An Optimization Study of Provincial Carbon Emission Allowance Allocation in China Based on an Improved Dynamic Zero-Sum-Gains Slacks-Based-Measure Model

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Abstract: In order to achieve its 2030 carbon emission peak target, China needs to adjust and allocate energy consumption and initial carbon emission allowances for each province in a phased and planned manner. Thus, this study applied an improved dynamic undesirable zero-sum-gains slacks-based-measure (ZSG-SBM) model to evaluate provincial CO₂ emission reduction scenarios and energy allocation for 2015–2019 and calculate the optimal allocation values of carbon emission allowances for each province in 2030. The results showed that China’s allocation efficiency values for total energy exhibited rising and then declining trends during 2015–2019 and that most input–output term efficiency values had room for improvement. Furthermore, after four adjustment iterations of the improved dynamic undesirable ZSG-SBM model, the modeled China achieved optimal carbon emission efficiency for the whole country. In the final model, 19 provinces were allowed to increase their carbon emissions in 2030, while the remaining 11 provinces needed to reduce their emissions. The findings of this paper can help regulators to establish fairer and more effective policy solutions to promote regional synergistic emission reduction, achieve the national goal of peak total carbon emissions, and promote the green, coordinated, and sustainable development of China’s economy.

Keywords: dynamic undesirable ZSG-SBM model; carbon emission allowance; energy allocation efficiency; carbon emission efficiency

1. Introduction

Data from the BP Statistical Review of World Energy 2021 showed that China’s CO₂ emissions in 2020 comprised 9.899 billion tons, or an increase of 0.88 billion tons from 2019. The world is currently facing the two huge problems of a lack of resources and harm to the environment, and climate change has become one of the most serious challenges facing humanity. As the world’s largest carbon emitter and its second largest economy, China is committed to reaching peak CO₂ emissions by 2030 and even striving to reach that point as early as possible.

To deal with energy and climate change issues, the Action Plan for Carbon Peaking by 2030 issued by the State Council stated that by 2030, nonfossil energy consumption will account for about 25% of total energy consumption, and the ratio of CO₂ emissions to GDP will decrease by more than 65% compared with 2005, thus laying the foundation for achieving carbon neutrality and carbon peaking targets. Considering that China’s CO₂ intensity should be reduced to 65% in 2030 relative to 2005, this study assumed that the growth rates of 2020–2025 and 2025–2030 would be 5.5% and 4.5%, respectively. As China’s GDP is expected to reach 135 trillion yuan in 2030, it was calculated that its carbon peaking volume in 2030 would be 348,000 tons. A reasonable distribution of the initial carbon amount among regions is the basis for achieving the carbon emission reduction.
target and the driving force for the orderly establishment of the national carbon emission trading market.

To achieve these emissions goals, it is necessary to adjust and allocate the energy consumption and initial carbon emission amounts of each province in a phased and planned manner. However, provinces have different levels of development, varied industrial focuses, and a diverse composition of energy used. A lack of scientific allocation may actually lead to ineffective implementation of national policies and difficulties in achieving optimal energy utilization. Therefore, the specifics of allocating CO$_2$ emission allowances among provinces and whether each province can achieve its own cap in a cost-effective manner largely depend on the effectiveness of the allocation scheme.

Data envelopment analysis (DEA) is a method for measuring efficiency. It was first introduced by Farrell with the concept of a frontier production function to calculate the level of productivity of a decision-making unit (DMU) [1]. For example, Charnes et al. used Farrell’s “frontier” concept as the basis for solving the CCR model with multiple inputs and multiple outputs under a fixed payoff of scale [2]. Banker et al. added the convexity restriction of a linear combination and replaced the assumption of fixed returns to scale (CRS) with variable returns to scale (VRS). Their BCC model could measure technical efficiency and scale efficiency [3]. Apart from the CCR and BCC DEA models, Tone, in 2001, proposed the slacks-based measure (SBM), which uses different variables as the basis of measurement, considers the difference between input and output items, and presents SBM efficiency with a single value via nonradial estimation. When a DMU’s efficiency value is 1, it means that the DMU has no differences in either input or output items.

Lins et al. [4] used this concept to propose the ZSG-DEA model, which implies that inefficient DMUs reduce their input quantity in order to achieve relative efficiency, while other DMUs increase their relative input quantity and finally achieve total input quantity. The total amount of inputs remains unchanged. The advantage of this model is that all DMUs are continuously optimized to reach the DEA frontier without changing the total carbon allowance [5]. This model has been applied to various energy and resource allocation studies [6–9].

The uses of ZSG-DEA for energy allocation can be broadly divided into energy trading systems and carbon trading systems. The former focus on the allocation of various fossil and clean energy sources among DMUs to achieve better efficiency values, while the latter focus on the allocation of carbon emissions and carbon trading to regulate the use of energy from the perspective of greenhouse gas emissions. In terms of DMUs, the relevant literature has introduced four categories: nation [6,7,10,11], region [12–14], industry [15,16], and company [17]. Scholars have also targeted energy distortion elimination for energy reengineering planning such that economic output and energy efficiency can improve after reengineering (see Chen et al. [18]). Liu et al. [19] found that the elimination of factor distortions facilitated the improvement of total factor energy efficiency. In recent years, scholars have made more attempts to narrow and refine industry and energy categories; e.g., Lei et al. reallocated carbon emissions in the transportation sector, while Ma et al. and Cui et al. explored the emission efficiency of electric energy [9,19,20].

Most studies have used the ZSG-DEA model in CO$_2$ rights trading, where CO$_2$ is often considered as an input. Gomes and Lins [21] applied the ZSG-DEA model to present a CO$_2$ emissions trading scenario that followed the flexible mechanisms of the Kyoto Protocol. They argued that the higher the population, energy consumption, and GDP were, the higher the efficiency was for the same level of emissions, and therefore, emissions were an input variable. Zheng [22] introduced the model to study the distribution of CO$_2$ emission reduction responsibilities among China’s provinces in 2015. Along with these developments, Wang et al. [23] took a similar approach to investigate not only CO$_2$ allocation in China in 2020 but energy allocation among provinces.

