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Article

Using LMDI to analyze the decoupling of carbon dioxide emissions from China's heavy industry

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Abstract: China is facing huge pressure on CO_2 emissions reduction. The heavy industry accounts for over 60% of China's total energy consumption, and thus lead to a large number of energy-related carbon emissions. This paper adopts the Log Mean Divisia Index (LMDI) method based on the extended Kaya identity to explore the influencing factors of CO_2 emissions from China's heavy industry; we calculate the trend of decoupling by presenting a theoretical framework for decoupling. The results show that labor productivity, energy intensity, and industry scale are the main factors affecting CO_2 emissions in the heavy industry. The improvement of labor productivity is the main cause of the increase in CO_2 emissions, while the decline in energy intensity leads to CO_2 emissions reduction, and the industry scale has different effects in different periods. Results from the decoupling analysis show that efforts made on carbon emission reduction, to a certain extent, achieved the desired outcome but still need to be strengthened.

Keywords: Decomposition; LMDI; Decoupling; Heavy industry

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1. Introduction

The heavy industry mainly produces production and other materials, and also serves as the technical basis for the economy. According to the National Bureau of Statistics (NBS), the division as to a light or heavy industry standard is based on whether the industry produces production or consumption materials (Lin and Liu, 2016). There are also some research studies which classify the heavy and light industry by the amount of energy consumed (Chen, 2011). In this paper, we use the classification method of NBS to determine a heavy or light industry (see Appendix A).

Heavy industry occupies an important place in China's economy. From 1949 to the beginning of the reform and opening up, China adopted the strategy of "heavy industry priority development"; it took the heavy industry as the top priority in the development of national economy and therefore pursued its growth. In this context, the heavy industry became the fastest- growing and the leading industry in that period. Average annual growth rate reached 15.3% during the period1949-1981. The proportion of the heavy industry to the total industrial output also increased rapidly from 26.4% to 48.6% during the same period (Lin et al., 2003). After the reform and opening up, the industry ushered in a new round of development. The proportion of heavy industry to total industry sector increased from 48.6% in 1981 to 75.5% in 2001, and then to 79.9% in 2016[1]. The industry has indeed occupied an absolutely important position in China's industrial structure.

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[1] The NBS has published the added value of each industrial sector in 1993-2007, and the growth rate in 2008-2016. Then the proportion of heavy industry in the total industrial output can be calculated.

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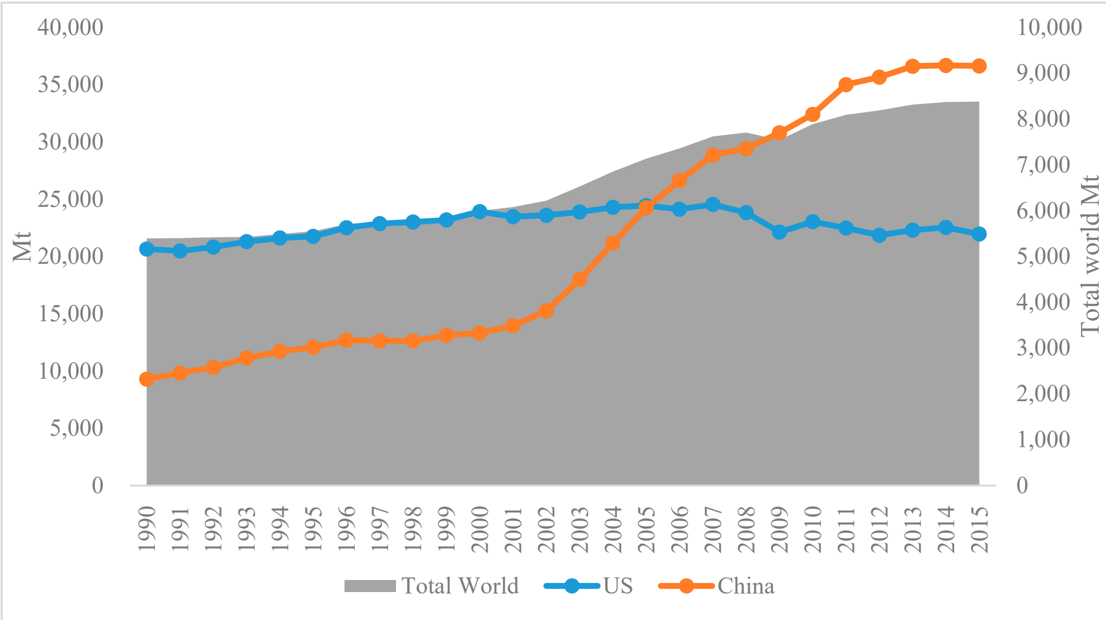
Most sub-sectors of the heavy industry are energy-intensive. With its rapid growth in China, energy consumption has also increased drastically; it accounts for over 65% of the total primary energy consumption (Lin and Li, 2014). China is in the period of industrialization and urbanization, and for that matter, the heavy industry will continue to develop in the future. As the primary energy consumption in China is dominated by fossil fuels, and that the burning of fossil fuels is the main source of carbon dioxide emissions, growth in carbon emission has experienced a sharp increase over the years (Figure 1).



Source: BP Statistical Review of World Energy 2016.

Figure 1. CO_2 emissions in China, USA, and the world

China overtook America as the world's largest emitter of carbon dioxide in 2006. As at 2015, total carbon emission was 9153.9 million tons, accounting for 27.3% of total emission in the world. It is worth noting that total carbon emission in China (in 2015) compared with 2014 dropped by 0.1%, due to a decline in the overall growth of the economy. As China's industrialization and urbanization process continue, energy consumption and energy-related carbon emissions are likely to grow rapidly when the economy is better.

In 2009, Chinese government proposed the emission reduction target, which seeks to ensure that CO_2 emissions per unit of GDP in 2020 drops by 40%-45% compared with the 2005 level. In order to achieve the emission reduction target, one of the most important things is to determine the driving factors of carbon emission growth and reduction. As the heavy industry contains almost all the energy-intensive sectors and accounts for over 65% of China's total energy consumption, energy conservation and emission reduction in the heavy industry is significant for the success of national energy conservation and emission reduction.

