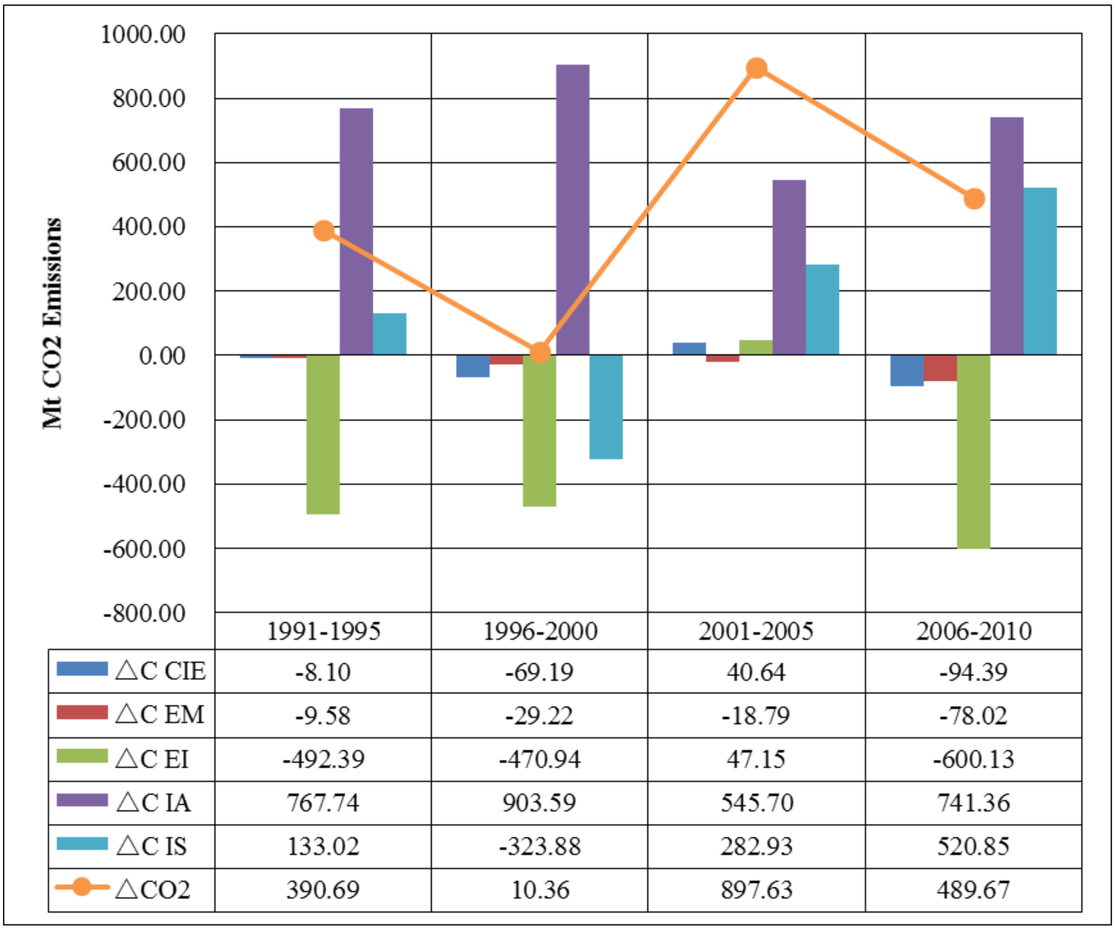
4. Empirical results and analysis

4.1. CO_2 emissions change in China's industrial sector

Decomposition analysis can quantify the impacts of determinants on the changes in energy-related CO_2 emissions. In our study, the contribution of each factor to CO_2

emissions change of China's industrial sector is analyzed by splitting the study period into four time intervals during 1990-2010 (Fig. 3).