Although the literature has very much focused on resource rationalization, the model architecture of ZSG-DEA for exploring resource rationalization is still stuck in the CCR-ZSG-DEA model, does not consider ray DEA to ignore the difference problem, and does
not consider bad output. Therefore, this paper broke through these past limitations and combined the ZSG model of Lins et al. with the difference-in-difference model of Tone and introduced bad output to construct an undesirable ZSG-SBM model [24]. In this paper, we first calculated the total efficiency of 30 provinces in China and their efficiency value in each year using the dynamic undesirable SBM model. Second, we calculated a reasonable configuration for increasing the total CO$_2$ emission peak target to 348,000 tons in the year 2030 using the undesirable ZSG-SBM model. Few studies have combined energy use efficiency with carbon dioxide distribution rights. Most of the literature has used only the ZSG-DEA model to study the better efficiency values that can be achieved in the process of energy rights or carbon rights trading and failed to consider the distribution problem on the basis of the actual use efficiency of various energies. Furthermore, most of the literature that has used the ZSG-DEA model to analyze energy efficiency has failed to refine to carbon dioxide, a single unintended output, and thus may not well reflect the carbon emission policy at this stage. Therefore, this paper carried out follow-up research based on the above points in order to fill the research gap in relevant aspects. The outline of the literature review was as follows (Table 1):

| Table 1. The outline of the literature review. |
|-----------------------------------------------|
| **Research method—DEA**                       |
|     frontier production function ([1])        |
|     CCR ([2])                                |
|     BCC ([3])                                |
|     SBM ([24])                               |
|     ZSG-DEA ([4])                            |
| **The use of ZSG-DEA**                        |
|     Energy Trading System                     |
|     Carbon Trading System                     |
| **Decision-making units**                    |
|     nation ([6,7,10,11])                     |
|     region ([12–14])                         |
|     industry ([15,16])                       |
|     company ([17])                           |

The research contributions of this paper are as follows: (1) To provide a deep analysis of environmental issues and gradually reduce carbon emissions, this paper started from the perspective of energy use and provided an accurate evaluation of energy efficiency to understand the extent of carbon dioxide emissions in each region and the efficiency of each undesirable output. The analysis of energy use efficiency can lay a foundation for the allocation and trading of CO$_2$ rights in each province. (2) Unlike previous studies using the ZSG-DEA model to analyze energy, the analysis herein was refined to carbon dioxide, a single unintended output, to better reflect the carbon emission policy at this stage. (3) According to the carbon peak target for 2030 proposed by China, this paper denoted carbon emissions as being consistent with the sustainable development energy policy. Therefore, this study evaluated the energy use efficiency of 30 provinces from 2015 to 2019 using a dynamic undesirable ZSG-SBM model and investigated a reasonable scenario for provincial CO$_2$ allocation in China in the year 2030.

The rest of this paper is organized as follows. Section 2 introduces the methods and materials used to conduct the research. Section 3 presents the results of the analysis and a discussion thereof. Section 4 provides the paper’s conclusions and policy recommendations.

2. Materials and Methods

2.1. ZSG Model

The zero sum gains DEA (ZSG-DEA) model proposed by Lins has the property that in order to achieve the most efficiency, some inefficient DMUs must reduce their inputs, while
other DMUs must increase their inputs accordingly. The total input remains unchanged. The equation for this model is illustrated as follows.

\[
\begin{align*}
\text{min } h_{R0} \\
\text{s.t. } h_{R0} & \geq \sum_{j} \lambda_j x_i \left[ 1 + \frac{x_0(1-h_{R0})}{\sum_{j=0}^{n} y_j} \right] \\
\sum_{j} \lambda_j y_j & \geq y_o \\
\lambda_j & \geq 0, \forall j
\end{align*}
\]  

(1)

In the model, \( h_{R0} \) evaluates DMU_{0}\text{'}s efficiency in the allocation of \( x_i \) and \( y_j \) as the original values of inputs and outputs, respectively, where \( y_o \) and \( x_0 \) are DMU_{0}\text{'}s outputs and inputs and \( \lambda_j \) represents DMU contributions to the efficient projection.

The ZSG-DEA model of Lins estimates efficiency values through the ray approach and ignores the nonradial problem. To solve the problem of ray estimation, some scholars, such as Chiu et al., applied the SBM model of Tone to the ZSG-DEA model of Lins and proposed an input-oriented ZSG-DEA SBM model with the following equation:

\[
\begin{align*}
\text{min } \rho_{R0} = 1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i^r}{s_i^o} \\
\text{s.t. } x_{io} = \sum_{i=1}^{n} \lambda_i x_i \left[ 1 + \frac{x_0(1-\rho_{R0})}{\sum_{j=0}^{n} y_j} \right] + s_i^x, \ i = 1, \ldots, m, \\
y_{ro} = \sum_{i=1}^{n} \lambda_i y_i - s_i^y, \ r = 1, \ldots, s, \\
\sum_{j=1}^{n} \lambda_j = 1, j = 1, \ldots, n, \\
\lambda_j \geq 0, s_i^x \geq 0, s_i^y \geq 0
\end{align*}
\]  

(2)

where \( x_i \) and \( y_j \) represent the input and output of DMU_{i}, respectively, \( h_{R0} \) is the efficiency value of DMU_{0}, and \( \lambda_j \) is the reference set of DMU_{0}.

2.2. Dynamic Undesirable SBM Model

The development of the dynamic DEA model was first introduced by Kloop with window analysis, which was followed by Färe, Grosskopf, Norris, and Zhang’s Malmquist index. However, none of these illustrated the effect of carry-over activities. Färe and Grosskopf were the first to add carry-over activities into dynamic analysis. Following them, Tone and Tsutsui extended the model to dynamic analysis of SBM. In this paper, we used Tone and Tsutsui’s model structure and introduced bad output [25]. We constructed a dynamic undesirable SBM model as follows:

\[
\rho^*_0 = \min \frac{1}{T} \sum_{t=1}^{T} W_t \left[ 1 - \frac{1}{m+n} \left( \sum_{i=1}^{m} \frac{s_i^r}{x_{io}} + \sum_{r=1}^{n} \frac{s_i^{input}}{Z_{rot}^r} \right) \right]
\]  

subject to:

\[
\begin{align*}
\sum_{r=1}^{n} z_{rot} \lambda_i^t & = \sum_{r=1}^{n} z_{rot} \lambda_i^{t+1} \ (i = 1, \ldots, m; t = 1, \ldots, T) \\
x_{iot} & = \sum_{j=1}^{n} x_{iot} \lambda_i^t + s_{i0}^- \ (i = 1, \ldots, m; t = 1, \ldots, T) \\
y_{iot} & = \sum_{l=1}^{s_1} y_{lot}^\lambda \lambda_i^t - s_{it}^- \ (l = 1, \ldots, s_1; t = 1, \ldots, T) \\
y_{iot} & = \sum_{l=1}^{s_2} y_{lot}^- \lambda_i^t + s_{it}^- \ (l = 1, \ldots, s_2; t = 1, \ldots, T)
\end{align*}
\]  

(4)
2.3. Undesirable ZSG-SBM Model

This study integrated the SBM (slack-based measure) model proposed by Tone with the ZSG-DEA model of Lins et al. and introduced bad output. We propose a nonintended ZSG-SBM, where the input and output terms and the interperiod indicators are shown as follows.

\[ z_{rot}^{\text{input}} = \sum_{r=1}^{n} z_{rot}^{\text{input}} \lambda^t_r + s^t_\text{rt} \quad (r = 1, \ldots, n_{\text{input}}; t = 1, \ldots, T) \]

\[ \sum_{j=1}^{n} \lambda^t_j = 1 \quad (t = 1, \ldots, T) \]

\[ \lambda^t_j \geq 0, S^t_{-i} \geq 0; s^t_{+g} \geq 0; s^t_{-b} \geq 0; s^t_{\text{input}} \geq 0 \]