Investigating the driving forces of energy consumption, pollutant or carbon emissions, and energy efficiency is an important issue in energy economic research. Base on methodology, research on driving forces can be divided into three categories: Econometric analysis, Computable General Equilibrium (CGE) analysis based on input-output (I-O), and Decomposition analysis. Compared with the econometric and CGE analyses, the decomposition analysis is relatively simple and clear and can be used to measure the effects of related factors based on the decomposition of identities, such as the Kaya identity. It also has a certain degree of flexibility for the definition of decomposition factors. In general, decomposition analysis can be divided into three different kinds: structural decomposition analysis (SDA), production-theory decomposition analysis (PDA), and index decomposition analysis (IDA).

 doi:10.20944/preprints201706.0129.v1

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SDA, which is based on I-O analysis, can make full use of an I-O data. In the case of energy consumption and carbon dioxide emissions analysis for an industrial or economic sector, SDA can distinguish the direct and indirect effects on the change of the production or consumption of the sector, analyzing the effect of changes in the final demand of one sector on the change of energy consumption of other sectors (Alcántara and Padilla, 2009). Compared with other methods about decomposition, the analysis of SDA on driving forces is more comprehensive and thorough, but the requirement on data is higher than other methods. (Hoekstra and Van den Bergh, 2003; Rose and Casler, 1996; Su and Ang, 2012) have made a comprehensive review of the application of SDA.

The SDA model based on I-O analysis is widely used in energy and environment analysis. According to the double-KLEM production function, Rose and Chen (1991) analyzed the main factors for the change in energy consumption in the United States. Their results show that economic growth and the substitution between energy and other factors are the main driving forces for the increase in energy consumption, and energy conservation, whiles technical change is the main reasons for the suppression of energy consumption. With the same method, Casler and Rose (1998) extended the research into carbon emission analysis. Lenzen (1998) adopted the SDA to describe the relationship between terminal energy consumption and carbon emission in Australia. Machado et al. (2001) and Butnar and Llop (2011) analyzed the effect of international trade, internal demand, external demand, and other factors on energy consumption and carbon emission in Brazil. This method is also widely used in the analysis of China's industrial and regional energy consumption and carbon emissions (Xie, 2014; Zhang, 2009), as well as analysis at the urban level (Wang et al., 2013).

In order to make an economic interpretation of the decomposition results, Wang (2007) proposed the method of PDA based on the data envelope analysis (DEA). Based on the output distance function, PDA can decompose the change in energy efficiency (the reciprocal of energy intensity) into technical efficiency changes, technological changes, and potential maximum energy efficiency change, where the potential maximum energy efficiency change includes the substitution between energy and capital, energy and labor, and structural changes in output. After this, PDA is widely used in the analysis of energy consumption and carbon emission (Fan et al., 2010; Lin and Du, 2014; Zhang and Da, 2015).

Compared with SDA and PDA, the method of IDA has relatively lower requirements for data, especially the results of PDA on the structural effect of output and energy may be inconsistent with reality (Du and Lin, 2015). In this case, IDA is originally used in the study of industrial energy consumption, and gradually used in energy-environmental analysis. IDA has different forms, among which Laspeyres decomposition and Divisia decomposition are the commonly used ones. Ang et al. (1998) proposed the Log-Mean Divisia Index Decomposition Method (LMDI), which is also one of the most commonly used methods in IDA. Ang and Zhang (2000) have to make a review of IDA.

(Xu et al., 2012) analyzed the driving forces of energy consumption and carbon emission in China's cement industry, the results show that output growth is the most important factor driving energy consumption up, whiles structural shifts mainly drives energy consumption down. The results are similar in China's transport sector (Wang et al., 2011; Zhang et al., 2011). (Zha and Ding, 2014) compared the differences in driving forces of residential carbon emissions in urban and rural China, and the results showed population effect to be significantly different. There are also research studies that focused on influencing factors of energy intensity (Liu et al., 2007; Ma and Stern, 2008)

After the decomposition analysis of driving factors for carbon emission, we also need to evaluate the effectiveness of carbon emission reduction policies, and decoupling analysis can be a good choice. Originally appearing in physics, decoupling refers to the process of eliminating the effect of mutual interference between signals. In 2000, it was used by the organization for economic cooperation and development (OECD) to investigate agricultural policies, and also assess environmental quality (OECD, 2001). Research on decoupling later expanded to the field of environment, stemming from the Driver-Pressure-State-Influence-Response (DPSIR) framework; it is mainly used to reflect the relationship between the driving force and the environmental pressure during the same period. Decoupling can simply and clearly explain the relationship between the resource environment and economic development, hence, it has been applied to study the relationship between economic

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growth and factors like environmental pollution, energy consumption, increase in house prices, arable land occupation etc. (Ayres et al., 2003; Ma et al., 2013; Secretariat, 2002; Zhang and Zhang, 2017).

OECD countries have attached great importance to research on the "decoupling" and its application. The decoupling is divided into relative decoupling and absolute decoupling. Relative decoupling is said to occur when the growth rate of the energy variable is positive but less than that of economic output. Absolute decoupling, however, is said to occur when the growth rate of energy use is zero or negative and the growth rate of economic output is positive (Ren et al., 2014). The OECD report showed that from the perspective of policy research, the pressure index and the corresponding decoupling index are better than the state index because they have the advantage that they can be easily changed in a short term (OECD, 2005). When it comes to evaluating specific policies, they can be more effective. Therefore, decoupling is often used to establish environmental indicators, and evaluate the effect of policy implementation.

To sum up, many studies have been conducted on decomposition and decoupling of different industries in different countries. However, as an industry with huge energy consumption and carbon emissions, China's heavy industry does not get enough attention. Thus, we extend our research to the heavy industry by using LMDI. We also calculate the decoupling to study the effect of each factor. The coupling state between CO_2 emissions and industry development will also be tested. The results of the study can help us understand the various influencing factors of carbon emissions in China's heavy industry. It can also help us measure the relationship between the industry development and carbon reduction.

The remainder of this paper is organized as follows. Section 2 shows the methods used in this paper. Section 3 reports the data sources as well as the data processing. Section 4 concludes the estimation results and also depicts the main conclusion. Section 5 presents some corresponding policy implications based on the empirical results, and the last section shows the references used in this paper.

2. Methodology

2.1 Decomposition Analysis

We use the Logarithmic Mean Divisia Index (LMDI) decomposition to analyze the influencing factors of carbon dioxide emissions of China's heavy industry.