Results show that there have been significant changes of carbon dioxide emissions in China's industrial sector during the last two decades. Driving forces need to be identified to design appropriate policies to mitigate the increasing trend of China's industrial CO_2 emissions. As shown in Fig. 3, industrial activity effect (IA) and energy intensity effect (EI) were the major driving forces of the energy-related CO_2 emissions change in China's industrial sector. Industrial value added per worker (IA) was the most important factor that led to the increase in CO_2 emissions, while energy consumption per unit of industrial value added (EI) was the most influential factor contributing to the decline in CO_2 emissions of China's industrial sector. Both industry size effect (IS) and carbon intensity of energy use effect (CIE) showed varying trends interchanging time intervals (increasing and decreasing) during the study period; however, the IS effect was the cause of the increase in industrial CO_2 emissions and the CIE effect was the cause of the decline in industrial CO_2 emissions. The varying trend of the IS effect may be the result of changes in ownership during the period of China's industrial restructuring. The varying trend of CIE effect may result from the accelerating industrialization and urbanization from the year 2000. Furthermore, the energy mix effect (EM) contributed to the reduction of the industrial CO_2 emissions, even though the effect is quite small.



	1991-1995	1996-2000	2001-2005	2006-2010
△C CIE	-8.10	-69.19	40.64	-94.39
△C EM	-9.58	-29.22	-18.79	-78.02
△C EI	-492.39	-470.94	47.15	-600.13
△C IA	767.74	903.59	545.70	741.36
△C IS	133.02	-323.88	282.93	520.85
△CO2	390.69	10.36	897.63	489.67

Fig. 3. Decomposition of changes of energy-related CO_2 emissions in China's industrial sector

Notably, the contributions of changes in industrial activity effect (IA) to the increase in energy-related carbon dioxide emissions were the highest among the variables, which were 747.74 Mt during 1991-1995, 903.59 Mt during 1996-2000, 545 Mt during 2001-2005 and 741.36 Mt during 2006-2010. Even though the impact of industrial activity effect (IA) was considerably reduced during 2011-2005, it was still the most important factor pushing up energy-related CO_2 emissions in China's industrial sector. On the other hand, energy intensity effect (EI) was the major contributor to the decline in energy-related CO_2 emissions during 2001-2005. Particularly, the impact of energy intensity effect (EI) on the decline in energy-related

CO_2 emissions reached 600.13 during the period of 2006-2010. Government policies in this area played a major role. The Chinese government committed to reduce energy intensity by 20 percent in 2010 compared to the year 2005. Followed by the industrial activity effect (IA), the effect of industry size (IS) was also a driving force contributing to the increase in CO_2 emissions expect the period of 1996-2000. The impact of industry size (IS) on CO_2 emissions showed an overall upward trend, and its contribution to the growth of CO_2 emissions reached 520.85 Mt during 2005-2010. In order to further explore different factors contributing to the changes of industrial CO_2 emissions, we calculate the annual effect of each determinant in this paper. Results are shown in Fig. 4.

