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Analysis and Measurement of Carbon Emission Aggregation and Spillover Effects in China: Based on a Sectoral Perspective

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Abstract: Faced with the environmental pressure of global warming, China has achieved certain results in emission reduction, but this needs to be completed more efficiently. Therefore, this article conducts a more comprehensive and in-depth study of China’s carbon emissions from the perspective of the development of national economic sectors and taps the potential for emission reduction in various sectors. Taking into account the adjustment of the national economic sector and the current status of carbon emissions, the study period was from 2003 to 2017. The logarithmic mean Divisia index (LMDI) method was used to measure and analyze the impact of seven factors, including urban construction conditions, on the carbon emissions of various sectors. According to the commonalities and differences of the impacts, 42 sectors were aggregated into four categories. At the same time, the input–output structure decomposition analysis (IO–SDA) model was used to analyze the spillover effects of intersectoral carbon emissions. According to the research results, based on the characteristics of the four types of sectors, and fully considering the spillover effects, the improvement of life cycle management to control energy consumption in the entire supply chain was taken as the leading idea. Moreover, combined with the actual development situation, four types of sectoral carbon emission reduction paths and optimization strategies are proposed to establish a more sustainable demand structure in order to achieve emission reduction.

Keywords: sectoral carbon emission; driving factors; aggregation effect; spillover effect; emission reduction optimization strategies

1. Introduction

The consumption of fossil energy leads to a large amount of carbon dioxide emissions, which intensifies the global climate change characterized by warming. Global warming is a common challenge faced by all mankind in the new era. The global greenhouse gas emissions from energy usage surged in 2018 and reached a record high of 33.1 billion tons. Greenhouse gas emissions have since increased by 1.7%, which is much higher than the average since 2010, although global emissions remained unchanged at 33 gigatons in 2019 [1]. With the rapid growth of the national economy, China has been ranked first in the world in terms of carbon emissions since 2006. China’s energy consumption accounted for 24% of the global energy consumption in 2019, and its carbon dioxide emissions were 9825.8 million tons; accounting for 28.8% of the global figure, its carbon emission per capita in 2019 is 6.85 tons [2]. It is slightly higher than the world average, but lower than developed countries such as the United States, as shown in the Figure 1.
Therefore, the task of emission reduction is facing intense international pressure. As a major country of emissions, China actively promotes the coordinated development of economic growth and environmental protection, and promised to achieve a total carbon emission peak by 2030 in the 2015 Paris Agreement and to reduce the carbon intensity in 2030 by 60–65% compared to the levels in 2005 [3]. After continuous efforts, China’s carbon emission reduction has achieved certain results. However, in the critical period of low-carbon development, carbon emission reduction tasks need to be completed efficiently. In order to effectively achieve the national emission reduction goal without sacrificing the development of the national economy, it is necessary to formulate corresponding policies based on the basic characteristics of China’s economic development and carbon emissions.

Many researchers study carbon emissions from different perspectives. Some researchers have studied carbon emissions from a national and regional perspective. For example, Li et al. [4] used the logarithmic mean Divisia index (LMDI) model and the improved multi-regional (M-R) spatial decomposition analysis model to compare the CO$_2$ emissions among Chinese provinces. From the perspective of eight regions in China, Mi et al. [5] applied the input–output structural decomposition analysis (IO–SDA) model of environmental expansion to study the driving factors of China’s CO$_2$ emission changes from 2007 to 2012. Li et al. [6] measured the carbon emission efficiency (CEE) of each province by using input-oriented three-stage data envelopment analysis (DEA) and the DEA–Malmquist model for panel data of 30 provinces in China during the 2000–2017 period. With the research of scholars both at home and abroad, in the face of energy and environmental pressures, many researchers found it is crucial to develop the research of the Chinese economic sector so as to realize its carbon
emission potential in a more effective way. Therefore, in the “13th Five-Year Plan period (2016–2020),” the Chinese government proposed to focus on the development of the regulation and control of carbon emissions in the fields of energy, construction, transportation, and industry [7]. In this period, China has made clear requirements for the implementation of sector and industry carbon emission regulation and control. Yu et al. [8] proposed a new model, based on the multi-objective optimization model, which has confirmed that industrial structure optimization can make China reach the peak ahead of time. Therefore, allocating national emission reduction targets to each sector is an important way to complete China’s carbon emission reduction task. Therefore, understanding the driving mechanism of carbon emissions in the entire national economic sector is very important and urgent for formulating different actual emission reduction targets. Therefore, this article conducts a more comprehensive and in-depth study of China’s carbon emissions from the perspective of the development of national economic sectors and taps the potential for emission reduction in various sectors.

Previous studies have mostly analyzed China’s carbon emissions from a single-sector perspective. For example, Luo et al. [9] studied the driving factors of carbon emission changes in the power industry from 2007 to 2015 based on the IO–SDA model. Zhang et al. [10] conducted a quantitative analysis of CO$_2$ emissions in China’s coal chemical industry based on data collected from 23 coal chemical companies and explored carbon emission reduction potential in China’s coal chemical industry through a scenario analysis. In the metallurgical industry in China, Lin and Xu [11] calculated the scale of fossil fuel subsidies in the Chinese metallurgical industry. They used logarithmic cost function analysis and found that it is impossible to achieve a low-carbon transformation simply by eliminating the subsidies for fossil fuels. Zhu et al. [12] conducted a quantitative assessment of the allocation of quotas for the Chinese steel industry according to the Emissions Trading Scheme (ETS), and proposed that the Chinese steel industry should adopt a production-based allocation method. Song et al. [13] and Moezzi et al. [14] focused on the construction sector and explored the green transition path of China’s construction industry from a policy perspective. Quan et al. [15] used the LMDI decomposition model to decompose the carbon-emission-influencing factors of the Chinese logistics industry from five aspects, namely, carbon emission coefficient, energy intensity, energy structure, economic level, and population size. Zhou et al. [16] constructed an emission inventory of air pollutants in the port of Shanghai and then used the weather research and forecasting and the community multiscale air quality (WRF–CMAQ) model to estimate the influence of port-related source emissions on air quality. Guo and Hu [17] used the entropy method to construct a synthetic index for measuring financial development to study the impact of financial development on carbon emissions in China from 1997 to 2016. Research from a single-sector perspective is very important for formulating emission reduction measures in this sector [18]. However, due to differences in the development characteristics of various sectors [19], when formulating policies from the perspective of national macroeconomic regulation and control, the same energy-saving and emission reduction measures have different effects when applied to different sectors. Therefore, in order to realize the role of energy-saving and emission reduction measures effectively, it is necessary to analyze different characteristics of the carbon emission influencing factors in multi-industry sectors from the perspective of multiple sectors.