Based on the Kaya identity, carbon emissions can be decomposed into several affecting variables (Kaya, 1990):

$$C = \frac{C}{E} \times \frac{E}{GDP} \times \frac{GDP}{P} \times P \tag{1}$$

Where C denotes CO_2 emissions, C/E denotes the carbon intensity of energy; E/GDP denotes energy efficiency; GDP/P denotes per capita income and P denotes population. According to the Kaya identity, the energy related CO_2 emissions are basically determined by carbon intensity, energy efficiency, per capita income, and the total population.

Further, the kaya identity can be extended as:

$$C = \frac{C}{E_f} \times \frac{E_f}{E} \times \frac{E}{Y} \times \frac{Y}{W} \times W \tag{2}$$

In this paper, we focus on CO_2 emissions from fossil energy consumption. (Ang and Lee, 1994) discussed several methodological and application issues related to the technique of the decomposition of industrial energy consumption. In Eq. (2), E_f denotes the fossil energy consumption and E is the total energy consumption of heavy industry, Y denotes the output of heavy industry, which is represented by the added value, and W denotes the labor input.

Table 1 shows the energy economic meaning of each factor in Eq. (2):

Table 1. Definition of variables

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Multiplier in Equation (2)	Abbreviation	Description
C/E_f	CI	Carbon intensity: The amount of carbon by weight emitted per unit of energy consumed
E_f/E	ES	Energy structure: the proportion of fossil energy in total energy consumption
E/Y	EI	Energy intensity: energy consumption per unit of GDP
Y/W	LP	Output per capita: industrial added value per capita
W	IS	Industry scale: the number of employees in the heavy industry.

For simplification, Eq. (2) can be expressed as:

$$C = CI \times ES \times EI \times LP \times IS \tag{3}$$

With LMDI, the cumulative change in CO_2 emissions in year *t* can be represented in five parts:

$$\Delta C = C_t - C_0 = \Delta C_{CI} + \Delta C_{ES} + \Delta C_{EI} + \Delta C_{LP} + \Delta C_{\mathrm{IS}} \tag{4}$$

Each part of Equation (4) can be computed as follows:

$$\Delta C_{CI} = L(C_0, C_t) \times \ln(CI_t/CI_0) \tag{5}$$

$$\Delta C_{CI} = L(C_0, C_t) \times \ln(\mathrm{ES}_t/ES_0) \tag{6}$$

$$\Delta C_{CI} = L(C_0, C_t) \times \ln(EI_t/EI_0) \tag{7}$$

$$\Delta C_{CI} = L(C_0, C_t) \times \ln(LP_t/LP_0) \tag{8}$$

$$\Delta C_{CI} = L(C_0, C_t) \times \ln(IS_t/IS_0) \tag{9}$$

where $L(C_0, C_t) = \frac{C_t - C_0}{\ln(C_t/C_0)}$, which is also called the logarithmic weight average. According to Equation (2)-(9), we can do the decomposition analysis of the CO_2 emissions of heavy industry, and get the effect of each factor.

2.2. The decomposition-based decoupling model

The ideal state of low-carbon economy is to achieve a negative growth of greenhouse gas while the economy keeps growing, but this is just an ideal state. The transition towards a low-carbon economy is a process of decoupling between economic growth and greenhouse gas emissions. That is, the growth rate of carbon emissions is lower than that of economic growth.

The Decoupling index (*DI*) is defined as:

$$DI = 1 - Environment/Drivingforce \tag{10}$$

Where *DI* is the decoupling index; *Environment* denotes the environment index, such as pollutant emissions and resource consumption; *Drivingforce* denotes factors like economic growth rate or industrial production growth rate. The decoupling indexes in different areas or different periods are compared to determine the stress intensity and change trend

We choose the change of CO_2 emissions (ΔC_t) to represent efforts in a certain sector to improve the environment in different periods; however, it doesn't imply the real efforts they have made. Because ΔC_t contains not only the real efforts to reduce emissions like optimizing the energy structure and reducing the energy intensity, but also the increase of emissions driven by industrial expansion. Based on the decomposition above, the real efforts to reduce CO_2 emissions ΔCR_t can be decomposed into carbon intensity (*CI*), energy structure (*ES*), and energy intensity (*EI*). The impetus factors are labor productivity (*LP*) and industry scale (*IS*):

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$$\Delta CR = \Delta C - \Delta Y = \Delta C_{CI} + \Delta C_{ES} + \Delta C_{EI} \tag{11}$$

$$\Delta Y = \Delta C_{LP} + \Delta C_{IS} \tag{12}$$

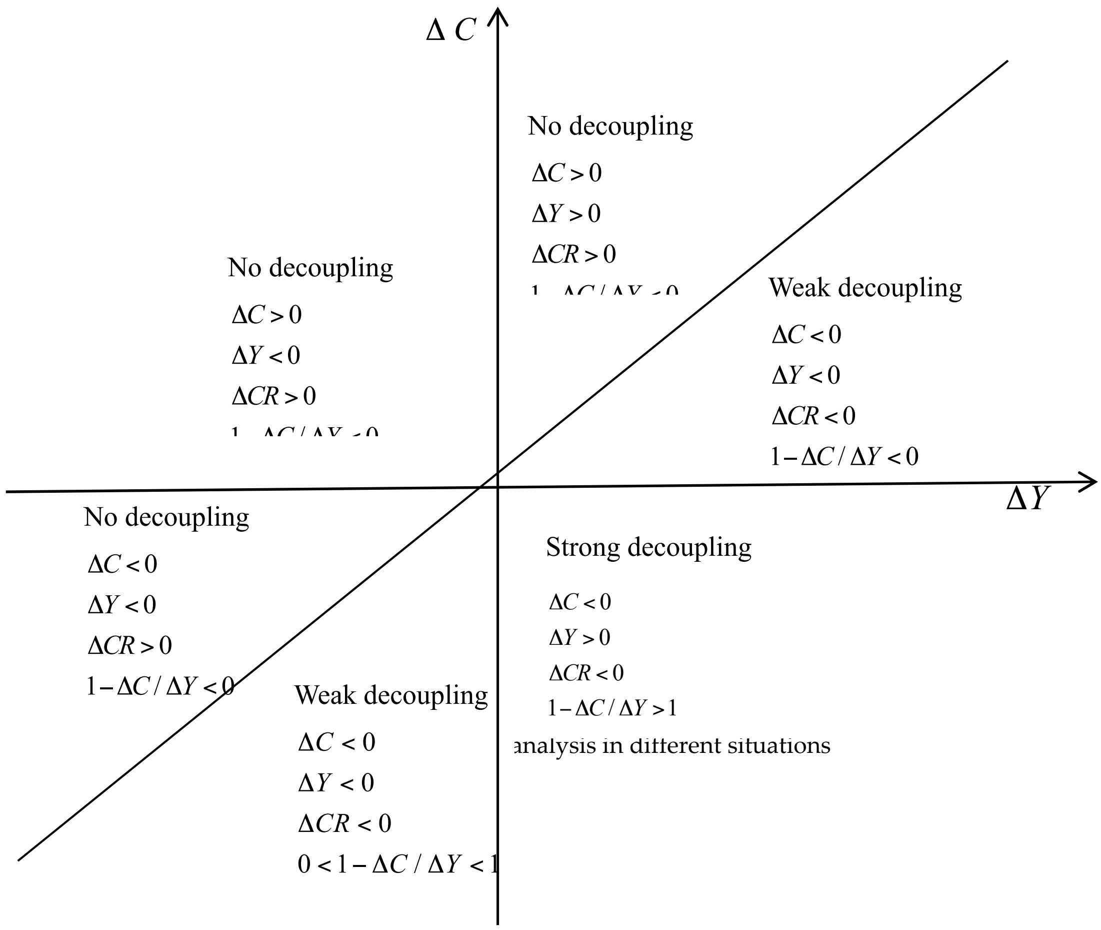
Thus, the decoupling index DI_t is defined as:

$$DI_t = 1 - \Delta C_t / \Delta Y_t = -(\Delta C_t - \Delta Y_t)/\Delta Y_t = -\Delta CR_t/\Delta Y_t \tag{13}$$

When $DI_t > 1$, it indicates strong decoupling. This means that emissions reduction after implementation of existing policies is greater than the emissions growth driven by industrial expansion. The bigger the DI_t, the more obvious the CO_2 reduction effect, and the energy structure is more optimized. As energy intensity decreases, the environmental stress per unit of output is relieved. That is to say, the existing emission reduction efforts are proved to be effective.

When $0 < DI_t < 1$, it indicates weak decoupling, which means that the existing emission reduction policies play a certain role in CO_2 reduction, and the growth rate slows down to a certain extent. But judging from the absolute amount, emissions reduction after the implementation of existing policies is greater than emissions growth driven by industrial expansion, implying that the total emissions are still increasing. The effectiveness and implementation efficiency of the emission reduction policies cannot be guaranteed.

When $DI_t < 0$, it indicates no decoupling. That is to say, the emission reduction policies are ineffective and inefficient, and that the emission reduction goal cannot be achieved. That means that the emission reduction policies cannot optimize the energy structure and reduce the energy intensity. The total emissions are increasing rapidly along with the industrial expansion. In this case, the environment pressures caused by economic growth will continue to increase. All the decoupling conditions is shown in Figure 2.



analysis in different situations

3. Data

In this paper, we employ China's annual data over the period 1991-2015, since earlier terminal energy consumption by industrial sectors is unavailable. Output of the heavy industry is represented

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by the added-value, and as already mentioned in the methodology, energy consumption and labor input are used in our analysis. All the data are obtained from *China Statistical Yearbook*, *China Energy Statistical Yearbook*, and *China Industrial Economy Statistical Yearbook*. If not specifically pointed out, all the data on prices in this paper are converted into constant prices in 1990 based on the GDP deflator. It is worth noting that the statistical criterion does not include heavy industry except the electricity consumption, so other data of heavy industry used in this paper is from the summary of the sub-sectors included in the heavy industry.

3.1 Energy consumption

The heavy industry contains a large number of sub-sectors, some of which are sectors of energy production, conservation, and storage. In the case of double counting, we use the terminal energy consumption of each sub-sector to get the total energy input of the heavy industry.

According to OECD/IEA, terminal energy consumption is the energy used by terminal energy equipment entrance. From the definition, terminal energy consumption is equal to primary energy consumption minus energy loss in energy processing, energy conversion, and energy storage, as well as the loss associated with energy production process in energy-related industries (Agency, 2005).

It is worth noting that the NBS adjusted the terminal energy consumption by industrial sectors in 2000, however, data before 2000 remains unchanged. In order to keep the coherence of data before and after 2000, we rebuilt the terminal energy consumption of the heavy industry before 2000 according to the original growth rate. Figure 3 shows the adjusted terminal energy consumption of China's heavy industry from 1991 to 2015. For convenience, raw coal, clean coal, and coke are merged as coal; crude oil, gasoline, kerosene, diesel, fuel oil, and PLG are merged as oil. Electricity is converted to coal equivalent by the electro-thermal equivalent. It can be seen that energy consumption has increased rapidly, especially after 2002. From the perspective of energy structure, coal has the highest proportion, followed by electricity. It is also imperative to note that the proportion of electricity has increased at a faster rate in the recent years. The proportion of natural gas and heat are relatively low.