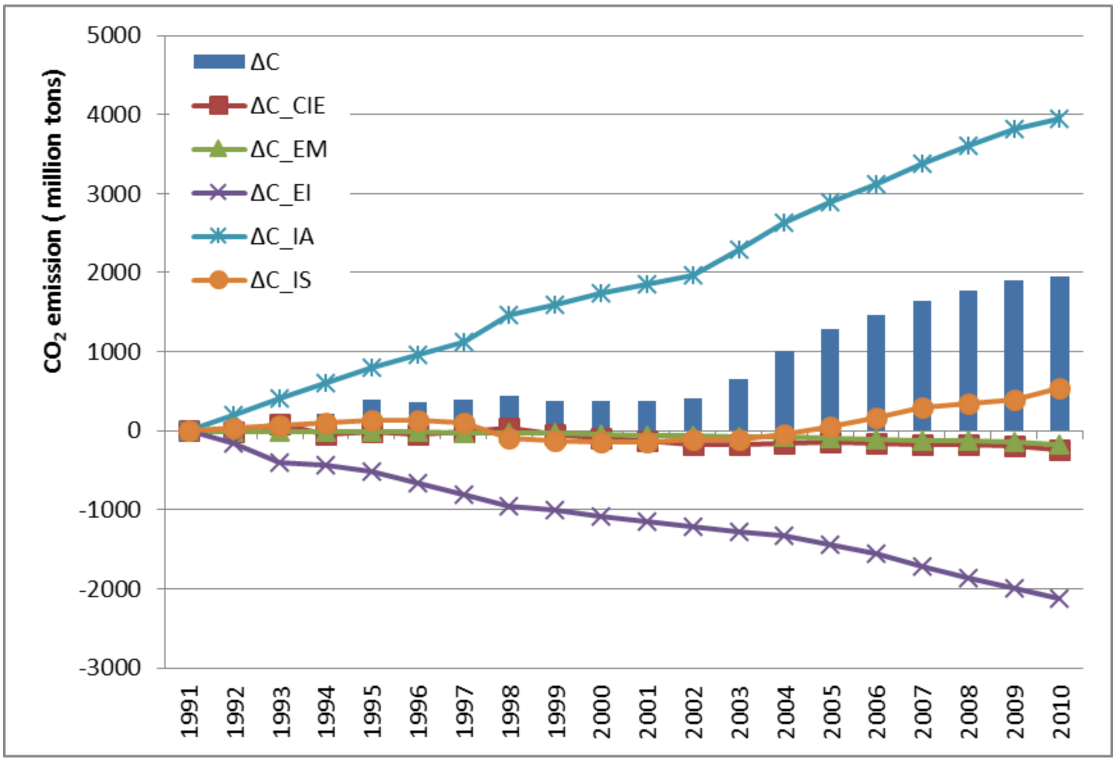


Fig. 4. Contributors to the annual changes of energy-related CO_2 emissions in China's industrial sector.

It can be seen that CO_2 emissions change in China's industrial sector increased from 63.64 Mt in 1992 to 1949.52 Mt in 2010, equivalent to a growth of 2962%. The growth rate of CO_2 emissions was the highest during the period of rapid industrialization. As shown in Fig. 4, the industrial activity effect (IA) was the major factor contributing to the increase in energy-related CO_2 emissions in China's industrial sector. Specifically, the contribution increased from 200.85 Mt in 1992 to 3939.63 Mt in 2010. On the contrary, the energy intensity effect (EI) was the major determinant for the decline in industrial CO_2 emissions, and its negative contribution increased from 153.46 Mt in 1992 to 2116.72 in 2010. Both energy mix effect (EM) and the effect of carbon intensity per unit of energy use (CIE) contributed to the decline in industrial CO_2 emissions. The contribution of energy mix effect (EM) to the decline in industrial CO_2 emissions increased from 2.39 Mt in 1991 to 167.72 Mt in 2010. Similarly, the contribution of changes in carbon intensity per unit of energy use (CIE) to the sectoral energy-related CO_2 emissions reduction increased from 12.00 Mt in 1992 to 244.85 Mt in 2010. However, contributions of the two effects were quite small compared to the effect of energy intensity (EI). Therefore, they had limited impacts on energy-related CO_2 emissions change in China's industrial sector. The effect of industry size (IS) fluctuated during the period 1998-2004 but showed an overall positive impact on the increase in energy-related CO_2 emissions in China's industrial sector. The U-shaped trend of contributions of industry size effect (IS) verified our deduction. As discussed before, the negative impacts on the increase in industrial CO_2 emissions can be attributed to the industrial restructuring caused by ownership change. Results demonstrate that the negative contributions of industry size effect (IS) to energy-related CO_2 emissions change increased from 90.25 Mt in 1998 (the beginning of industrial restructuring) to the peak 147.80 Mt in 2000, and then dropped to 50.81 Mt in 2004 (the end of industrial restructuring). In summary, the driving forces of industrial CO_2 emissions change are effects of industrial activity (IA) and energy intensity (IE). The effect of industry size (IS) varied during the study period because of China's industrial restructuring during 1998-2004, but indicated overall positive impacts on CO_2 emissions increase. Although the impacts were quite small, the effects of carbon intensity of energy use (CIE) and energy mix (EM) contributed to industrial carbon dioxide emissions decrease.

4.2. Factors affecting China's industrial CO_2 emissions

4.2.1. Tests and results

Before proceeding to the cointegration analysis, we should test the unit root for the stationarity of time series.