However, due to the limitation of data acquisition, there are relatively few studies on carbon emissions in multi-industry sectors. For research on changes in sector carbon emissions, factor decomposition and the STRIPAT model, which is the IPAT(I = PAT) model in stochastic form, are generally used for empirical research, but they are mostly limited to three industries or rough industry classifications, such as the study of Li et al. [20], which proposed a correlation between China’s carbon emission intensity and the primary, secondary, and tertiary industries. On this basis, they explored carbon emission reduction strategies for future industrial structure adjustment in China. There are few studies on the influencing factors of carbon emission intensity based on specific industry sectors. Even if some studies involve multi-sector situations, they are mostly concentrated on high-emission and high-energy consumption sectors. For example, Du et al. [21] analyzed six major energy-intensive industries in China (i.e., steel, nonferrous metals, nonmetallic minerals,
petroleum coking industry, chemical industry, and power industry) and the energy-related CO\textsubscript{2} emission driving factors. Tan and Lin [22] used a combination of the LMDI and PDA methods to analyze the factors that affect the energy intensity decline of China’s energy-intensive industries and found that technological progress has promoted this decline and that the replacement of labor with energy has led to an energy intensity increase. Zhang and Andrews-Speed [23] focused on energy industries such as oil, natural gas, and power industries and studied how to make the market mechanism realize its potential efficiency improvement and emission reduction under the current institutional background. Busby et al. [24] established a theoretical framework to study the emission reduction possibilities of nine major emission sectors in China, including electricity (i.e., disaggregating renewables, nuclear, and coal), road transportation, four disaggregated industry sub-sectors (i.e., steel, cement, fertilizers, and oil refining), and buildings. The above studies highlight the huge contribution made by high-energy-consuming sectors to China’s carbon emission reduction, but no detailed research has been done on the emission reduction potential in other sectors of the entire national economic industry, and they have ignored the national economic sector system as a whole and the interaction between subsystems. Therefore, this paper is based on the belief that it is necessary to conduct a comprehensive analysis of the carbon emissions of the entire national economic sector to identify the commonalities and differences in carbon emissions between different sectors. At the same time, the synergy between the various sectors needs to be considered, so that institutional theory can be applied to low-carbon energy transition to obtain policies that are more suitable for different sectors [25]. As far as possible, this paper provides reasonable suggestions for the interaction and coordination of China’s carbon emission reduction policies [26].

To achieve this, this article first takes 42 national economic sectors as research objects, uses time series data from 2003 to 2017 to study the characteristics of carbon emission changes in different national economic sectors, identifies the current changes in carbon emission growth in China, and uses the LMDI method decomposition model of sectoral carbon emission change factors to analyze the driving effect and contribution of different driving factors on carbon emission change. Second, by analyzing the aggregate effect of sectoral carbon emissions and the sectoral spillover effect based on the IO–SDA model, the differences in carbon emission driving factors of different national economic sectors are revealed, and carbon emission reduction paths are planned for the national economic sector. Ultimately, the carbon emission reduction policy makes relevant recommendations. It must be said that the carbon emission data in this paper are all obtained through the carbon emission accounting method of Intergovernmental Panel on Climate Change (IPCC) [27]. The IPCC carbon emission calculation method is a greenhouse gas inventory guide compiled by the United Nations Climate Change Commission, and greenhouse gas emissions are fully considered in the calculation process.

2. Materials and Methods

This article used relevant data from 2003 to 2017 as a research sample, combined with the advantages of the LMDI method and the IO–SDA method to analyze the carbon emission aggregation and spillover effects of China’s 42 national economic sectors (Figure 2). First, the carbon emission characteristics of various sectors of the Chinese national economy from 2003 to 2017 were analyzed. Second, the LMDI decomposition method was used to decompose the carbon emission changes of each sector into seven factors (i.e., energy structure, energy intensity, industrial structure, economic scale, urban–rural structure, population size, and urban construction situation), and then the differences in the driving effects of carbon emissions in various sectors were analyzed. Third, the carbon emission aggregation effects of various sectors in China from 2003 to 2017 on the scale factor effect, structural factor effect, efficiency factor effect, and policy factor effect were analyzed based on the LMDI [28] driving factor decomposition model. Forth, a decomposition model of carbon emissions spillover effects was built based on the IO–SDA method [29]. Finally, the emission reduction potentials of each sector were evaluated and relevant suggestions for the optimization of emission reduction paths are proposed based on the analysis of the carbon emission characteristics and driving factors of
various sectors of the Chinese national economy and the analysis of the carbon emission aggregation and spillover effects of various sectors.

Figure 2. Research framework.

2.1. Decomposition Model of Sectoral Carbon Emission Driving Factors Based on the LMDI Method

Factor decomposition analysis usually has two methods: index decomposition analysis (IDA) and structural decomposition analysis (SDA). Up to now, there have been many research results using these two methods to analyze the influencing factors of carbon emissions. Compared with the SDA method, LMDI has relatively small data requirements and is simpler to use [30]. The LMDI method is an improvement of the Divisia method in IDA. It decomposes the result of the target variable into the effect of the factors based on the relationship between the factors related to the target variable, and obtains the contribution of each influencing factor through quantitative analysis and shows the degree of effect of different factors on the target variable [31]. The LMDI method is generally applied to the time series analysis of carbon emissions, and is currently the most used in the research of carbon-emissions-related issues. From the review of 124 research papers on IDA method by Ang and
Zhang [32], it can be found that the logarithmic mean Divisia method as a whole has an edge over the refined Laspeyres method that also is a type of IDA method.

The LMDI method has two decomposition modes: additive decomposition and multiplicative decomposition. This paper uses the additive decomposition method. In this paper, we appropriately expand the KAYA identity [33] and use the LMDI decomposition method to decompose according to the research purpose. The identity was decomposed as follows:

$$Ci = \sum_i \frac{Ci}{Ei} \times \frac{Ei}{GDPi} \times \frac{GDPi}{GDP} \times \frac{P}{UP} \times \frac{UP}{A} \times A$$  \hspace{1cm} (1)

where $Ci$ refers to the carbon emissions generated by the $i$ industry sector, million tons; $Ei$ is the total amount of standard coal converted from the energy consumption of the sector, million tons; $GDPi$ is the increase value of domestic production in the $i$ sector industry, hundred million yuan; $GDP$ is the total value of domestic production, hundred million yuan; $P$ is the total population of China, 10,000 people; $UP$ is the total urban population, 10,000 people; $A$ is the urban built-up area, square kilometers.