2.4. Input, Desirable Output, and Undesirable Output Efficiency

Hu and Wang used total factor energy efficiency to overcome possible errors in traditional energy efficiency indicators with seven key models for calculating efficiency [26]: labor, energy consumption, oil consumption, GDP, SO₂, CO₂, and NO₂. Here, “i” stands for region, and “t” stands for time. The formula for calculating efficiency values is as follows.

\[ \rho^*_o = \min \frac{1 - \frac{1}{m} \left[ \sum_{l=1}^{n} \frac{S^l_{-i}}{X_{lo}^i} \right]}{1 + \frac{1}{s^i_{+g} + s^i_{-b}} \left[ \sum_{l=1}^{s1} \frac{S^l_{+g}}{Y_{lo}^i} + \sum_{l=1}^{s2} \frac{S^l_{-b}}{Y_{lo}^i} \right]} \quad (5) \]

subject to:

\[ x_{lo} = \sum_{j=1}^{n} x_{lo} \lambda^t_j + s^t_i \quad (i = 1, \ldots, m) \]

\[ X_{lo}^p = \lambda^t X_{lo}^p \left[ 1 + \frac{X_{lo}^p (1 - \rho_{\text{RO}})}{\sum_{j \neq 0} X_{lo}^j} \right] + s^t_i \]

\[ Y_{lo} = \sum_{l=1}^{s1} y_{lo}^{+g} \lambda^t_j - s^t_{+g} \quad (l = 1, \ldots, s1) \]

\[ Y_{lo} = \sum_{l=1}^{s2} y_{lo}^{-b} \lambda^t_j + s^t_{-b} \quad (l = 1, \ldots, s2) \]

\[ \sum_{j=1}^{n} \lambda^t_j = 1 \quad (t = 1, \ldots, T) \]

\[ \lambda^t_j \geq 0, S^t_{-i} \geq 0; s^t_{+g} \geq 0; s^t_{-b} \geq 0; s^t_{\text{input}} \geq 0 \]
2.5. Data Sources and Description

This paper used data from the China Environmental Statistical Yearbook, the China Statistical Yearbook, and the China Energy Statistical Yearbook and utilized panel data to conduct empirical research on 30 provinces, autonomous regions, and municipalities in China. The variables are shown in Table 2 below.

Table 2. Input and output variables.

| Input Variable     | Output Variable | Carry-Over     |
|--------------------|-----------------|----------------|
| Labor              | GDP             | Fixed assets   |
| Energy consumption | SO$_2$          |                |
| Oil consumption    | CO$_2$          |                |
|                    | NO$_2$          |                |

Input variables:

A. Labor (unit: 10,000 persons): Number of urban labor registrations in each region at year-end.

B. Energy consumption (unit: 10,000 tons): Total value of regional energy consumption in each province, municipality, and autonomous region.

C. Oil consumption (unit: 10,000 tons): Total regional oil consumption of all provinces, municipalities, and autonomous regions converted into unified energy units and 10,000 tons of standard coal.

Output variables:

D. GDP (unit: 100 million CNY): Gross domestic product value of each province, municipality, and autonomous region calculated based on prices in the current year.

E. CO$_2$ (unit: 10,000 tons): Carbon dioxide gas in the air.

F. SO$_2$ (unit: 10,000 tons): Sulfur dioxide gas in the air, one of the main air pollutants.

G. NO$_2$ (unit: 10,000 tons): Nitrogen dioxide gas in the air, one of the more potent air pollutants.

Carry-over variable:

H. Fixed assets (unit: 100 million CNY): Fixed asset investment of each region, including domestic investment, foreign investment, real estate investment, etc.

This study used the dynamic undesirable ZSG-SBM model as a framework (see Figure 1) to study the relationships among the economy, environmental pollution, and natural resources of 30 provinces, autonomous regions, and municipalities in China. The input variables were labor, energy consumption, and oil consumption. Combined with the availability of data and previous research experience, the “desirable output” in this study was GDP, which reflects the economic growth driven by labor and energy input and is beneficial to the society. The “undesirable outputs” were SO$_2$, CO$_2$ and NO$_2$. These outputs represent unavoidable environmental pollution caused during the production process, reflecting a bad impact on the society. In the process of energy allocation and use, the two accompany but are opposed to each other. It is scientific and practical to combine the two and comprehensively evaluate the efficiency of energy allocation. The carry-over factor was fixed assets. This study used MAXDEA to conduct the empirical analysis.
3. Empirical Analysis

3.1. Descriptive Statistics of Inputs and Outputs

Figure 2 illustrates the variation in the input and output indicators and depicts the results of statistical analysis for the input items of labor, energy consumption, and oil consumption; the output items of GDP, CO$_2$, SO$_2$, and NO$_2$; and the carry-over indicator of fixed assets.

From 2015 to 2019, the maximum and minimum values of labor increased slowly, which was mainly due to the disappearance of China’s demographic dividend and slow population growth, while the amount of labor also appeared to decline gradually. The maximum value of energy consumption increased steadily from 2016, and the mean value, maximum value, and standard deviation all had the highest growth rate in 2018–2019. The gap between the maximum and minimum values appeared to be increasing. For oil consumption, except for the maximum value, which showed a certain increase in fluctuation, the indicators did not fluctuate much.

The maximum value of GDP showed a significant and continuous increase, the minimum value had a more moderate increase, and the average value increased steadily and slowly. All indicators of SO$_2$ showed a clear downward trend, especially the maximum and average values presenting a significant decrease in 2015. All indicators of CO$_2$ had some fluctuations, among which the maximum value had the most significant movement, showing a small increase first in 2017. The maximum value was lower than that in 2016, but from 2017 onwards, the average value was the lowest in 2018, and the other years showed a small increase. For NO$_2$, the indicators had a similar trend of change. All of them decreased significantly in 2015, and for the rest of the years, although the change was lower, it maintained a lower state.

In terms of fixed assets, the mean, maximum, and standard deviation of all provinces from 2015 to 2019 showed a gradual upward trend. The minimum value from the first three years also showed an upward trend but started to decline from 2017.

3.2. Results

3.2.1. Analysis of the Total Efficiency of Energy Allocation

In order to comprehensively analyze the total energy allocation efficiency of each province in China, this paper used the dynamic undesirable ZSG-SBM DEA model to measure the total energy allocation efficiency of the 30 provinces (except Tibet) from 2015 to 2019, as shown in Table 3.
Figure 2. Data description of input–output variables.