1. Unit root test

In this article, we adopt the ADF test and PP test simultaneously to test the existence of unit root. Results of unit root test are shown in Table 4. All variables are stable at the 1% significance level with the second difference. Therefore, time series are considered stable with the second difference, which satisfies the necessary conditions for the construction of the cointegration equation.

Table 4 Unit root test.

Series	Level		First difference		Second difference	
	ADF	PP	ADF	PP	ADF	PP
LnGHG	0.216947	0.370449	-2.761565*	-3.376542**	-7.123797***	-7.123797***
LnCI	-1.427550	-1.192163	-6.425172***	-6.575105***	-9.461870***	-29.75722***
LnIVA	-1.289392	-2.251391	-4.090982***	-1.697991	-2.244858	-4.653348***
LnLP	-2.028839	-4.367619***	-4.444809***	-1.920054	-6.449129***	-13.78485***
LnEFF	-0.024238	0.248056	-2.424200	-2.918669	-5.306580***	-7.844329***

Note: [1] We carry out the tests using EViews8; [2] ***, **, and * indicate that variables are significant at the 1%, 5% and 10% levels, respectively; [3] The hypothesis is that the test equation contains only the intercept.

2. Selection of lag intervals for the VAR model

In order to determine the optimal lag order *k* of each variable, the AIC (Akaike information criterion), SC (Schwarz information criterion), sequential modified LR test statistic LR (Likelihood Ratio), FPE (Final prediction error), and HQ (Hannan–Quinn) information criterion are used in this paper. Table 5 shows the lag order of the VAR model based on various selection criteria.

Table 5 VAR Lag Order Selection Criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	112.7299	N.A.	8.18e-12	-11.3399	-11.0915	-11.2979
1	241.8422	176.6800*	1.59e-16	-22.2992	-20.8080	-22.0468

2	285.1438	36.4646	4.70e-17*	-24.2257*	-21.4918*	-23.7630*

Note: [1] Endogenous variables include LNTCO$_2$, LNCIE, LNIVA, LNLP, and LNEFF, and exogenous variable includes C; [2] * indicates the lag order selected by the criterion.

3. Johansen cointegration test

If the integration of each series is of the same order, we can further test the existence of the cointegration relationship over the sample period. The most commonly used methods are the Engle-Granger two-step procedure provided by Engle and Granger [46] and Johansen-Juselius method proposed by Johansen and Juselius [56] and Johansen [57]. The Engle-Granger two-step method is applied to the co-integration test in a single equation, while the Johansen-Juselius method not only can detect the existence of co-integration between the variables, but also can accurately determine the number of cointegration vectors. Therefore, based on the fact that a multitude of variables are used in this paper, we use the Johansen-Juselius method to study the co-integration relationship among economic variables. Results are presented in Table 6.

Table 6 Johansen cointegration test.

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.973073	154.9458	76.97277	0.0000

At most 1 *	0.880622	86.26776	54.07904	0.0000
At most 2 *	0.794411	45.88395	35.19275	0.0025
At most 3	0.466458	15.82827	20.26184	0.1826
At most 4	0.185230	3.892133	9.164546	0.4284
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.973073	68.67800	34.80587	0.0000
At most 1*	0.880622	40.38381	28.58808	0.0010
At most 2 *	0.794411	30.05569	22.29962	0.0034
At most 3	0.466458	11.93613	15.89210	0.1897
At most 4	0.185230	3.892133	9.164546	0.4284

Note: [1] The tests are carried out using EViews8; [2] Trace test indicates 3 cointegrating eqn(s) at the 0.05 level and the Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level of significance; [3] * denotes rejection of the hypothesis at the 0.05 significance level; ** denotes the MacKinnon-Haug-Michelis [63] p-values.

Table 6 shows that the null hypothesis - there is no cointegration equation is rejected at the 5% significance level. Therefore, there exists a long-term equilibrium relationship among variables.

4. Stability test

It should be noted that in the prediction of the VAR model, a small sample size and the low freedom degree would affect the validity of parameter estimation in the model. Therefore, it is highly necessary to test the robustness of the VAR model. In this paper, we use inverse roots of AR characteristic polynomial to test the stability of the model.