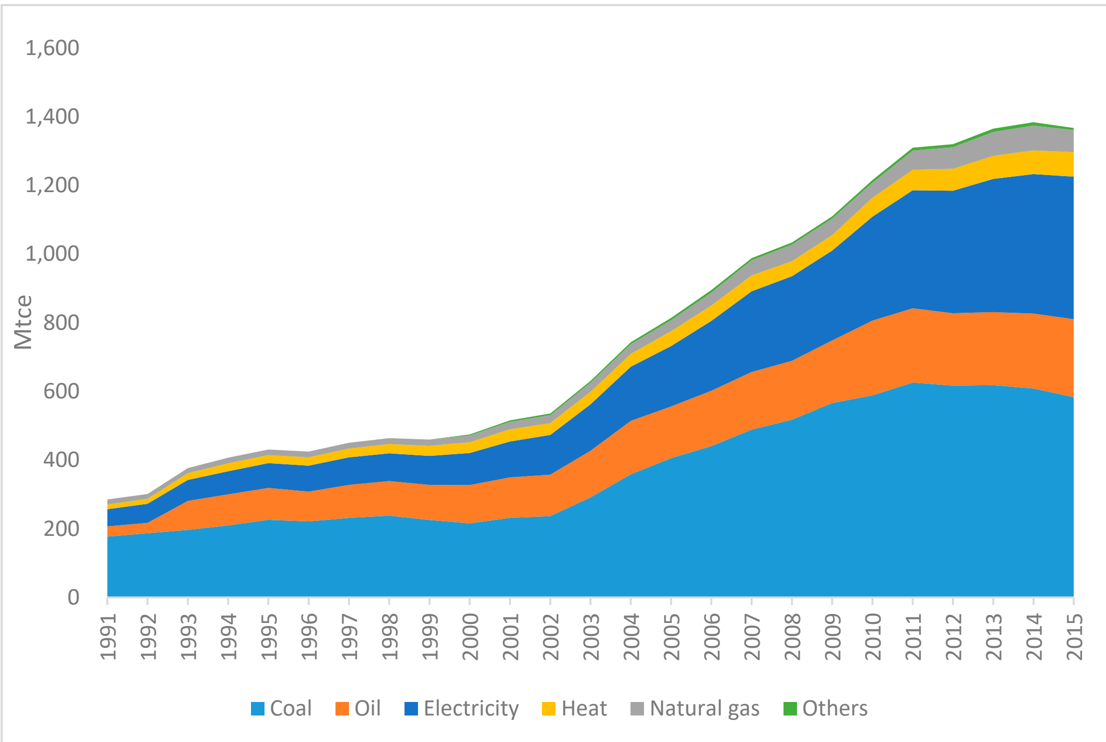

Figure 3. The terminal energy consumption of China's heavy industry

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3.2 Carbon emission

According to (IPCC, 2006), we can get energy-related carbon emissions by aggregating emissions from each type of energy consumption. *China Energy Statistical Yearbook* has published the physical quantity of terminal energy consumption by industrial sectors, and the carbon emissions coefficient of each type of energy is shown in Table 2:

Table 2. The carbon emissions coefficient of each type of energy

Energy type	Raw coal	Cleaned coal	Other washed coal	Coke
Carbon emissions coefficient	1.980356	2.495249	1.107727	3.046316
unit	Mt/ Mt	Mt/ Mt	Mt/ Mt	Mt/ Mt
Energy type	Coke oven gas	Other goal gas	Other coke products	Crude oil
Carbon emissions coefficient	929.4696	776.149	3.135913	3.409916
unit	Mt/Mm^3	Mt/Mm^3	Mt/ Mt	Mt/ Mt
Energy type	Gasoline	kerosene	Diesel oil	Fuel oil
Carbon emissions coefficient	3.044655	3.198454	3.174568	3.04218
unit	Mt/ Mt	Mt/ Mt	Mt/ Mt	Mt/ Mt
Energy type	LPG	Refinery dry gas	Other petroleum products	Natural gas
Carbon emissions coefficient	3.022209	3.617395	3.35	2090.427
unit	Mt/ Mt	Mt/ Mt	Mt/ Mt	Mt/Mm^3

4. Results and conclusion

4.1 Decomposition of carbon emission

We can get the terminal energy consumption of China's heavy industry and the carbon emission coefficients of each type of energy. Moreover, we can get the total carbon emissions by aggregating emissions from each type of energy consumption. The estimated carbon emission of China's heavy industry is shown in Figure 4:

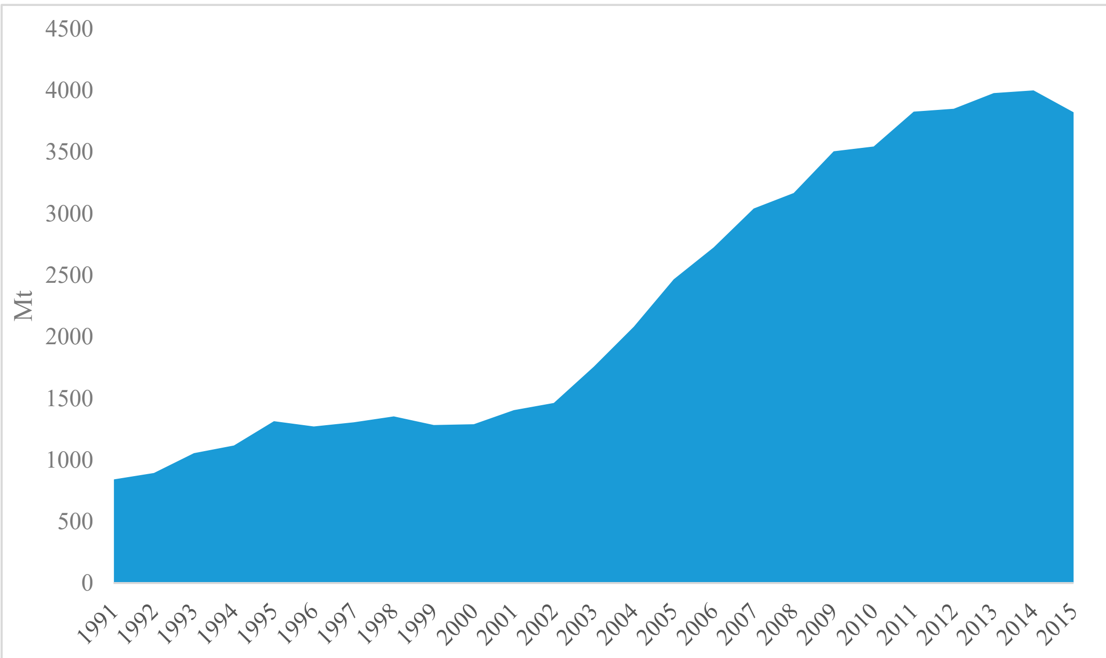

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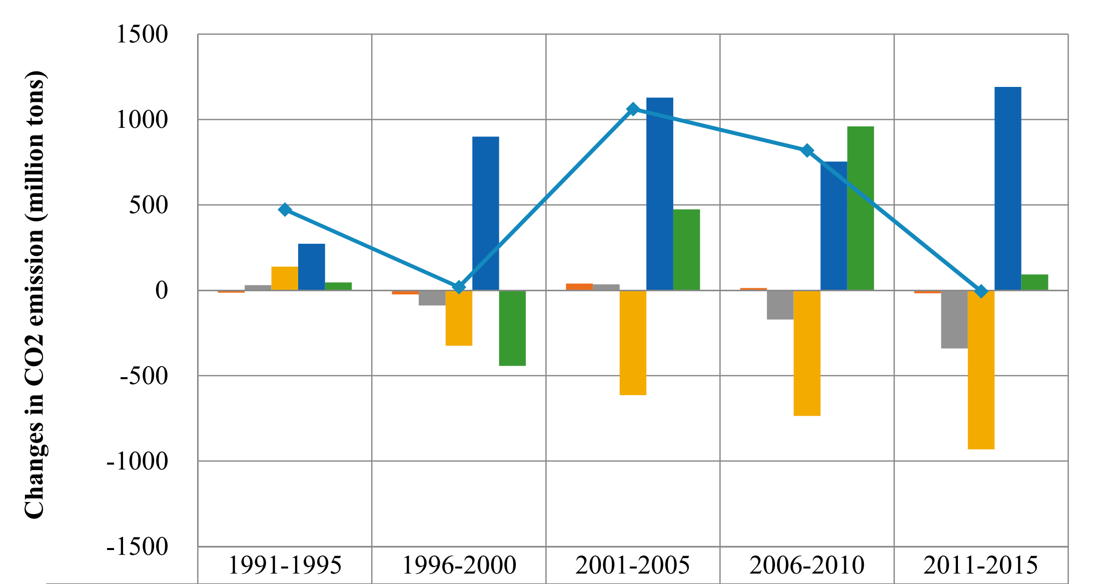
Figure 4. Carbon emission of China's heavy industry

To analyze the periodic change of carbon dioxide emissions of the heavy industry, the sample interval is divided into five sub-intervals according to the "five-year plan" by the central government: 1991-1995, 1996-2000, 2001-2005, 2006-2010, and 2011-2015. According to Eq. (3) - (9), the change of carbon emission in each interval is decomposed into five driving factors, namely *CI, ES, EI, LP,* and *IS*, which can reflect the effect of change in carbon intensity, energy structure, energy intensity, labor productivity, and industry scale on the change of carbon emission, respectively. The decomposition results are shown in Figure 5.



	1991-1995	1996-2000	2001-2005	2006-2010	2011-2015
ΔC_CI	-13.94	-24.21	39.74	13.26	-17.74
ΔC_ES	30.15	-89.11	34.34	-171.35	-340.16
ΔC_EI	138.84	-324.78	-613.95	-735.51	-931.53
ΔC_LP	272.15	899.78	1127.99	753.57	1191.36
ΔC_IS	45.75	-442.70	474.06	959.61	92.64
ΔC	472.94	18.98	1062.18	819.57	-5.43

Figure 5. Increment of carbon dioxide emissions in each sub-interval and decomposition of influencing factors

During the period 1991-1995, among the increment of 472.94 Mt carbon dioxide emissions, 272.15 Mt was caused by labor productivity; 138.84 Mt was due to energy intensity; 45.75 Mt resulted from growth of industry scale; 30.15Mt was driven by energy structure, while the change of carbon intensity contributed to the only carbon emission reduction, which was -13.94 Mt during the interval.

According to the decomposition results above, the principal reason for the increase in CO_2 emission in China's heavy industry is the improvement of labor productivity (*LP*). Since the end of the nineteenth century, the increase in fixed assets per capita has been the main reason for the improvement in labor productivity of industrial enterprises. This resulted in the replacement of manual labor with machinery and equipment, leading to an increase in energy consumption and carbon dioxide emissions in industrial sectors. This effect was particularly evident in the heavy industry. The increase in industry scale (*IS*) and the change in energy structure (*ES*) also contributed to CO_2 emissions increase in the heavy industry during this period; however, the effects were relatively small. It is worth noting that the industry scale of China's heavy industry did not expand significantly during this period; it only contributed 9.67% to the total carbon emission increases. The proportion of coal-dominated fossil energy in the energy structure of the heavy industry also increased, leading to an increase of total carbon emission by 30.15 Mt. Energy intensity was also a

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main driving force of the carbon emission increases in this period, indicating that the energy consumption per unit of output increased rapidly during this period, which may also be the reason for the replacement of labor with machinery.

During the period 1996-2000, the increase in carbon emission was positive, however, the absolute value was small, which may be the reason for the decline in the industry scale during the Asian financial crisis. The decline in energy intensity also contributed to carbon emission reduction, and this might have been caused by an improvement in energy efficiency. The decomposition of carbon emission in the periods 2001-2005 and 2006-2010 are almost the same. The only difference is the effect of energy structure, which has a positive effect in the former period and negative in the latter. It indicates that the energy structure of China's heavy industry is moving in the direction of low-carbon. During the period 2011-2015, the change of energy structure and the decline of energy intensity, together with a low growth rate of industry scale, led to the decline of carbon emission in China's heavy industry, which is unprecedented in the past periods.

Moreover, we find that the effects of the five factors in different periods have both similarities and differences. As for the labor productivity (*LP*), it had a positive effect on CO_2 emissions in each period. Energy intensity (*EI*) had a significantly negative effect on carbon dioxide emissions since 1996. The effect of industry scale (*IS*) is positive except for the period 1996-2000. The influence of energy structure (*ES*) is positive in the periods 1991-1995 and 2001-2005, but became negative since 2006. The influences of carbon intensity (*CI*) are not so obvious that we can only undertake a qualitative analysis.

In order to make a detailed analysis of the changes in CO_2 emissions of China's heavy industry and the effect of each factor, the annual increment of CO_2 emissions and the impact of each factor are calculated. The results are shown in Figure 6:

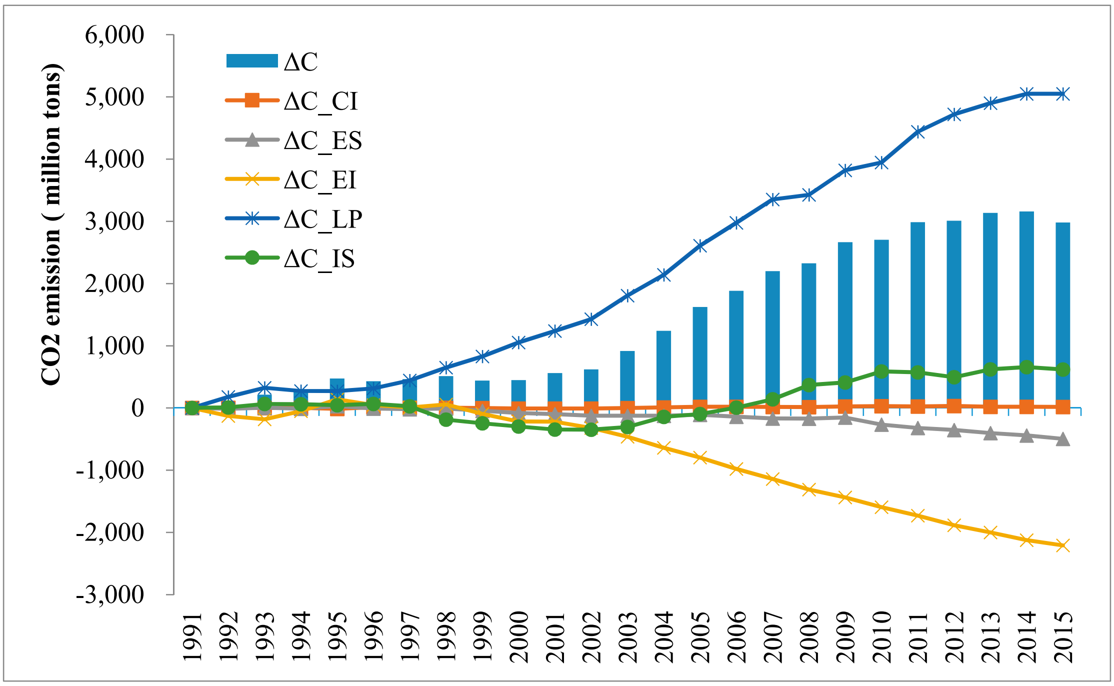

Figure 6. The accumulated change of carbon dioxide emissions and decomposition results of influencing factors

Firstly, during the period 1991-2015, labor productivity had a positive effect on carbon emissions and the effect showed an increasing tendency except in some years. The positive correlation between Labor productivity and its effect on CO_2 emissions showed that too much attention had been paid to equipment and machinery. The substitution of labor with machinery increased energy consumption and carbon emissions. Output of the heavy industry depends on labor and capital. Capital includes all non-labor inputs such as machinery. The improvement of labor productivity does not only rely on workers' technical proficiency and technical progress but also relies on the replacement of labor by

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machine. Different ways directly lead to different influences on CO_2 emissions. If labor is replaced by a machine, the improvement of labor productivity will have a positive impact on energy consumption.

Secondly, during the observed period, the influence of industry scale varied significantly. From 1991 to 1995, the effect was positive but small. This contributed to an increment of 45.75 tons of carbon dioxide emissions. During the period 1996-2000, the influence of industry scale changed significantly. As can be seen from Figure 6, the contribution of the industry scale to carbon emissions begins to decline. The accumulated effect of industry scale became negative in 1998, and kept declining until 2002; it became positive again in 2006. In 2014, the effect of industry scale decline again.

In general, the change in the effect of industry scale is consistent with the development of China's heavy industry. After the reform and opening up, with the rapid development of China's economy, the heavy industry accounted for a rising proportion in economic structure, which brought about a series of problems such as economic imbalance and environmental pollution. The government started to adjust the economic structure and set the goal of "adjust industrial layout, optimize industrial structure" during the "Ninth Five-Year plan" period (1996-2000). Specifically, backward production capacity should be eliminated to reduce the proportion of heavy industry with high energy consumption and high pollution in the economic structure. This policy worked well. The growth rate of the heavy industry in 1996 started to slow down. Therefore, industry scale in this period had a negative effect on carbon dioxide emissions. The financial crisis in 1998 further strengthened the negative effect, and the proportion or number of heavy industries declined significantly during this period. After 2000, the heavy industry began to expand again until 2014, when China's economy began to enter "new normal". Therefore, it can be concluded that expansion of the heavy industry will cause a significant increase in carbon dioxide emissions.

Thirdly, during the period 1991-2015, the coal-dominated energy structure of the heavy industry has fundamentally not changed. Energy structure was always negatively correlated with carbon emissions, and the negative effect was particularly obvious since 2010. In 2009, China made the promise of carbon emission reduction, and began to optimize the energy structure in the "Eleventh Five-Year plan". The results indicate that China's energy structure has been gradually optimized. The optimization of energy structure played a positive role in reducing carbon emissions of the heavy industry. The government began to eliminate the backward production capacity in 1996. This played a role in optimizing the energy structure in the heavy industry. China then began to face tremendous pressure from the resources constraint and also from the environment, which eventually contributed to the industrial structure adjustment.

4.2 Decoupling analysis

Based on the decomposition results and Eq. (13), we can derive the decoupling indexes of carbon dioxide emissions of China's heavy industry for the period 1992 -2015. From the definition of decoupling index, when $DI_t > 1$, it indicates strong decoupling, which means emissions reduction after implementation of existing policies is greater than the emissions growth driven by industrial expansion. When $0 < DI_t < 1$, it indicates weak decoupling, which means that the existing emission reduction policies play a certain role in CO_2 reduction, and the growth rate slows down to a certain level. When $DI_t < 0$, it indicates no decoupling. That is to say, the emission reduction policies are ineffective and inefficient, and that the emission reduction goal cannot be achieved.

As can be seen from Table 3, the decoupling index (DI) are all smaller than 1 during the period 1992-2015, indicating weak decoupling. Though the highest (DI 0.73) appears in 1992, the DI of other years during 1992-1999 are relatively small, especially the DI in 1995, 1996, and 1998, which are -0.49, -0.13 and -0.11, respectively. The indication is that the effects on carbon emission reduction are relatively poor in this period. While the decoupling effect has been increasing since 2005, suggesting that the efforts of carbon emission reduction have accomplished a certain effect (with the absolute value of DI still less than 1), the weak decoupling indicates that it still needs to be strengthened in the efforts of carbon emission.