Let $CE = Ci/Ei$, the carbon emission per unit energy, which characterizes the cleanliness of the energy consumption structure; $EG = Ei/GDPi$, the energy consumed by the unit industry added value of each sector, which characterizes the energy consumption intensity of the sector; $GK = GDPi/GDP$, the ratio of industrial added value of each sector to $GDP$, which characterizes the sectoral industrial structure; $GP = GDP/P$, $GDP$ per capita, which characterizes the economic scale; $PUP = P/UP$, the reciprocal rate of urbanization, which characterizes the urban–rural structure; $UPA = UP/A$, urban population density, which characterizes the population size; and $A$ equal the urban built-up area, which characterizes urban construction (Table 1). Then (1) can be expressed as:

$$Ci = CE \times EG \times GK \times GP \times PUP \times UPA \times A$$  \hspace{1cm} (2)

Table 1. Symbols and meanings of variables in the model.

| Variable | Implication, Unit |
|----------|-------------------|
| $Ci$     | the carbon emissions generated by the $i$ industry sector, million tons |
| $Ei$     | the total amount of standard coal converted from the energy consumption of the sector, hundred million tons |
| $GDPi$   | the increase value of domestic production in the $i$ sector industry, hundred million yuan |
| $GDP$    | the total value of domestic production, hundred million yuan |
| $P$      | the total population of China, 10,000 people |
| $UP$     | the total urban population, 10,000 people |
| $A$      | the urban built-up area, square kilometers, which characterizes urban construction |
| $CE$     | $CE = Ci/Ei$, the carbon emission per unit energy, which characterizes the cleanliness of the energy consumption structure |
| $EG$     | $EG = Ei/GDPi$, the energy consumed by the unit industry added value of each sector, which characterizes the energy consumption intensity of the sector |
| $GK$     | $GK = GDPi/GDP$, the ratio of industrial added value of each sector to $GDP$, which characterizes the sectoral industrial structure |
| $GP$     | $GP = GDP/P$, $GDP$ per capita, which characterizes the economic scale |
| $PUP$    | $PUP = P/UP$, the reciprocal rate of urbanization, which characterizes the urban–rural structure |
| $UPA$    | $UPA = UP/A$, urban population density, which characterizes the population size |

According to the LMDI addition decomposition method, with 0 and T representing the calculated base period and calculation period, respectively, Formula (2) can be decomposed as:
\[ \Delta C = C^T - C^0 = \Delta C_{CE} + \Delta C_{EG} + \Delta C_{GK} + \Delta C_{GP} + \Delta C_{PUP} + \Delta C_{UPA} + \Delta C_A \] (3)

Among them, the energy structure effect:

\[ \Delta C_{CE} = \frac{C^T - C^0}{\ln C^T - \ln C^0} \times \ln \frac{CE^T}{CE^0} \] (4)

Energy intensity effect:

\[ \Delta C_{EG} = \frac{C^T - C^0}{\ln C^T - \ln C^0} \times \ln \frac{EG^T}{EG^0} \] (5)

Industrial structure effect:

\[ \Delta C_{GK} = \frac{C^T - C^0}{\ln C^T - \ln C^0} \times \ln \frac{GK^T}{GK^0} \] (6)

Economic scale effect:

\[ \Delta C_{GP} = \frac{C^T - C^0}{\ln C^T - \ln C^0} \times \ln \frac{GP^T}{GP^0} \] (7)

Urban-rural structure effect:

\[ \Delta C_{PUP} = \frac{C^T - C^0}{\ln C^T - \ln C^0} \times \ln \frac{PUP^T}{PUP^0} \] (8)

Population size effect:

\[ \Delta C_{UPA} = \frac{C^T - C^0}{\ln C^T - \ln C^0} \times \ln \frac{UPA^T}{UPA^0} \] (9)

Urban construction effect:

\[ \Delta C_A = \frac{C^T - C^0}{\ln C^T - \ln C^0} \times \ln \frac{A^T}{A^0} \] (10)

The LMDI method can be used to decompose the total changes in sectoral carbon emissions into seven factors (i.e., energy structure, energy intensity, industrial structure, economic scale, urban–rural structure, population size, and urban construction) (Table 1), which can achieve a detailed description of the internal factors of carbon emission changes in various sectors.

2.2. Decomposition Model of Sectoral Carbon Spillover Effects Based on the IO–SDA Method

The IO–SDA method takes the consumption coefficient matrix as the basis of the method, and uses a relatively static input–output table to perform a more detailed decomposition analysis of each influencing factor [34]. Compared with the IDA method, the IO–SDA method can analyze the indirect effects of changes in factor variables on other sectors [35], so through the Leontief inverse matrix, the direct and indirect carbon emission of all sectors induced by the final demand can be calculated. In this paper, the spillover effect value proposed reflects the indirect impact of the final output of one sector on the emissions of other sectors due to increased input. Based on the input–output theory, this paper analyzed the carbon emissions spillover effect of the sector by the IO–SDA model [36]. The analysis process was carried out as follows.

In the input–output model, the mathematical expression of the sector is:

\[ x_i = \sum_{j=1}^{n} x_{ij} + y_i \] (11)

where \( x_i \) represents the total output of sector \( i \); \( x_{ij} \) represents the intermediate input of sector \( i \) to the products of sector \( j \); \( y_i \) represents the final demand for the products of sector \( i \).
Direct input coefficient

\[ a_{ij} = \frac{x_{ij}}{x_j} \]  

(12)

where: \( 0 \leq a_{ij} < 1 \) represents the intermediate consumption of the unit output of sector \( j \) to the product of sector \( i \). Combining Equation (12), Equation (11) becomes:

\[ x_i = \sum_{j=1}^{n} a_{ij}x_j + y_i \]  

(13)

Equation (11) can be expressed as a matrix in the form as flow:

\[ X = AX + Y \]  

(14)

where \( X \), \( A \), and \( Y \) represent the total output matrix, the intermediate input coefficient matrix, and the final demand matrix, respectively.

According to the nature of \( A \), \( (I - A) \) is a full-rank matrix, which is invertible. Therefore, the expression (14) can be rewritten as:

\[ X = (I - A)^{-1}Y \]  

(15)

where \( (I - A)^{-1} \) is the Leontief inverse matrix \([37]\), which represents the complete demand of the final product of the production unit for the products of the input sector.