The total efficiency values of Shanghai, Shandong, Tianjin, Beijing, Jiangsu, Hebei, Henan, Shaanxi, Hunan, Fujian, Guangxi, and Guangdong from 2015 to 2019 were all 1, indicating that their energy allocation efficiency reached the optimum compared with other provinces. The remaining provinces showed an overall upward trend in their three-stage efficiency values from 2015 to 2019, which showed that the national energy allocation efficiency was generally developing in a good direction from 2015 to 2019. Among them, Shanxi Province and Yunnan Province improved fastest. Shanxi Province increased sharply from 0.4325 in 2015 to 1 in 2017 and then remained at 1. Yunnan Province increased from 0.5866 in 2015 to 1 in 2019. These provinces should continue to maintain their current trends, allocate their energy structures rationally, and further promote efficient energy allocation.

Hainan and Ningxia had an increasing but not significant trend in total efficiency values during the 5-year period, and their efficiency values were at a low level of 0.2–0.3 from 2015 to 2019. A few provinces, such as Inner Mongolia, Gansu, Jilin, Qinghai, Heilongjiang, Xinjiang, and Liaoning, showed a downward trend in total efficiency values from 2015 to 2019 in general. Among them, Inner Mongolia, Heilongjiang, and Liaoning all had their
efficiency values decline sharply from 1 in 2015 to 0.400, 0.265, and 0.358, respectively in 2019, while the remaining four provinces had values of less than 0.5 in these five years. These provinces have more room for improvement and should reasonably adjust their industrial structures, formulate relevant energy use policies, and reduce energy emissions.

Table 3. Total efficiency value of each province from 2015 to 2019.

| Rank | DMU       | 2015    | 2016    | 2017    | 2018    | 2019    |
|------|-----------|---------|---------|---------|---------|---------|
| 1    | Shanghai  | 1.0000  | 1.0000  | 1.0000  | 1.0000  | 1.0000  |
| 2    | Shanxi    | 0.4325  | 0.4500  | 1.0000  | 1.0000  | 1.0000  |
| 3    | Shandong  | 1.0000  | 1.0000  | 1.0000  | 1.0000  | 1.0000  |
| 4    | Inner Mongolia | 1.0000 | 0.4547  | 0.4985  | 0.3838  | 0.4002  |
| 5    | Tianjin   | 1.0000  | 1.0000  | 1.0000  | 1.0000  | 1.0000  |
| 6    | Beijing   | 0.5855  | 0.5681  | 0.5141  | 0.4395  | 0.3228  |
| 7    | Sichuan   | 0.2061  | 0.2174  | 0.2027  | 0.2107  | 0.2990  |
| 8    | Gansu     | 0.5234  | 0.5681  | 0.5141  | 0.4395  | 0.3228  |
| 9    | Jilin     | 0.9312  | 0.6325  | 0.5247  | 1.0000  | 1.0000  |
| 10   | Anhui     | 0.6474  | 0.5524  | 0.5021  | 0.6330  | 0.6985  |
| 11   | Jiangxi   | 0.1000  | 0.1000  | 1.0000  | 1.0000  | 1.0000  |
| 12   | Jiangsu   | 0.4259  | 0.4955  | 0.4909  | 0.4792  | 0.4369  |
| 13   | Hebei     | 0.2730  | 0.2763  | 0.2697  | 0.3075  | 0.3028  |
| 14   | Henan     | 0.9288  | 1.0000  | 0.9741  | 0.8262  | 0.5820  |
| 15   | Qinghai   | 0.3331  | 0.3125  | 0.2564  | 0.2442  | 0.2452  |
| 16   | Chongqing | 0.4056  | 0.4967  | 0.4498  | 0.4078  | 0.6494  |
| 17   | Hainan    | 0.2730  | 0.2763  | 0.2697  | 0.3075  | 0.3028  |
| 18   | Zhejiang  | 0.9288  | 1.0000  | 0.9741  | 0.8262  | 0.5820  |
| 19   | Shaanxi   | 1.0000  | 1.0000  | 1.0000  | 1.0000  | 1.0000  |
| 20   | Hunan     | 1.0000  | 1.0000  | 1.0000  | 1.0000  | 1.0000  |
| 21   | Guizhou   | 0.4259  | 0.4955  | 0.4909  | 0.4792  | 0.4369  |
| 22   | Yunnan    | 0.5866  | 0.9741  | 0.8262  | 0.5820  | 1.0000  |
| 23   | Heilongjiang | 1.0000 | 1.0000  | 1.0000  | 1.0000  | 1.0000  |
| 24   | Xinjiang  | 0.2654  | 0.2447  | 0.2178  | 0.2838  | 0.2387  |
| 25   | Ningxia   | 0.2188  | 0.2282  | 0.2244  | 0.2394  | 0.2189  |
| 26   | Fujian    | 1.0000  | 1.0000  | 1.0000  | 1.0000  | 1.0000  |
| 27   | Guangxi   | 1.0000  | 1.0000  | 1.0000  | 1.0000  | 1.0000  |
| 28   | Guangdong | 1.0000  | 1.0000  | 1.0000  | 1.0000  | 1.0000  |
| 29   | Liaoning  | 1.0000  | 1.0000  | 1.0000  | 1.0000  | 1.0000  |
| 30   | Average   | 0.7524  | 0.7634  | 0.7659  | 0.7698  | 0.7388  |

Figure 3 shows the national energy allocation efficiency trend for 2015–2019. From the average value of each year, there was a fluctuating downward trend of energy allocation efficiency in 2015–2019, first upward from 0.7524 in 2015 to 0.7698 in 2018 and then downward to 0.7388 in 2019. This indicates that the government’s efforts to build “Beautiful China” have achieved certain results in the coordinated development of economy, society, and environment, but there is still room for more substantial improvement in energy transformation and low-carbon economic development. This means that the implementation of China’s energy policy during this period has not been effective, and further strengthening of energy use and distribution is needed.

Further analysis reveals that in 2015–2019, eight provinces, Gansu, Jilin, Jiangxi, Qinghai, Chongqing, Hainan, Guizhou, and Ningxia, had annual efficiency values lower than the overall national average. Most of these provinces are resource-based and economically underdeveloped regions.

3.2.2. Efficiency Analysis of Input and Output Indicators

Based on the efficiency values of the input and output variables of dynamic DEA of the 30 provinces from 2015 to 2019 (Figures 4a–c and 5a–d), the efficiency values of all indicators for 2015–2019 in 12 provinces, Shanghai, Shandong, Tianjin, Beijing, Jiangsu,
Hebei, Henan, Shaanxi, Hunan, Fujian, Guangxi, and Guangdong, were 1. The efficiency of each indicator was high, and all resources were fully and effectively utilized.

**Figure 3.** China’s energy allocation efficiency trends for 2016–2019.

**Figure 4.** Cont.
Sustainability 2022, 14, 7087

Yunnan, Xinjiang, and Ningxia, had a significant downward trend in the efficiency of SO\textsubscript{2} emissions in these provinces is low, and the provinces should set stricter pollution emission standards and pay attention to China’s long-held green development concept.