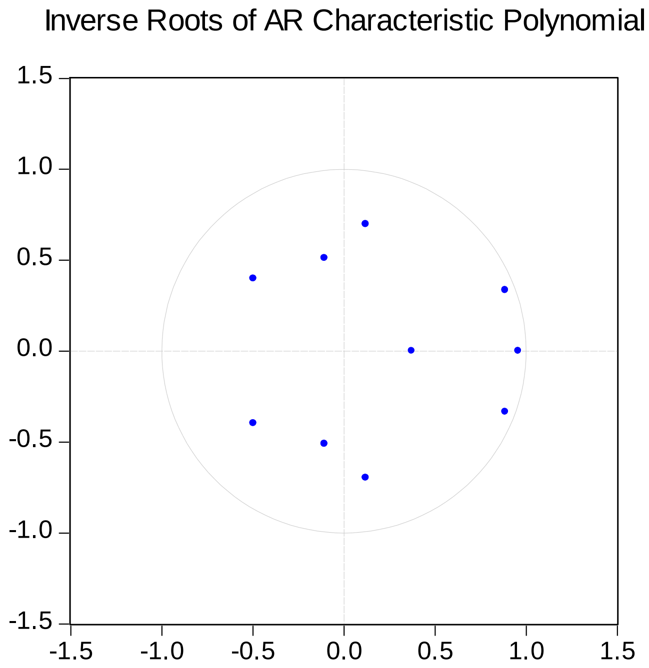


Fig. 5. Inverse Roots of AR Characteristic Polynomial.

As shown in Fig. 5, all the eigenvalues of adjoint matrix are smaller than one except those unit roots assumed by the VECM model itself, which means that there isn't any characteristic root outside the unit circle and the model in this paper satisfies the stability condition.

4.2.2. The cointegration relationship

We choose the cointegrating vector that meets the priori expectations, and drop other cointegrating vectors based on the statistical insignificance and inconformity of the coefficients. The selected and normalized cointegration vector is shown in Table 7.

Table 7 Long-run estimation results.

Regressor	Coefficient	Standard error
LNCIE	0.5457	0.0753
LNY	0.3270	0.0364
LNLP	-0.0365	0.0259
LNEFF	0.6573	0.0307
C	0.4163	0.0966

Note: Log likelihood 242.01.

As shown in Table 7, all coefficients are in line with expectation. Carbon intensity of energy use (CIE), industrial value added (IVA) and fossil fuel consumption (EFF) are the driving forces of the growth of energy-related CO_2 emissions in China's industrial sector. Based on the above analysis, the improvement of labor productivity (LP) helps reduce the energy-related CO_2 emissions from industry. However, the estimated coefficient is quite small in our model. Major reasons include: first, the industrial growth is extensive during China's rapid industrialization process, and most employees are not well-skilled because of the shortage of talents and the relatively low educational level; second, there are a large number of backward production facilities that need to be closed down in China's industrial sector, and there is very little substitutability between capital and labor.

Elasticity coefficients show that a 1 percent increase in carbon intensity of energy use (CIE), industrial value added (IVA) and fossil fuel consumption (EFF) will result in a 0.546 percent, 0.327 percent and 0.657 percent increase of energy-related carbon dioxide emissions from industry, respectively. Furthermore, the impact of fossil fuel use (EFF) on energy-related CO_2 emissions is the largest, followed by carbon intensity of energy use (CIE) and industrial value added (IVA).

Historical data were substituted into the estimated equation to examine the prediction accuracy of the model. Results are illustrated in Fig. 6. It can be seen that the model fits the historical data of $LNTCO_2$ well (the average relative error is 0.0045), thus providing the evidence that the cointegration equation has good prediction accuracy.