In order to link carbon emissions with the input–output model, we introduce the carbon emission coefficient, which is the amount of carbon emissions per unit of economic output:

\[ E = (e_j) \]  

(16)

where: \( E \) is the carbon emission coefficient matrix, \( ce_i \) is the carbon emission coefficient of \( i \) sector, \( c_i \) is the carbon emission of \( i \) sector, and \( x_i \) is the output of \( i \) sector. The following formula represents carbon emissions:

\[ C = ceL\hat{y} \]  

(17)

where \( C \) is the \((n \times 1)\) vector of the total carbon emissions caused by the final output of goods and services, \( ce \) is the \((n \times 1)\) vector of the economic emission efficiency of all sectors, \( L = [l_{ij}] = (I - A)^{-1} \) is the Leontief inverse matrix, and \( \hat{y} \) is the diagonal vector of \( y \).

The emissions caused by the total output of sector \( i \) are defined as the emissions caused by the output. The formula is as follows:

\[ C_i = ce_i l_{ii} y_i + \sum_{i \neq j} ce_i l_{ij} y_j = C_{ii} + \sum_{i \neq j} C_{ij} \]  

(18)

Through symmetry, the total emissions caused by the final demand of sector \( i \) are calculated as follows:

\[ C_i' = ce_i l_{ii} y_i + \sum_{i \neq j} ce_i l_{ji} y_i = C_{ii} + \sum_{i \neq j} C_{ji} \]  

(19)

where \( C_i' \) refers to the carbon emissions that all sectors must produce to meet the final demand of sector \( i \). The total carbon emissions of the sector are decomposed into direct and indirect carbon emissions. The formula is as follows:

\[ C_i' = ce_i y_i + (ce_i l_{ii} + \sum_{i \neq j} ce_j l_{ji} - ce_i) y_i \]  

(20)

where \( ce_i y_i \) represents the direct carbon emissions caused by the increase in the final demand of sector \( i \), and \( (ce_i l_{ii} + \sum_{i \neq j} ce_j l_{ji} - ce_i) y_i \) refers to the indirect carbon emissions. Indirect carbon emissions can be
further decomposed into internal emissions and overflow emissions [38]. The carbon emissions caused by the total demand of sector $i$ can be broken down into:

$$C_i' = c_i y_i + c_i (l_{ii} - 1) y_i + \sum_{i \neq j} c_{ij} l_{ji} y_i = DE_i + IE_i + SE_i$$ (21)

where the total emission of sector $i$ is decomposed into three parts: $c_i y_i$ refers to the direct effect (DE), $c_i (l_{ii} - 1) y_i$ represents the internal effect (IE), and $\sum_{i \neq j} c_{ij} l_{ji} y_i$ indicates the spillover effect (SE). The direct effect reflects the direct carbon emissions caused by the increase in the final demand of sector $i$. The internal effect reflects the indirect emissions within the sector caused by the final demand of sector $i$. The spillover effect reflects the impact on the carbon emissions of other sectors. Therefore, it is possible to determine the cross-sectoral transfer of CO$_2$ emissions in various sectors by analyzing the carbon spillover effects of said sectors.

2.3. Data Sources

This study took 2003–2017 as the observation period, which mainly comprised 42 sectors’ (i.e., the classification of the national economic sectors during the observation period; thus, this paper used the method in Table 2 for classification purposes) data. Four main types of data were required:

1. The carbon emission data ($C_i$) of each sector was adopted using the data published in the CEADs China Carbon Accounting Database [39]. The carbon emissions in the database followed the Intergovernmental Panel on Climate Change (IPCC) emissions accounting method with a territorial administrative scope of the inventories, which includes energy-related emissions (17 fossil fuels in 47 sectors) and process-related emissions (cement production). CO$_2$ emissions for fossil fuel consumption and for industrial processes are calculated based on energy consumption data and emission factors. The first version of the dataset presents emission inventories from 1997 to 2015. Currently, the inventories have been updated up to 2017.

2. Energy consumption data ($E_i$) (standard volume) of various sectors, the initial data of which came from the “energy consumption by sector” subclause in the China Energy Statistical Yearbook and the China Statistical Yearbook over the years [40]. The energy standard coal conversion coefficient was taken from the Reference Standard Coal for Various Energy Sources of the China Energy Statistical Yearbook.

3. Gross domestic product (GDP) and industrial added value of the various sectors ($GDP_i$), which came from the “China Industrial Economic Statistical Yearbook” and the “China Statistical Yearbook” over the years. The total output of each sector and the industrial added value came from the input–output table [41] in the China Statistical Yearbook. Due to changes in statistical indicators, the industry-added value of the sector from 2012 to 2017 was calculated from the total output value of each sector (Lu et al., 2019). Since the industry-added value data of the industrial subordinate sectors in from 2015 to 2017 were missing, they were estimated by interpolation [42,43].

4. Population ($P$), urban population ($UP$), and urban area ($A$). This article used the permanent urban population at the end of the year to represent the total urban population. These data were mainly derived from statistical information networks such as the China Statistical Yearbook and the website of the National Bureau of Statistics.
Table 2. Classification of the national economic sectors.