Figure 4. (a) The efficiency value of labor in each province for 2015–2019. (b) The efficiency value of coal consumption in each province for 2015–2019. (c) The efficiency value of oil consumption in each province for 2015–2019.

Figure 4a–c show the efficiency values of input indicators for each province. Specifically, the efficiency values of labor in each province (Figure 4a) reveal that in addition to the above 12 provinces wherein all the input and output efficiency values were 1, Hubei, Heilongjiang, and Liaoning had efficiency values of 1 for 5 years. Most of the remaining provinces, such as Inner Mongolia, Gansu, Jilin, Qinghai, Chongqing, Hainan, Guizhou, Yunnan, Xinjiang, and Ningxia, had a significant downward trend in the efficiency of employed persons. Among them, the efficiency of Hainan fluctuated down from 0.9335 in 2015 to only 0.0661 in 2019, while that of Xinjiang and Ningxia dropped sharply from about 0.8 and 0.7, respectively, in 2015 to both less than 0.1 in 2019. Labor resources in these provinces were not properly allocated.

As shown in Figure 4b, which depicts energy consumption efficiency values by province from 2015–2019, excluding those provinces where this efficiency value was 1 in all years, most of the remaining provinces showed a fluctuating upward trend. The use of coal in provinces was relatively reasonable, but more reasonable energy use standards still need to be developed.

Figure 4c illustrates the efficiency value of oil consumption by province from 2015 to 2019. Overall, China’s provincial oil consumption was not very good. Most provinces’ efficiency values were between 0.1 and 0.5 and still had large room for improvement. For Inner Mongolia, Gansu, Qinghai, Chongqing, Hainan, Guizhou, and Ningxia, the efficiency values relatively declined, which gave a warning that if China wants to achieve peak oil emissions in 2025, then it should pay more attention to the oil use of each province and develop a more effective and practical plan.

Figure 5a–d shows the efficiency values of the output indicators of each province. Figure 5a shows that the GDP efficiency values of all provinces were generally at a high level, except for those of Shanxi, Sichuan, Anhui, Hubei, and Yunnan, which were not always 1 but around 0.9.

Figure 5b presents the provincial SO\textsubscript{2} efficiency values. Excluding 12 provinces of which the efficiency values were all 1, Gansu, Jiangxi, Qinghai, Chongqing, Hainan, Guizhou, Xinjiang, and Ningxia had efficiency values below 0.5 in the majority of years. This indicates that the efficiency of SO\textsubscript{2} emissions in these provinces is low, and the provinces should set stricter pollution emission standards and pay attention to China’s long-held green development concept.
Figure 5. Cont.
After the fourth iteration was carried out, the carbon emission efficiency of all provinces reached efficiency, and the calculated CO₂ emission of all provinces after being allocated by the dynamic undesirable ZSG-SBM DEA model.

Although the efficiency value of Hainan showed an upward trend, its efficiency value of Henan was just 0.1997. The initial efficiency value of the provinces varied greatly, which shows that the carbon emission efficiencies of Inner Mongolia, Gansu, Jilin, Jiangxi, Qinghai, and Guizhou all had a significant decreasing trend, among which that of Jiangxi continuously declined from an efficiency value of 1 in 2015 to one of below 0.6 in 2019. Although the efficiency value of Hainan showed an upward trend, its efficiency value dropped sharply after reaching the peak of 1 in 2018 and was around 0.3 in 2019. Provinces should reasonably emit various polluting emissions and strictly implement relevant moisture emission standards to help contribute to the construction of a green, healthy, and sustainable country.

3.2.3. Provincial CO₂ Emission Reduction Plan for 2030

Using the dynamic undesirable ZSG-SBM DEA model, the carbon emission efficiency of all provinces in China was made effective after several iterations of adjustment, after which the calculated CO₂ emissions represented the final carbon emission allocation. The carbon emission allocations of all provinces after each iteration were thereby measured. After the fourth iteration was carried out, the carbon emission efficiency of all provinces reached efficiency, and the calculated CO₂ emission allocation was the CO₂ emission of all provinces after being allocated by the dynamic undesirable ZSG-SBM DEA model.

Table 4 lists the iterative process of adjustment according to the 2030 carbon emission reduction target in order to achieve the highest overall efficiency value of all provinces in the country. Table 4 shows that 19 provinces, Shanghai, Shanxi, Shandong, Tianjin, Beijing, Sichuan, Jilin, Jiangxi, Jiangsu, Hebei, Hainan, Zhejiang, Hubei, Hunan, Xinjiang, Inner Mongolia, Guangdong, Liaoning, and Shaanxi, had initial efficiency values of 1. The remaining 11 provinces had efficiency values of less than 1, especially Gansu, Ningxia, Henan, Chongqing, Fujian, Inner Mongolia, and Guangxi, the initial efficiency values of which were less than 0.4 and among which the efficiency value of Henan was just 0.1997. The initial efficiency value of the provinces varied greatly, which shows that the...
carbon dioxide emission reduction plan proposed by the government is insufficient and has obvious efficiency loss and that carbon dioxide emissions therefore need to be adjusted.

After one iteration, the efficiency value greatly improved. The efficiency value of all provinces was more than 0.8 but did not reach optimal efficiency. After the third iteration, the efficiency of provinces of which the initial efficiency values were not 1 improved, and the efficiency value of most provinces reached the frontier. However, the efficiency values of some provinces were lower than 1 and did not reach the optimal efficiency value. The overall efficiency value of all provinces in China still needed to be improved. Therefore, further iteration was needed.

After four iterative adjustment processes, all provinces became efficient after redistribution according to ZSG-DEA, reaching the frontier of ZSG-DEA and realizing the optimal overall carbon dioxide emission efficiency of the country. Therefore, the carbon dioxide emissions of ZSG after the fourth iteration can be used as the final carbon dioxide emission allocation quota of all provinces in the country. Figure 6 shows the change in efficiency value during the iterative process in each province. Accordingly, Yunnan, Gansu, Ningxia, Anhui, Henan, Qinghai, Chongqing, Heilongjiang, Fujian, Inner Mongolia, Guangzhou, Guizhou, and other provinces had large improvements in efficiency value during the iterative process.