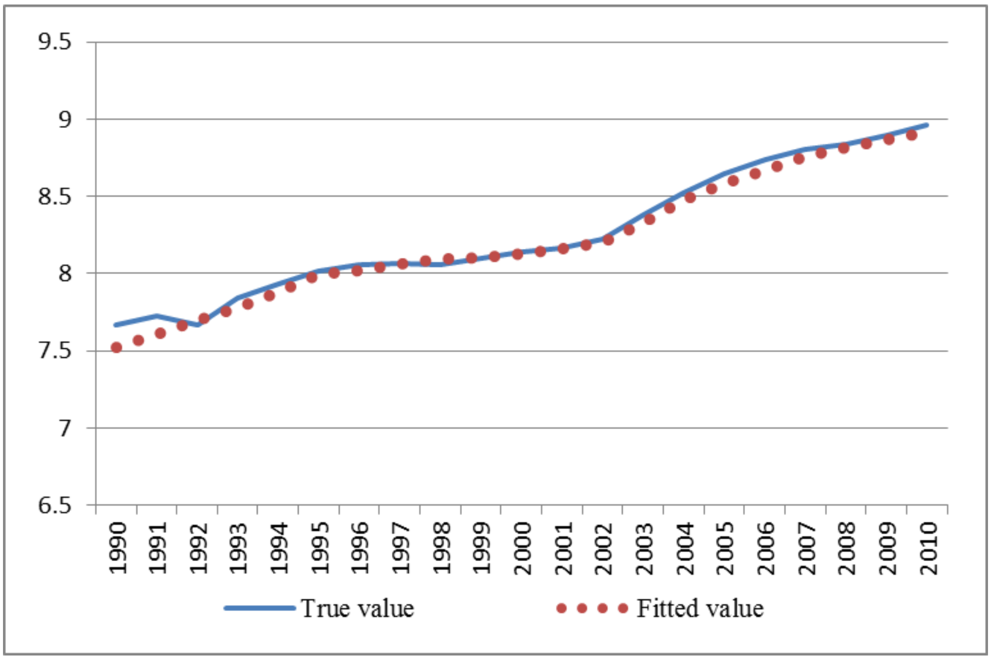


Fig. 6. True value and fitted value of energy-related carbon dioxide emissions in China's industrial sector.

5. Conclusions and policy suggestions

The purpose of this paper is to investigate the changes as well as the driving forces of energy-related carbon dioxide emissions in the China's industrial sector. Application of decomposition analysis was based on the Logarithmic Mean Divisia Index (LMDI) that provided a quantitative analysis on how effects of carbon intensity of energy use (CIE), energy mix (EM), energy intensity (EI), industrial activity (IA) and industry size (IS) influenced the sectoral energy-related carbon dioxide emissions from 1991 to 2010. Results show that the industrial activity effect (IA) and energy intensity effect (EI) were the major driving forces of the changes in energy-related CO_2 emissions in China's industrial sector. The industrial activity effect (IA) contributed to the significant increase of the sectoral CO_2 emissions. On the contrary, the energy intensity effect (IE) was the major contributor to the reduction of CO_2 emissions. The effect of industry size (IS) varied during 1998-2004 but showed an overall positive impact on the sectoral CO_2 emissions increase. Moreover, the impacts of fuel diversification (energy mix effect) and carbon intensity of energy use (CIE) were more prominent in the aspect of reducing energy-related CO_2 emissions. Results in this paper are consistent with the previous studies such as Liu et al. [15], Lin and Moubarak [19], etc.

In order to further explore the determinants of energy-related CO_2 emissions in China's industrial sector, we establish a long-run equilibrium relationship between the sectoral energy-related CO_2 emissions and factors such as carbon intensity of energy use (CIE), industrial value added (IVA), labor productivity (LP) and the fossil fuel use (EFF) based on the cointegration model. Factors including carbon intensity of energy use (CIE), industrial value added (IVA) and fossil fuel use (EFF) have positive impacts on the energy-related CO_2 emissions increase in China's industrial sector, while the improvement of labor productivity (LP) is conducive to reducing the industrial CO_2 emissions. Elasticity coefficients show that a 1 percent increase in carbon intensity of energy use (CIE), industrial value added (IVA) and fossil fuel consumption (EFF) will result in a 0.546 percent, 0.327 percentand 0.657 percent of increase in the sectoral energy-related CO_2 emissions, respectively.

Policy implications and measures for mitigating the energy-relatedCO_2 emissions increase in China's industrial sector are suggested.