| Economic Sector Number | National Economic Sector                                      | Economic Sector Number | National Economic Sector                                      |
|------------------------|---------------------------------------------------------------|------------------------|---------------------------------------------------------------|
| 1                      | Farming, Forestry, Animal Husbandry, and Fishery              | 22                     | Medical and Pharmaceutical Products                            |
| 2                      | Coal Mining and Dressing                                      | 23                     | Chemical Fibers                                               |
| 3                      | Petroleum and Natural Gas Extraction                         | 24                     | Rubber and Plastic Products                                   |
| 4                      | Ferrous Metal Mining and Dressing                             | 25                     | Nonmetal Mineral Products                                     |
| 5                      | Nonferrous Metal Mining and Dressing                         | 26                     | Smelting and Pressing of Ferrous Metals                       |
| 6                      | Nonmetal Mineral Mining and Dressing                         | 27                     | Smelting and Pressing of Nonferrous Metals                    |
| 7                      | Other Mineral Mining and Dressing                             | 28                     | Metal Products                                                |
| 8                      | Food Processing                                               | 29                     | Ordinary Machinery                                            |
| 9                      | Food Production                                               | 30                     | Equipment for Special Purposes                                 |
| 10                     | Beverage Production                                           | 31                     | Transportation Equipment                                       |
| 11                     | Tobacco Processing                                           | 32                     | Electric Equipment and Machinery                               |
| 12                     | Textile Industry                                             | 33                     | Electronic and Telecommunication Equipment                    |
| 13                     | Garments and Other Fiber Products                             | 34                     | Instruments, Meters, and Cultural and Office Machinery       |
| 14                     | Leather, Fur, Down, and Related Products                     | 35                     | Other Manufacturing Industry                                  |
| 15                     | Timber Processing and Bamboo, Cane, Palm Fiber, and Straw Products | 36                     | Scrap and Waste                                               |
| 16                     | Furniture Manufacturing                                       | 37                     | Production and Supply of Electric Power, Steam, and Hot Water |
| 17                     | Papermaking and Paper Products                                | 38                     | Production and Supply of Gas                                  |
| 18                     | Printing and Record Medium Reproduction                      | 39                     | Production and Supply of Tap Water                            |
| 19                     | Cultural, Educational, and Sports Articles                    | 40                     | Construction                                                  |
| 20                     | Petroleum Processing and Coking                               | 41                     | Transportation, Storage, Post, and Telecommunication Services |
| 21                     | Raw Chemical Materials and Chemical Products                 | 42                     | Wholesale, Retail Trade, and Catering Services               |

3. Calculation Results and Discussions

3.1. Analysis of the Sector Carbon Emission Characteristics and Driving Factors

Since 2003, China’s overall carbon emissions and the carbon emissions of various sectors of the national economy have shown a significant growth trend, from 4086 billion tons in 2003 to 9339 billion tons in 2017, with an absolute increase of nearly 2.3 times and an average annual growth rate of 9.18%. Among them, there was a significant increase from 2003 to 2013, with an average annual growth rate of 13.33%. It can also be seen from Figure 3 that 2007 was a turning point, after which the growth rate of total carbon emissions slowed down. During the period 2003–2007, the average annual growth rate was 17.71%, after which the growth rate of total carbon emissions slowed down, and the average annual growth rate during the period 2007–2013 was 7.61%. This is consistent with the view of Yuan et al. [38]. At the same time, they estimated that China’s emissions from 1997 to 2012 increased from 3118 Mt to 8090 Mt, which is lower than the 9080.5 Mt [39] in 2012 used in this paper, in which the emissions from industrial processes were considered, and cement process emissions accounted for about 9% of China’s total CO₂ [44]. At the same time, according to Figure 3, 2013 is also a critical time point, after which the total carbon emissions of various sectors showed a slight downward trend. As the growth rate of the output value of each sector was higher than the growth rate of the total carbon emissions [45], the carbon emission intensity of the various sectors from 2003 to 2017 experienced a significant downward trend, i.e., from 2.97 t/10,000 yuan in 2003 to 1.12 t/10,000 yuan in 2017, with an average annual decline of 0.13 t/10,000 yuan.
Within the national economic sector, the structural proportion of carbon emissions in each sector was not consistent in each year (Figure 3). During the study period, the production and supply of electric power, steam, and hot water (sector 37) had large carbon emissions and rapid growth trends. The proportion of its carbon emissions has been as high as 40%, and it is the main contributor to the growth of national carbon emissions. The smelting and pressing of ferrous metals (sector 26), whose carbon emissions were second only to sector 37, also has obvious high-carbon characteristics. Moreover, the nonmetal mineral products (sector 25), as well as the raw chemical materials and chemical products (sector 21), also represent an obvious growth trend and a large proportion.

Meanwhile, the carbon emissions of the transportation, storage, post, and telecommunication services (sector 41) increased from 265.80 Mt in 2003 to 723.87 Mt in 2017, an increase of up to 1.7 times, and its carbon emissions as a proportion of total emissions increased from 6.51% in 2003 to 7.75% in 2017. In contrast, the carbon emissions of machinery and equipment, transportation equipment, and electrical and electronic equipment manufacturing (sectors 29–33) accounted for less than 5% of the total carbon emissions; meanwhile, the carbon emissions of food processing (sector 8) and food production (sector 9), as well as the textile industry (sector 12) and garments and other fiber products (sector 13), accounted for less than 4%. The proportion of carbon emissions in the other sectors were relatively stable and had no significant features.

The above analysis reveals the differences in the characteristics of carbon emissions in different sectors. In order to further quantitatively measure the internal factors of carbon emission changes in different sectors, this section is based on the total carbon emissions of the various sectors of the Chinese national economy from 2003 to 2017. According to the Formulas (1)–(10) in Section 2.1, taking the first and last years of the observation period as the 0-th and T-th years of accounting, and obtaining the seven driving factors of carbon emission coefficient (CE), energy consumption intensity (EG), industrial structure (GK), economic scale (GP), urban–rural structure (PUP), population size (UPA),...
and urban construction (A), the contribution to changes in carbon emissions in various sectors can be observed (Figure 4). The results show that the seven driving factors have different driving directions and degrees, and there are differences between the different sectors. From the perspective of the various driving factors, the two factors of the GP and the UPA mainly exert a positive driving effect on the increase in carbon emission, while the EG, the CE, the PUP, and the A mainly exert a negative driving effect, and the driving directions of the GK for different sectors are quite different and need to be analyzed by specific sectors.

Figure 4. The contribution of various factors to the driving effect of 42 sectors.

According to Figure 4, first of all, compared with other factors, the economic scale (GP) has the most prominent impact on the 42 sectors, the relative contribution of the economic scale factor (GP) to almost all sectors in the influence degree exceeds 20%, and the carbon emission change of each sector is shown as a positive driving effect to the increase in carbon emission. This indicates the rapid growth of the Chinese economy is the main motivation of China’s carbon emissions. This is consistent with the conclusion of Wang et al. [46]. Second, the population size (UPA) also shows a positive driving effect on all sectors; population growth leads to an increase in carbon emission, which is consistent with the views of Knapp et al. [47]. They used a Granger causality test to analyze the causal relationship between population growth and CO$_2$ emissions globally and concluded that population growth is the reason for the increase in CO$_2$ emissions. The National Population Development Plan (2016–2030), issued by the State Council on 30 December 2016, pointed out that the total population of the country will reach about 1.45 billion in 2030, and the total population will reach its peak around 2030 [48]. This time coincides with Chinese commitment in 2015 to the peak time of carbon emissions by 2030. In this article, on the one hand, we found that the positive effect of the UPA is especially obvious in sector 37, sector 26, and the transportation, storage, post, and telecommunication services (sector 41). On the other hand, the UPA has a weak driving effect on the scrap and waste (sector 36), the other mineral mining and dressing (sector 7), and the production and supply of gas (sector 38) sectors. The effect is not much different on the other sectors.