According to the data in the last column of Table 4, by 2030, 19 provinces, Shanghai, Shanxi, Shandong, Tianjin, Beijing, Sichuan, Jilin, Jiangxi, Jiangsu, Hebei, Hainan, Zhejiang, Hunan, Xinjiang, Inner Mongolia, Guangdong, Liaoning, and Shaanxi, were allowed to increase their CO\textsubscript{2} emissions, while the remaining 11 provinces’ emissions needed to be reduced. After the analysis, it was found that the total original CO\textsubscript{2} emissions of the 30 provinces were 348,000 tons, and after the iterative adjustment of national CO\textsubscript{2} emissions, the total CO\textsubscript{2} emissions of the provinces were still 348,000 tons. Among the provinces that were allowed to increase their CO\textsubscript{2} emissions, only Shanxi, Shandong, and Jiangsu were able to increase their emissions by more than 10,000 tons. The other provinces were allowed to increase their emissions by only a small amount. Shandong was able to increase emissions by 32,655,000 tons, Jiangsu by 10,325,000 tons, and Shanxi by the largest amount at up to 103,570,000 tons. Both Shanxi and Shandong are major energy provinces in China, and therefore, the CO\textsubscript{2} emission policy could be relaxed appropriately, making the overall efficiency value of each province increase. This was followed by the more economically developed regions of Shanghai, Beijing, Jilin, Hebei, and Hubei, all of which increased by a few thousand tons or so. These samples cover the more economically developed and efficient developed provinces, all of which should increase their CO\textsubscript{2} emissions if the amount due to each province is to be allocated under the policy target scenario of carbon peaking.
Table 4. CO₂ allocation efficiency and adjustment results of 30 provinces in China in 2030.

| DMU        | Initial Gas | DEA | First Iteration | Second Iteration | Third Iteration | Fourth Iteration | Optimized gas | Adjustment amount |
|------------|-------------|-----|-----------------|------------------|-----------------|------------------|---------------|------------------|
| Shanghai   | 3784.416    |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 7802.352         |
| Shanxi     | 97,551.606  |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 201,122.710      |
| Shandong   | 30,757.517  |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 63,412.951       |
| Yunnan     | 34,102.772  | 0.4230 | 33,984.268 | 0.8347           | 20,660.958      | 0.9774           | 31.880        | 7802.352         |
| Tianjin    | 550.620     |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 1135.216         |
| Beijing    | 4627.667    |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 9540.888         |
| Sichuan    | 159.715     |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 329.286          |
| Gansu      | 1646.414    | 0.3320 | 1517.443 | 0.8576           | 1080.186        | 0.9231           | 3.695         | 265.898          |
| Ningxia    | 5121.262    | 0.3569 | 4947.786 | 0.8445           | 3471.681        | 0.8986           | 10.593        | 357.648          |
| Jilin      | 2315.491    |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 4773.862         |
| Anhui      | 4911.120    | 0.6272 | 4688.232 | 0.8480           | 3292.476        | 0.9014           | 9.951         | 459.519          |
| Jiangxi    | 69.017      |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 142.293          |
| Jiangsu    | 9724.531    |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 20,049.121       |
| Hebei      | 2897.560    |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 5973.917         |
| Henan      | 1142.859    | 0.1997 | 754.820 | 0.9179           | 538.417         | 0.9973           | 1.730         | 800.018          |
| Qinghai    | 979.391     | 0.5828 | 854.910 | 0.8710           | 610.215         | 0.9440           | 2.131         | 256.644          |
| Chongqing  | 122,508.468 | 0.2725 | 121,813.895 | 0.8408 | 21,110.888 | 0.8900 | 2265.397 | 0.9967 | 23.825 | 1431.914 | −121,076.555 |
| Hainan     | 134.160     |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 276.599          |
| Zhejiang   | 150.129     |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 3175.293         |
| Hubei      | 4966.327    |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 10,239.105       |
| Hunan      | 318.895     |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 657.468          |
| Heilong jiang | 4751.419 | 0.4084 | 4616.894 | 0.8427           | 3244.555        | 0.8827           | 10.127        | 277.346          |
| Xinjiang   | 382.288     |     | 1.000          | 0.000            | 1.000           | 0.000            | 1.000         | 788.166          |
| Fujian     | 97.738      | 0.3374 | 68.488 | 0.9101           | 49.030          | 0.9752           | 0.180         | 60.387           |
| Inner Mongolia | 1304.649 | 0.2895 | 0.000 | 1.000         | 0.000           | 1.000           | 0.000         | 2689.803         |
| Guangxi    | 1676.555    | 0.2736 | 1304.764 | 0.8940 | 928.677 | 0.9662 | 159.050 | 0.9992 | 2.950 | 766.518 | −910.037 |
| Guangdong  | 1402.830    | 1.000 | 0.000 | 1.000         | 0.000           | 1.000           | 0.000         | 2892.222         |
| Guizhou    | 5342.706    | 0.5609 | 4656.185 | 0.8719           | 3264.021        | 0.9475           | 8.307         | 1413.374         |
| Liaoning   | 1592.788    | 1.000 | 0.000 | 1.000         | 0.000           | 1.000           | 0.000         | 3283.860         |
| Shaanxi    | 1639.089    | 1.000 | 0.000 | 1.000         | 0.000           | 1.000           | 0.000         | 3379.319         |
The 11 provinces with lower initial DEA efficiency, Yunnan, Gansu, Ningxia, Anhui, Henan, Qinghai, Chongqing, Heilongjiang, Fujian, Guangxi, and Guizhou, need to further reduce their CO\textsubscript{2} emissions. Among these, Chongqing had the largest required adjustment, needing to reduce 120.77 million tons of CO\textsubscript{2} emissions. Yunnan, Gansu, Ningxia, Anhui, Heilongjiang, and Guizhou also needed to reduce their CO\textsubscript{2} emissions by more than 1000 tons. These provinces are mostly less economically developed and were initially allocated according to the policy target. Their CO\textsubscript{2} emissions are still at an unreasonable level, and if their CO\textsubscript{2} emissions are not adjusted, then their energy allocation efficiency will continue to be at a low level. This implies the need to strengthen the control of exhaust gas pollution, adjust the industrial structure, set stricter policies on pollution emissions, and set higher emission reduction targets to reduce CO\textsubscript{2} emissions.

Table 4 shows only the final adjustment results for each province, and Figure 7 is used to further illustrate the competition and trade-off process between any two provinces in terms of emission reductions. The circles on the vertical axis of the figure indicate the CO\textsubscript{2} emissions from one province to another province, while the circles on the horizontal axis indicate the CO\textsubscript{2} emissions that a province receives from the other province. Solid circles mean positive values and hollow circles mean negative values, where a positive value indicates a province’s external CO\textsubscript{2} emissions and a negative value indicates its CO\textsubscript{2} absorption. If the former is greater than the latter, then the province needs to reduce its emissions by setting a more stringent CO\textsubscript{2} control target, and vice versa. Figure 7 shows that 11 provinces needed to reduce their CO\textsubscript{2} emissions, while 19 provinces could be allowed to increase their CO\textsubscript{2} emissions, which was consistent with the above findings.

Further analysis shows that Shanxi and Shandong were allowed to increase their CO\textsubscript{2} emissions, and the other provinces were allowed to buy CO\textsubscript{2} emission rights from these two provinces. Shanxi and Shandong are both major energy provinces in China, and energy-intensive regions tend to transfer large amounts of carbon emissions to energy-scarce regions. The provinces of Beijing, Jilin, Jiangsu, Hebei, and Hubei were also able to transfer CO\textsubscript{2} emission rights to most other provinces. These provinces mostly have a good level of economic development, and regions with high levels of economic development tend to transfer CO\textsubscript{2} emissions to less economically developed regions as well in order to keep the national CO\textsubscript{2} emissions within limits and achieve optimal energy allocation.