Reducing energy intensity is the major strategy for CO_2 emissions reduction in China's industrial sector. Firstly, the policy of total energy consumption control, which is the most powerful impetus to limit industrial energy intensity, will directly promote energy efficiency improvement and make energy saving measures more specific in China's industrial sector. For example, according to the notice of "*Decomposition of the Key Tasks of Clean Air Action Plan (2013-2017) in Beijing*", all coal-fired power plants are required to be disabled in 2016. Secondly, energy-saving technologies can effectively improve the efficiency of energy use, and thereby save a sizeable amount of electric energy, emissions and utility bill in the industrial sector [64]. For instance, Hasanbeigi et al. [65] and Hasanbeigi and Price [66] indicated that development of new energy-efficiency and CO_2 emission-reduction technologies and their deployment in the market would be key for energy intensive industries' mid-and long-term climate change mitigation strategies. Therefore, China's industrial sector should promote the application of advanced energy efficient and low-carbon technologies to reduce energy/carbon intensity [67]. The effectiveness of government policies to facilitate the adoption of those technologies is also highly important. Thirdly, phase-out of low efficient production capacity also helps reduce energy consumption in the industrial sector. The backward capacities are still substantial in China's energy-intensive industries such as the iron and steel industry, building materials industry, chemical industry, nonferrous metals industry, etc. In 2013, Tianjin city claimed that it would no longer approve the new capacity expansion projects of energy-intensive industries including steel, cement and non-ferrous metals, and the construction of coal projects would be implemented the policy of "coal consumption reduction and replacement". In conclusion, future policies should focus on industrial upgrading accompanied by reducing backward production capacity and the growth of energy-intensive industries. Meanwhile, industrial energy intensity can be reduced by setting better reduction targets supplemented with a scientific and effective management system [68].The long-term approach is to increase the research and development (R&D) investments in energy conservation technologies. Considering the investment risks and the external benefits of energy efficient technologies, the government should support the development of energy conservation and low-carbon technologies by providing subsidies, favorable financing or tax exemptions.

Energy diversification and energy structure adjustment is crucial for mitigating energy-related CO_2 emissions in China's industrial sector. The share of coal in the primary energy use structure must be reduced as much as possible to mitigate the sectoral energy-related CO_2 emissions. However, changing industrial energy structure will inevitably lead to higher cost of energy, which would reduce the speed of industrial growth. In the short term, because of the shortage of oil and gas, the price differences between oil, gas and coal, as well as the safety concerns of nuclear power, coal is difficult to be substituted substantially. Therefore, using coal in a more efficient and clearer way is an important solution. Specifically, the government measures should focus on encouraging and strengthening the supervision and punishment for both the demand side and the supply side. On the demand side, increasing energy costs to make energy prices reflect the externalities of energy - the cost of scarcity and the environmental cost, which makes energy conservation and emissions reduction meaningful to individual sectors in the aspect of finance, and promotes energy efficiency and energy conservation by market forces. Policy instruments such as enacting and implementing more strict technical standards of industries, building standards and pollution emission standards to encourage energy efficiency improvement. The establishments of appropriate funding mechanisms by green loans and the adoption of special policies ensure technological and capital investment on energy conservation and emissions reduction. On the supply side, the government can develop effective strategic planning for clean energy, and encourage the development of new technology, new energy through policy measures. In the meantime, the market competitiveness of clean energy could be improved by increasing the cost of fossil fuels, which could reserve a space for renewable energy development [69-70], adjust energy structure from the supply side, and gradually get rid of the dependence on traditional fossil fuels.

Energy price reform is a fundamental mitigation strategy for energy-related CO_2 emissions in China's industrial sector. It should be noted that energy efficiency improvement alone does not necessarily reduce the total energy consumption. If energy prices remain unchanged, the decline in costs of products or energy services resulted from energy conservation will lead to a rebound in energy demand, that is, the "excessive" consumption problem that resulted from the policies of low-cost energy [71]. The long-term mechanism of increasing energy costs (energy pricing reforms) is an effective means of promoting energy efficiency and reducing energy intensity in the long term. Rising in energy prices will reduce energy demand in China’s industrial sector. If energy becomes more expensive compared to other production factors, the producers would seek alternatives or choose more energy-efficient technologies to promote the decline in energy intensity.

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