According to Figure 4, we found that energy intensity (EG) and energy structure (CE) factors both mainly suppress the increase of carbon emissions in sectors and have a negative driving effect on changes in carbon emissions in most sectors. Except for sector 39 and the petroleum and natural gas extraction (sector 3), the contribution value of the driving effect on the increase in carbon emission of the EG factor is negative for the sectors, indicating that the EG factor is the main factor driving the reduction
of sectoral carbon emissions, especially for sector 37 and sector 25, while the relative contribution value of the driving effect the EG factor for most sectors is higher than 20%. This is mutually corroborated with the views of Wang et al. [49] and Du et al. [21]. They believe that energy intensity is the main factor that promotes the reduction of CO$_2$ emissions, and the latter proposed that its impact is the most significant in the chemical industry (same as sector 21 in this article) and non-metallic mineral products industry (same as sector 25 in this article). The driving effect of the CE factor for all sectors is negative, except for sectors 3, 37, and 26. The absolute value of most sectors is less than 0.1, which shows a small clean trend of the energy consumption structure. In comparison, the driving effects on the changes in carbon emission for sector 41, the wholesale, retail trade, and catering services (sector 42), and sector 12 are relatively large. The reason is inseparable from China’s policy of adjusting the energy consumption structure. This is consistent with the view of Shimada K et al. [50], which proposed that the increase in the proportion of clean energy will promote the development of a low-carbon economy.

Furthermore, the urban–rural structure (PUP) and urban construction (A) factors show a negative driving effect on the increase in carbon emission for the 42 sectors. In comparison, the negative driving effect on carbon emissions growth of the PUP is weaker than that of the EG. It must be said here that the reciprocal of the PUP is used when calculating through the model in Section 2.1, which is the urbanization rate. Therefore, when the calculated contribution degree result is positive, it indicates that the increase in the PUP defined in this article promotes a reduction in sectoral carbon emissions; that is, the increase in the level of urbanization will promote carbon emission. This is consistent with the views of Wu [51] and Wang et al. [52]. According to Figure 4, the UPA factor has a significant CO$_2$ emission reduction effect on farming, forestry, animal husbandry, and fishery (sector 1), sector 42, and sector 41. The A factor contributes significantly to the negative driving effect on the printing and record medium reproduction (sector 18), the cultural, educational, and sports articles (sector 19), and the instruments, meters, cultural, and office machinery (sector 34) sectors, among others; however, the effect on the other sectors is not much different.

The driving directions of each sector of the industrial structure (GK) are inconsistent, with some being positive and some being negative. When a contribution value is positive, it indicates that the change of the GK is not conducive to the reduction of carbon emissions in this sector. A total of 16 sectors’ carbon emissions changes are driven by it positively, including sectors 25, 42, 27, 40, 8, 15, 38, 6, 4, 22, 9, 36, 5, 28, 19, and 16. Among them are the carbon emissions of sectors 22, 9, 36, 5, 28, 19, and 16. The positive effects of the GK factor on construction (sector 40), sector 36, and sector 38 are very significant. In contrast, the carbon emissions of the remaining sectors are driven by their negative effect. Among them, the negative effect of the i GK on the sector 3 is very significant, which is related to the decline in the proportion of the sector’s output value in the total output.

3.2. Analysis of the Aggregate Effect of Carbon Emissions by Sector

According to the calculation and analysis results of the carbon-emission-driving factors of various sectors, this study found that there are inextricable links between the seven driving factors that affect the energy consumption of the national economic sector and the changes in carbon emissions from process emissions. For most sectors, the energy structure (CE) and energy intensity (EG) are the main negative driving factors [53]. The urban–rural structure (PUP) and urban construction (A) factors also reduce the carbon emissions of the sectors through a negative driving effect, while the economic scale (GP) and population size (UPA) are the positive driving factors of the increase in the carbon emissions of the various sectors. The relationship between the industrial structure (GK) factor and the other factors is not obvious, and the effect on the various sectors does not show obvious rules. Therefore, based on the contribution value of the seven driving factors to the changes in the carbon emissions of the 42 national economic sectors in China, this section shows the results of an analysis of the aggregate effects of carbon emissions in the sectors.

In this paper, based on the strong correlation between the three factors of energy structure and energy intensity, population size and economic scale, urban–rural structure and urban construction,
seven factors were aggregated into four effects, namely, scale effects, technological effects, structural effects, and policy effects. Changes in sectoral carbon emissions caused by changes in the UPA and the GP are called scale effects, those caused by the EG and the CE are called technological effects, and those caused by changes in the GK are called structural effects. Meanwhile, changes in the PUP and the A are called policy effects. Based on the four effects, clustering analysis of the carbon emissions of the 42 sectors was carried out, and finally, the 42 national economic sectors were divided into four types (Figure 5): scale-driven, technology-driven, structural-driven, and policy-driven.

![Graph showing analysis of the aggregate effects of carbon emissions by sector.](image)

**Figure 5.** Analysis of the aggregate effects of the carbon emissions by sector.

Results can be drawn from Figures 5 and 6: sector 39, sector 26, sector 25, and sector 41 are typical representatives of scale-driven sectors. These sectors are typical energy-intensive sectors, and an increase in the scale of output value will drive the growth of larger-scale CO₂ emissions. Especially in the research years, with the growth of the national economy and the increase in the demand for energy-based raw materials for economic development, the proportion of these sectors in the total industrial economic output value has increased, thereby driving the increase in the proportion of their CO₂ emissions.

Since the magnitude of the absolute value of the scale effect is relatively large, it has an impact on the identification of the impact of the other three effects. Taking this into account, after identifying scale-driven sectors through Figure 5, we eliminated sectors 39, 26, 25, and 41, and then analyzed the aggregation characteristics of the remaining sectors. According to Figure 6, for the technology-driven sectors, sector 1, sector 21, coal mining and dressing (sector 2), sector 12, papermaking and paper products (sector 17), and sector 8 show characteristics of a dominant technical effect. The proportion of primary products with higher energy consumption in these sectors shows a continually decreasing trend, gradually giving way to high-tech and high-value-added back-end products. Therefore, as energy consumption intensity gradually decreases, the proportion and growth rate of carbon emissions gradually decreases.
For the structure-driven sectors, the structural effects of petroleum and sector 3, sector 20, and sector 42 are prominent, and cultural, educational, and sporting goods manufacturing (sector 19) also has a slight structural-driven trend in comparison to other sectors in this category. During the “13th Five-Year Plan” period (2016–2020), the national government has made major initiatives in the adjustment of industrial structure, the proportion of sector 3 and sector 20 has been lowered, and the share of the service consumption sectors such as sector 42 has continued to increase.