Figure 8 shows a comparison between the initially allocated CO\textsubscript{2} emission allowances and the reallocated CO\textsubscript{2} emission allowances through the dynamic undesirable ZSG-SBM model. The results showed a large gap between the optimal CO\textsubscript{2} emission targets of some provinces after reallocation in 2030 and the initial CO\textsubscript{2} emission targets, such as Shanxi, Shandong, and Jiangsu needing to significantly increase their CO\textsubscript{2} emissions and Yunnan and Chongqing needing to further reduce their CO\textsubscript{2} emissions. These provinces are struggling to achieve their emission reduction targets to maximize their utility. The remaining provinces and cities had relatively small changes in their CO\textsubscript{2} emissions. Although Shanxi’s initial CO\textsubscript{2} emissions were second only to those of Chongqing, its final emissions were the largest after adjustment and significantly higher than those of the remaining 29 provinces. Chongqing changed from the highest-emitting province to a low-emitting province after adjustment. It is closely related to Shanxi by being a large coal mining province.
value of 1 for all provinces, the efficiency of all provinces could be maximized and optimal
dynamic unintended ZSG-SBM model to evaluate and optimize China’s provincial carbon
carbon emissions of provinces and cities in China in 2030 was calculated. It was found
China’s energy allocation efficiency showed an overall upward trend from 2015 to
The above results showed that the dynamic undesirable ZSG-SBM DEA model allo-
The above results showed that the dynamic undesirable ZSG-SBM DEA model allo-
4. Discussion

Figure 7. Competition and trade-offs for interprovincial emission reductions in 2030.

Figure 8. Carbon emission control targets for 2030.

The above results showed that the dynamic undesirable ZSG-SBM DEA model alloca-
tion worked better according to the efficiency maximization principle. With an efficiency
value of 1 for all provinces, the efficiency of all provinces could be maximized and optimal
allocation could be achieved according to the readjusted quota.
4. Discussion

According to the previous discussion, the zero sum income DEA model (ZSG-DEA) has been widely used to solve various resource allocation problems. In the research related to carbon trading, most scholars have regulated the use of energy from the perspective of greenhouse gas emissions. In this process, carbon is often regarded as an input. However, according to the “Carbon Dioxide Trade Scenario” proposed later, carbon emissions as an input variable is more in line with the reality of carbon emissions trading. Many scholars have conducted research on China’s carbon emissions based on this but failed to combine it with China’s “Double Carbon” goal, so this research has lacked a certain practical strategic significance. This study first calculated the energy allocation efficiency of provinces and cities in China in the past five years and came to the conclusion that China’s energy allocation efficiency showed an overall upward trend from 2015 to 2019. However, some provinces had downward trends. Then, based on this and in combination with China’s carbon emission targets, the efficiency of the initial allocation of carbon emissions of provinces and cities in China in 2030 was calculated. It was found that most provinces had a range of efficiency increases and that the efficiency was optimal after several iterations. Therefore, compared with other studies, this study overcame the simple allocation of energy or emission rights and adjusted the initial allocation value in combination with the energy use efficiency value. This will help China to achieve the “Double Carbon” goal as soon as possible.

Comparing the research methods of this paper with those in previous studies, this paper broke through the limitations of previous studies that lacked “bad output” and research that combined energy efficiency with carbon emission resource allocation, used the dynamic unintended ZSG-SBM model to evaluate and optimize China’s provincial carbon emission reduction schemes in 2030 by using an iterative method, and concluded that there was an efficiency loss in China’s initial allocation of carbon emission resources in 2030 and that this allocation needed to be readjusted to achieve the optimal carbon emission efficiency of each province. This was also one of the contributions mentioned in the introduction of the first part of this study. Although the literature has focused on the rational allocation of resources, with ZSG-DEA used to discuss this, the model architecture has stayed within the CCR ZSG-DEA model, ray DEA has not been used to ignore the difference problem, and bad output has not been considered.

In the process of this paper, we chose the optimal and most feasible solution after constant iteration and found that the optimal efficiency value could be obtained after four iterations. Before this, we also used the CCR-ZSG-DEA model widely used in previous studies, but the effect was not good. In this paper, we finally combined the ZSG model and difference variable model and introduced bad output to construct a nonintended ZSG-SBM model. Using the dynamic undesirable ZSG-SBM model, this study evaluated and optimized carbon reduction options at the provincial level in China in 2030 by using an iterative approach to provide recommendations for regulators to establish more equitable and effective policy options. The empirical analysis led to the following conclusions.

The analysis of the empirical results showed that the total efficiency value of energy distribution in China decreased from 0.7524 in 2015 to 0.7388 in 2019. The total efficiency values of each province and territory during these five years, except for Shanghai, Shandong, Tianjin, Beijing, Jiangsu, Hebei, Henan, Shaanxi, Hunan, Fujian, Guangxi, and Guangdong, were all are 1. The total efficiency values of some provinces showed an increasing trend. However, Inner Mongolia, Gansu, Jilin, Qinghai, Heilongjiang, Xinjiang, and Liaoning had total efficiency values that generally showed a downward trend. The efficiency values of some provinces were at a low level, or less than 0.5, indicating great room for improvement, energy savings, and emission reduction. From the efficiency values of various input and output indicators, only the output indicator of GDP efficiency values was stable in all provinces at above 0.9, reflecting the significant role of energy allocation efficiency in China’s economic development at present. In addition, based on the input indicators, the efficiency values of all provinces fluctuated widely, and in terms of the input indicator
of oil consumption, most provinces had efficiency values between 0.1 and 0.5, and some had a relatively large decrease in this efficiency value. For example, Inner Mongolia fell precipitously from 1 in 2015 to 0.0705 in 2019, denoting that oil consumption under the energy allocation of these regions does not match their industrial development and that there is more room for improvement. In terms of the output indicator of CO$_2$ emissions, most provinces had efficiency values between 0.7 and 1.0, except for Inner Mongolia, Gansu, Jilin, Qinghai, Hainan, Guizhou, Xinjiang, and Ningxia, the efficiency values of which were not high or even presented downward trends. The other provinces were on an upward trend.

The current carbon reduction program proposed by the China government for 2030 is not the optimal program. Nineteen provinces were on the efficiency frontier, but the remaining eleven provinces all had lower efficiency values. The initial efficiency values varied widely among provinces, which indicates that the carbon reduction scheme proposed by the government is deficient and has significant efficiency losses. Thus, the scheme needs to be adjusted for the carbon emissions of each province. The results of this study showed that after four iterations of the adjustment process, the efficiency values of all provinces reached 1. All provinces aimed at maximizing efficiency and became effective at achieving the optimal overall national carbon emission efficiency after reallocation according to the dynamic undesirable ZSG-SBM DEA model.