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Table 3. Change of CO_2 emissions, driving force, reduction effect and decoupling index of China's heavy industry in each year

	ΔC	ΔY	ΔCR	DI		ΔC	ΔY	ΔCR	DI
1992	51.92	188.81	-136.89	0.73	2004	323.87	1998.89	-759.19	0.38
1993	161.43	390.92	-177.57	0.45	2005	384.72	2510.61	-886.19	0.35
1994	62.78	335.08	-58.96	0.18	2006	259.78	2984.30	-1100.10	0.37
1995	196.82	317.90	155.05	-0.49	2007	315.24	3494.10	-1294.65	0.37
1996	-42.96	379.21	50.78	-0.13	2008	126.05	3793.79	-1468.29	0.39
1997	34.16	471.13	-6.99	0.01	2009	338.89	4229.36	-1564.97	0.37
1998	47.56	460.82	50.88	-0.11	2010	39.39	4532.74	-1828.96	0.40
1999	-70.09	583.59	-141.98	0.24	2011	282.43	5011.61	-2025.40	0.40
2000	7.36	756.94	-307.97	0.41	2012	22.69	5214.92	-2206.01	0.42
2001	113.28	892.05	-329.81	0.37	2013	128.41	5520.21	-2382.90	0.43
2002	59.28	1078.33	-456.81	0.42	2014	22.09	5705.91	-2546.51	0.45
2003	294.31	1501.47	-585.63	0.39	2015	-178.61	5668.47	-2687.68	0.47

5. Conclusions and policy implications

With the development of the economy, energy consumption and the CO_2 emissions of China's heavy industry are still rising. This paper, for the first time, applies the LMDI approach to decompose CO_2 emissions and then analyze the decoupling effect of carbon emission reduction policies in China's heavy industry.

The empirical results show that energy efficiency and labor productivity are two key factors influencing the CO_2 emissions. High energy efficiency is the principal contributor to low CO_2 emissions, while high labor productivity leads to high CO_2 emissions. This is mainly due to the fact that improvement in labor productivity in China principally depends on the replacement of manual labor by machinery and equipment, which leads to more energy consumption and eventually more CO_2 emissions. Industry scale is also an important cause of the carbon emissions. Expansion of industry scale leads to the increase of CO_2 emissions, which was verified by the empirical results during the period 1991-2015. In addition, during the observed period in this paper, energy structure had negative effects on CO_2 emissions, but the effects were relatively small. We also show that upgrading energy structure and improving energy efficiency will significantly reduce CO_2 emissions. Overall, the upgrading of energy structure during 1991-2015 was effective, although the effect was not very obvious.

The government and academia have focused on economic development constrained by the environment for a long time. With global warming becoming more serious, reduction of CO_2 emissions will be a constraint for economic growth. By analyzing CO_2 emissions of the heavy industry and the decoupling, weak decoupling was found in most years except 1998, which indicated that the efforts to reduce CO_2 emissions in the heavy industry achieved a certain but not significant effect. To reduce CO_2 emissions while guaranteeing the development of the heavy industry, the following suggestions can be considered.

Firstly, the development pattern of the heavy industry should be transformed, and the operation efficiency and management level of enterprises should be improved. Based on the above research results, the increase in labor productivity is the main cause of the growth in CO_2 emissions. That is, the increase in labor productivity depends principally on the expansion of industry scale and the replacement of manual labor by machinery and equipment. In terms of sustainable development, the improvement of labor productivity should be achieved by upgrading industrial structure and also making improvements in the management level. In this way, the effect of labor productivity growth on CO_2 emissions will change from positive to negative, reducing CO_2 emissions while guaranteeing the development of the heavy industry. The positive effect of labor productivity on CO_2 emissions diminished during 2006-2010, which was smaller than that of the two previous time periods.

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Secondly, the energy market reform should be accelerated and energy prices should be raised. Price is the core element of the market; reasonable energy prices play an important role in energy efficiency improvement and the sustainable development of the heavy industry. It also plays an important role in the regulation of energy consumption in most industries, especially the heavy industry. At present, energy prices are still controlled by the government. The government has to keep energy prices low for the sake of economic development. Once energy prices are allowed to get out of control, the increase in cost resulting from a rise in energy prices will provide a powerful incentive for the heavy industry to improve energy efficiency and lower energy intensity.

Last but not the least, the industrial structure should be optimized and upgraded. Carbon emission per unit of output of the heavy industry is much higher than that of the service and tertiary industry because heavy industry is particularly energy intensive. Therefore, in order to guarantee economic growth under the restraint of carbon emissions reduction, it is necessary for China to accelerate the upgrading of industrial structure, vigorously develop hi-tech industries, and also transfer low-end industries to foreign countries. Furthermore, moving up the value chain is a prerequisite for boosting national competitiveness.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "X.X. and Y.Y. conceived and designed the experiments; X.X. performed the experiments; X.X. and Y.Y. analyzed the data; W.W. contributed reagents/materials/analysis tools; Y.Y. wrote the paper." Authorship must be limited to those who have contributed substantially to the work reported.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A:

The classification standard of heavy and light industry

No.	SIC code	Heavy industry	No.	SIC code	Light industry
1	6	Mining and washing of coal	27	13	Agricultural food processing
2	7	Extraction of petroleum and natural gas	28	14	Manufacture of food
3	8	Mining and processing of ferrous metal ores	29	15	Manufacture of drink
4	9	Mining and processing of non-ferrous metal ores	30	16	Manufacture of tobacco
5	10	Mining and processing of nonmetal ores	31	17	Textile industry
6	20	Processing of timber, manufacture of wood, bamboo, rattan, palm and straw products	32	18	Manufacture of textile and garment, shoes, hats
7	25	Processing of petroleum, coking, processing of nuclear fuel	33	19	Manufacture of leather, fur, feather
8	26	Manufacture of raw chemical materials and chemical products	34	21	Manufacture of furniture
9	27	Manufacture of medicines	35	22	Paper and paper products
10	29	Manufacture of rubber	36	23	Copy of printing and recording medium

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11	30	Manufacture of plastics	37	24	Manufacture of cultural and educational sporting goods
12	31	Manufacture of non-metallic mineral products	38	28	Manufacture of chemical fiber
13	32	Smelting and pressing of ferrous metals	39	42	Manufacture of arts and crafts, and other
14	33	Smelting and pressing of non-ferrous metals			
15	34	Manufacture of metal products			
16	35	Manufacture of general purpose machinery			
17	36	Manufacture of special purpose machinery			
18	37	Manufacture of transport equipment			
19	39	Manufacture of electrical machinery and equipment			
20	40	Manufacture of communication equipment, computers and other electronic Equipment			
21	41	Manufacture of measuring instruments and machinery for cultural activity and Office work			
22	44	Production and supply of electric power and heat power			
23	45	Production and supply of gas			
24	46	Production and supply of water			
25	11	Mining of other ores			
26	43	Recycling and disposal of waste			

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