For the policy-driven sectors, they are more obviously affected by the policy effect. Sector 4, sector 7, sector 30, sector 38, and sector 39 obviously fall into this category. For example, the ferrous metal mining and dressing (sector 4), as the upstream supply sector of the steel industry, due to the macro-adjustments to the steel smelting industry by national policies, it will inevitably be affected by fluctuations in the demand of the steel industry. Except for the above-mentioned sectors, the other sectors do not have obvious aggregation characteristics of scale, technology, structure, and policy orientation.

3.3. Analysis of the Sectoral Carbon Emission Spillover Effects

The previous section analyzed the aggregate effect of the carbon emissions in the various sectors from the perspective of driving factors. However, the final output of a sector not only causes its own carbon emissions, but also increases the carbon emissions of the other sectors [54]. Therefore, in order to further measure the spillover effect of the interaction of the carbon emissions in different sectors, through the Formulas (11)–(21) based the IO-SDA method in Section 2.2, the input–output table and the total carbon emissions of each sector in 2017 were used to calculate the effect of the three parts of the direct emission effect (DE), internal emission effect (IE), and spillover emission effect (SE). Among them, the spillover effect refers to the indirect effect of the final output of one sector on the emissions of the other sectors due to increased input. For example, for the manufacture of pharmaceutical products, the pharmaceutical sector requires input from other sectors in the supply chain, resulting in additional carbon emissions in the production process of other sectors as the inter-sector spillover effect. If the
spillover effect of a sector is large, the sector has a strong effect on China’s overall carbon emissions by stimulating production in other sectors.

Through calculation, we were able to obtain the effects of the three parts of carbon emissions in the various sectors in China, and to reveal a gap between the spillover effects of carbon emission in each sector by analyzing the three effects of each sector (Figure 7). According to Figure 7, we found that the proportion of spillover effect value is relatively large in the following sectors: Heavy industry (sectors 2–7, 20–24, 27, 28, and 36); heavy equipment manufacturing (sectors 29–35); farming, forestry, animal husbandry, and fishery (sector 1); construction (sector 41); and wholesale, retail trade, and catering services (sector 42). The share of the spillover effects in these sectors is large, reaching almost 40%. These sectors are important carbon emission conversion sectors, as they consume a significant amount of energy and resource-consuming products, which are produced by other sectors, leading to large amounts of carbon emissions spread out to those other sectors. Heavy industry sectors, such as the metal products (sector 28), raw chemical materials and chemical products (sector 21), petroleum processing and coking (sector 20), smelting and pressing of nonferrous metals (sector 27) sectors all have a share of over 45%, and many inputs from other sectors are needed to support the final output of the heavy industry sectors. Sector 40 and sector 42 have a large demand for input of basic industrial sectors (such as the electricity from sector 37). Therefore, carbon emissions are mainly transferred from the basic industrial sectors to sector 40 and sector 42, and the spillover effect of these sectors promotes carbon emissions in sectors such as sector 37. For sector 37, sector 25, sector 26, and sector 41, the spillover effect is smaller than that of the other sectors, mainly as an upstream sector of the other sectors. As the upstream sectors of other sectors, they do not require high input from other sectors, and therefore have less impact on carbon emissions from other sectors, and their direct emissions make a greater contribution to total carbon emissions than spillover effects. In summary, the relative importance of spillover effects depends on the position of the sector in the supply chain. Sectors upstream in the supply chain (such as sector 37) have a higher share of direct emissions, while sectors at the end of the supply chain have higher spillover emissions (such as sector 42).

![Figure 7. Sectoral carbon emission spillover effect.](image-url)
4. Conclusions and Recommendations

China is actively promoting the coordinated development of economic growth and environmental protection. The current focus is to analyze the energy-saving and emission reduction potential of China’s national economic sector and to implement emission reduction. Considering the structure of China’s national economic sector for a long time, as well as taking into account the status of carbon emissions in China, this paper analyzed the carbon emission characteristics of various sectors of China’s national economy from 2003 to 2017 and used the LMDI decomposition method to analyze the causes of changes in carbon emissions in various sectors. By calculating the effect of the seven driving factors of changes in a quantitative way and analyzing the differences in the driving effects of carbon emissions in various sectors, this paper provides a reference for the aggregate analysis of carbon emissions in sectors. Based on the contribution values of the various driving factors, the carbon emission aggregation effect of the various sectors in China from 2003 to 2017 on the four effects (i.e., scale effect, technology effect, structural effect, and policy effect) were analyzed; at the same time, based on the IO–SDA method, a decomposition model of sectoral carbon spillover effects based on IO–SDA method l was built to determine the spillover effects d. Based on the research, following conclusions can be drawn:

(1) During the study period, the production and supply of electric power, steam, and hot water (sector 37) was the main contributor to the growth of national carbon emissions; the proportion of its carbon emissions has been as high as 40%. Meanwhile, carbon emissions in the transportation, storage, post, and telecommunication services (sector 41) grew rapidly, increasing from 265.80 Mt in 2003 to 723.87 Mt in 2017, an increase of up to 1.7 times, and their carbon emissions as a proportion of total emissions increased from 6.51% in 2003 to 7.75% in 2017.

(2) There is a certain internal correlation between the structural, technological, and policy effects. The effectiveness of the three effects on each sector are almost synchronous, with obvious dynamic interactive synergy and action on most of sectors. The three effects all exert influence to promote the decline in the growth rate of sectoral carbon emissions, especially in the three sectors of textile industry (sector 12), raw chemical materials and chemical products (sector 21), and production and supply of tap water (sector 39). The reason is that China was in important periods of the “11th Five-Year Plan (2005–2010)”, the “12th Five-Year Plan (2010–2015)”, and the “13th Five-Year Plan (2016–2020)” during the research period. The national government’s development strategy for environmental protection, resource conservation, and green development put forward a series of policies to control the output value of large-scale leading industries, such as iron and steel smelting and electricity and thermal production, with huge carbon emissions, and encouraged relevant enterprises in order to actively explore clean and energy-saving production technologies, improve production efficiency, and vigorously promote low-technology-driven carbon sectors to achieve China’s carbon emission reduction goals.