The optimal carbon emission level of each province in China needs to be adjusted. For China’s target of reaching peak carbon emissions of 348,000 tons in 2030, there was a large gap between the optimal carbon emission target and the initial carbon emission target in some provinces after redistribution through the model. Some provinces struggled to achieve the emission reduction target and obtain the maximum utility. Nineteen provinces, Shanghai, Shanxi, Shandong, Tianjin, Beijing, Sichuan, Jilin, Jiangxi, Jiangsu, Hebei, Hainan, Zhejiang, Hubei, Hunan, Xinjiang, Inner Mongolia, Guangdong, Liaoning, and Shaanxi, were allowed to increase their carbon emissions, while the remaining eleven provinces needed to reduce their carbon emissions. Among the provinces allowed to increase carbon emissions, only Shanxi, Shandong, and Jiangsu were able to increase the amount by more than 10,000 tons. The reduction in carbon emissions in Chongqing was the greatest at 120,707,000 tons. Yunnan, Gansu, Ningxia, Anhui, Heilongjiang, and Guizhou also needed to reduce their emissions by more than 1000 tons of CO$_2$, implying the need to strengthen the control of pollution emissions.

This paper mainly confirmed that to achieve China’s total carbon emissions peak, efforts must still be made among Chinese provincial government departments to allocate carbon quotas and regulate regional emissions. The adjustments proposed herein can contribute to China’s green economy and sustainable development as well as the development of the world, as China makes considerable contributions to the world economy. This study can also help the healthy development of the ecological environment and contribute to more quickly achieving a global carbon peak and strengthening China’s position on the world stage. However, in the process of specific response or policy implementation, each department should consider the reality of specific environmental characteristics and other factors.

5. Conclusions and Recommendations
5.1. Conclusions
Under China’s “Double Carbon” goal, the overall allocation of energy and the promotion and improvement of carbon rights trading are very important. Therefore, studying the overall energy allocation efficiency of various regions in China in recent years and replanning the distribution of carbon rights based on these studies in the future will help China reach the carbon peak as soon as possible and achieve the “Double Carbon” goal. At the same time, it will help China to promote supply-side structural reform and achieve high-quality green development. Especially for China’s industrial sector, this process can promote more effective use of energy and reduce carbon emissions. On the other hand, it is
conducive to the innovation of production techniques in the industrial sector, which can in turn lead to the transformation and upgrading of heavy-energy-consumption and heavy-pollution industrial enterprises.

This study showed that China’s total energy distribution efficiency showed an upward trend from 2015 to 2018 and decreased in 2019, but the range of these changes was small. Moreover, the efficiency value of some provinces was at a low level, less than 0.5. This shows that there is a large room for improvement in energy conservation and emission reduction. From the efficiency subvalues of each input–output index, only that of the output index GDP was relatively stable for each province in China at above 0.9, which reflects that China’s energy allocation efficiency plays a significant role in economic development. In addition, based on the input variables, the efficiency value of each province fluctuated greatly. The 2030 carbon emission reduction plan proposed by the Chinese government is not the optimal plan. Eighteen provinces were at the forefront of efficiency, but the efficiency values of the remaining twelve provinces were low, and the initial efficiency values of the provinces varied greatly, which indicates that the carbon emission reduction plan proposed by the government has shortcomings and obvious efficiency losses and that it is therefore necessary to adjust the carbon emissions of each province.

Complete linearization of the proposed environmental ZSG-DEA model was not achieved in this study, and future studies can further focus on the linearization of such models. In addition, for units with no feasible solutions, the efficiency values obtained by the proposed model are not comparable with the efficiency values of other solution units. Based on their input–output dominance over the other units, the paper simply assigned all the efficiency values of these units a value of 1. However, considering that the hyperefficiency model is a special case of the ZSG-DEA model, the optimal efficiency value is greater than 1, and therefore, new models have been constructed to be more precise. Evaluation of units without feasible solutions remains a worthwhile study.

5.2. Recommendations

Based on the above findings, there is still much room for improvement in China’s provinces to achieve optimal energy allocation efficiency based on the policy goal of achieving carbon peaking by 2030. We propose the following countermeasures to achieve this target.

(1) Rational use of energy and further optimization of energy structure. At this stage, the level of efficiency of energy allocation in China’s provinces is not high and is still in a phase of fluctuation and decline [27]. For this reason, traditional energy use should be transformed, the development and utilization of new energy sources should be increased, and industrial transformation and upgrading should be strengthened. The focus should be to effectively reduce the unreasonable loss of energy resources, reduce pollution emissions in each province, further improve the efficiency of inputs and outputs, and set the carbon emission threshold from the source so that the efficiency of energy use in key industries in key provinces is significantly improved and maintained at a good level [28]. China has approved seven provinces (Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen) to carry out carbon trading pilot projects, but the government needs to further improve carbon pricing. It can refer to and learn from the basic environmental control system of pollution permit trading to establish a good carbon auction system, effectively apply government supervision, strengthen environmental pollution control, and ensure carbon emission limits and the long-term effectiveness of the policy system. Doing so can help improve the overall efficiency of energy allocation.

(2) National coordination and promotion for each province according to local conditions. Since the conditions of resource endowment, industrial structure, and environment vary from place to place, each province should be categorized according to its specific situation, and specific emission reduction targets should be introduced for each province to clarify the responsibilities of each party [29]. Localities should be encouraged to assume responsibility for emission reduction and make reasonable use of the carbon trading system.
to take the lead in reaching the peak. Energy-rich regions should transfer carbon emissions to energy-poor regions, and regions with high levels of economic development should transfer carbon quotas to less economically developed regions. Each province in the country contributes to the overall energy allocation efficiency according to its own development characteristics [30,31]. Developed provinces should strengthen energy-saving and emission reduction technology research and development and carry out green energy innovation. Less developed provinces should transform their economic development mode, adjust their industrial structure, and accelerate the development of service and high-tech industries [32]. This will help promote China’s green, sustainable, and healthy development in all aspects.

(3) Combination of effective government and efficient market. The government should enhance its own energy conservation and emission reduction, comprehensively promote national energy conservation and emission reduction, improve policy mechanisms, establish a comprehensive and specific assessment and monitoring accountability system, and promote the integration of relevant laws and regulations to make emission reduction measures more targeted and effective [33]. The government should also strengthen public education to help enhance low-carbon awareness in society, incorporate green development into the education system, and improve the public’s concept of green living. The market can make low-carbon products strongly competitive through incentive and restraint mechanisms, promoting low-carbon and environmentally friendly product labels, strengthening price reform of resource-based products, and implementing tax systems and fiscal policies that are conducive to energy conservation and emission reduction [34,35]. The market and the government can assist in ensuring the timely achievement of carbon peak and carbon neutrality.

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