(3) The final aggregation of the 42 national economic sectors has four types: scale-driven, technology-driven, structure-driven, and policy-driven. Among them, typical representatives in the scale-driven sectors are sector 39, sector 26, sector 25, and sector 41. Meanwhile, the technology-driven sectors that show significant characteristics of dominant technology effects include sector 1, sector 21, sector 2, sector 12, sector 17, and sector 8. For the structure-driven sectors, the structural effect is relatively more prominent. Sector 3, sector 20, and sector 42 obviously belong to this category, and there is also a slight structure-driven trend for sector 19 compared with the other sectors. For the policy-driven sectors in which policy-driven trends are more obvious, typical representatives are sector 4, sector 7, sector 30, sector 38, and sector 39. The rest of the 42 sectors have no obvious aggregation characteristics of scale, technology, structure, or policy orientation.

(4) The carbon emission spillover effects of the 42 national economic sectors have significant sectoral heterogeneity, with a huge impact on the carbon emissions of various sectors, as well as the direct carbon emissions of each sector. The spillover effect of each sector is mainly reflected in the heavy industry and heavy products manufacturing sectors, such as sector 28, sector 21, sector 20,
sector 27, and other heavy industry sectors, as well as sector 1, sector 40, and sector 42. Their share of the spillover effects is large, almost reaching over 40%. These sectors are important carbon emission conversion sectors, which consume a lot of energy- and resource-consuming products, leading to a large amount of carbon emissions spread to the other sectors. The relative importance of spillover effects depends on the position of the sector in the supply chain. Sectors upstream of the supply chain (such as sector 37) have a higher share of direct emissions, while sectors at the end of the supply chain have higher spillover emissions (such as sector 42).

China is in a critical period of socialist modernization. Under the high pressure of the national environmental protection policy, various economic sectors are subject to strict supervision. However, due to the different characteristics of the sectors, in order to achieve the dual goals of fulfilling the carbon emission reduction task and developing a sustainable domestic economy, China must focus on the carbon emission reduction of the different sectors of the national economy, promote the low-carbon transformation of the economic development of various sectors, and realize the emission reduction goals. According to the above research results, based on the characteristics of the different sectors, differentiated measures were taken into account. At the same time, the spillover effects of the sectoral carbon emissions were fully considered, which refers to the production links between sectors. The improvement of life cycle management to control energy consumption in the entire supply chain was taken as the leading idea, and attention was paid to the needs of the downstream sectors such as the wholesale, retail trade, and catering services sector (sector 42), which causes indirect carbon emissions in the heavy industry, transportation, and power sectors and can be reduced by establishing a more sustainable demand structure. After overall consideration, we offer the following specific recommendations for the optimization of the emission reduction path of the sector:

(1) For scale-driven sectors, it is recommended to adopt a path of controlling the scale of investment to improve the company’s environmental awareness level, actively guide the industry clustering effect, increase the concentration through the construction of industrial parks, take the route of large-scale cluster production [55], promote industry standardization production and industrialized operation, improve production efficiency, reduce costs and energy consumption, and lay the foundation for the sustainable development of the sectors. For example, for the production and supply of electric power, steam, and hot water sector (sector 37), as an upstream sector of the various industries in the development of the national economy, its output value and carbon emissions are large, which is the focus of attention in the implementation of carbon emission control. When regulating its carbon emissions, considering that economic development has a large demand for electricity and that there will be no significant decline in a short period of time, it is necessary to increase the concentration and industry threshold of the power industry, to gradually eliminate outdated production capacity, and to promote standardized production across the industries. according to the power industry standardized management measures issued by the National Energy Administration. With the development of energy storage technology and energy Internet, carbon emission intensity can be reduced and carbon emission control strategies optimized.

(2) For technology-driven sectors, it is recommended to implement a path to increase investment in innovation, guide enterprises to use low-carbon technology for product upgrades, and promote the establishment of sectoral energy-saving and emission reduction technical service systems. Combining the use of the Internet and other information technologies, intelligent control technology can be used to transform and upgrade existing technologies to achieve the goals of improving quality, reducing energy consumption, and reducing emissions. For example, the farming, forestry, animal husbandry, and fishery sector (sector 1) is a technology-driven sector; as the basic sector of economic development, this sector has an irreplaceable impact on people’s daily necessities, food, shelter, and transportation. Soilless agriculture, drip irrigation, and other energy-saving and emission reduction technologies, using geographic information technology and computer automatic control technology, can develop precision agriculture while protecting
natural resources and acquiring materials needed for daily life. Of course, with the change in lifestyle, the development of tourism agriculture such as farmhouses can be encouraged to play basic production function, but also play a role in regulating carbon emissions in conjunction with its downstream industries.

(3) For structure-driven sectors, it is recommended to adopt an optimized sector structure path, to vigorously develop the producer service and high-tech service industries, to increase the degree of industry service, and to increase the proportion of the service industry in economic development. At the same time, this would promote the development of industry sectors in a more refined direction, increase product value, and highlight the important position of industries in the supply chain. For example, the wholesale, retail trade, and catering services sector (sector 42) is a structure-driven sector, and in the process of gradual refinement of the social division of labor, advanced management methods are used to continuously improve the service level of the industry and consumer satisfaction, stimulate consumption, and increase output value and the proportion of wholesale and retail accommodation and catering in the national economy. On the other hand, it is recommended to continue to extend the industrial chain, form an industrial integration chain with downstream industries such as tourism, increase the added value of products, promote the brand effect, and take a unique carbon emission control path.

(4) For policy-driven sectors, the implementation of a strengthened government supervision path is recommended to establish a complete monitoring network for high-energy-consumption and high-emission industries, and to regularly check the operation status of an enterprise’s production equipment and exhaust gas emission levels. For companies that do not meet the standards, they must take immediate measures to rectify such issues within a time limit, must strive to improve the development environment of the entire industry, and must promote the sustainable development of the industry. For example, for the ferrous metal mining and dressing sector (sector 4), a policy-driven sector, the environmental protection requirements in the process of ferrous metal mining and dressing can be strengthened, and enterprise production standards can be strictly regulated. The regulation of steel production and manufacturing in its downstream industries eliminates excess capacity in the process of urbanization and reduces the demand for raw materials, thereby reducing the mining and selection of ferrous metal minerals and realizing the reduction targets of carbon emissions in this type of sector.

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