# Provincial Carbon Quota Allocation of China's Iron and Steel Industry Considering Environmental Factors Under the Goal of Carbon Peak

Yanling Zhu, Mengzhu Gao

*Abstract*—**Based on the 2030 carbon peak target, this paper studies the top-down provincial carbon quota allocation in China's iron and steel industry. Considering the principles of fairness, efficiency, sustainability and development, three provincial carbon quota allocation schemes are constructed based on entropy method, three-stage DEA and ZSG-DEA model respectively, which make up for the gap of carbon quota allocation scheme with the total amount of carbon peak target of the iron and steel industry. The allocation results show that the allocation based on the entropy method can roughly solve the problem of uneven distribution of carbon quota of the steel industry in various provinces, and the carbon quota in the steel industry decreases from the eastern region to the western region. Considering the two environmental indicators of local government competition and urbanization level, the initial carbon quota allocation scheme can be effectively adjusted, which is conducive to promote the enthusiasm of some underdeveloped areas. The allocation scheme, which combines the entropy method with the ZSG-DEA model, can enhance the efficiency of carbon quota allocation among provinces while ensuring fairness. However, this fairness is limited and more advantageous to economically developed regions.**

*Index Terms*—**carbon peak, carbon quota, environmental factors, three-stage DEA model, ZSG-DEA model.**

## I. Introduction

ANTHROPOGENIC economic activities have significantly increased the emission of greenhouse gases, exacerbating the issue of haze pollution [1, 2]. The frequent occurrence of extreme events underscores the imperative to take decisive action towards achieving carbon dioxide net zero emissions and adapting to climate change. During the 2020 Leaders' Climate Summit, China's leaders made a global declaration that carbon dioxide emissions will reach their peak by 2030 and committed to striving towards achieving carbon neutrality by 2060. The steel industry, as a crucial pillar of the national economy and a vital catalyst for the establishment of a modern power, has propelled China's economic growth at an accelerated pace. However, the exponential expansion of China's steel industry has posed significant environmental challenge [3, 4]. According to a report published by BP, China ranked as the top emitter of greenhouse gases globally in 2006. The steel industry in China accounted for approximately 15% of the total emissions, establishing itself as one of the key contributors to carbon emissions in the country [5, 6]. Therefore, developing a scientifically sound provincial carbon quota allocation scheme for the steel industry can effectively delineate the carbon reduction responsibilities of each province's steel sector. This endeavor holds immense significance in attaining an early peak in carbon dioxide emissions from the steel industry and facilitating China's achievement of its carbon peak target.

Due to the diverse economic growth patterns, energy consumption modes, and technological levels across different provinces in China, it is impractical for each region to be treated equally and assume a common responsibility for reducing carbon emission targets, instead, they must embrace a principle of "common but differentiated responsibility" [7]. Diverse carbon quota allocation schemes yield varying impacts on economic development [8]. Addressing the equitable and efficient distribution of carbon emission reduction responsibilities among regions, in line with China's overarching targets, constitutes a crucial pragmatic undertaking for our government. In terms of allocation methods, scholars commonly employ one or more indicators to assign carbon quotas. Although the single index method is user-friendly, its oversimplification of the problem may result in skewed distribution outcomes [9]. When formulating a carbon emission rights allocation plan, it is essential to incorporate diverse allocation principles in order to achieve a more rational and robust allocation strategy.

The novelty and significance of this paper reside in: Firstly, the allocation of carbon quotas in the steel industry entails calculating province-specific carbon emissions within the sector, while national-level data only captures overall industry emissions. Therefore, this paper obtain the proportion of energy consumption of various energy sources in the steel industry from the national level, and finally converts it into provincial data in proportion. Furthermore, it is imperative to incorporate the principles of sustainability into those of fairness and efficiency, while simultaneously considering environmental factors during economic

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development. The entropy method is employed to incorporate multiple initial allocation principles, enhancing the comprehensiveness and accuracy of the allocation outcomes. Thirdly, considering the influence of environmental factors on the basis of the principles of fairness, efficiency and sustainability, the three-stage DEA model is used to eliminate environmental factors and random noise, so as to make the allocation scheme more equitable. Fourthly, based on the initial allocation scheme, the ZSG-DEA model is employed for continuous optimization while maintaining a constant total amount of input variables. After multiple iterations, the carbon quota allocation efficiency of each province is at the forefront of efficiency.

## II. Literature Review

Currently, the research on the allocation of responsibility for carbon emission reduction primarily encompasses three key dimensions.

Firstly, conduct research from the perspective of equity and impartiality. Various principles such as egalitarianism, economic efficiency, grandfathering, ability to pay, and historical responsibility all embody the notion of fairness. According to Zhou and Wang (2016), it is crucial to prioritize the consideration of population factors. Subsequently, scholars explored a range of equity principles in their examination of the allocation of carbon quotas [10].

Secondly, conduct research from an efficiency standpoint. The efficiency principle underscores the potential for carbon reduction, indicating that in situations with equal carbon emissions, regions exhibiting higher efficiency values also demonstrate greater output. In their subsequent investigation, Kong et al. (2019) incorporated the costs associated with emission reduction in each province, leading to more precise allocation outcomes [11]. Miao et al. (2016) employed the ZSG-DEA model to investigate the efficiency of regional carbon quota allocation in China [12].

Thirdly, Integrating multiple principles of distribution, including equity, efficiency, and sustainability. Allocating carbon emission quotas based on regional economic levels, development situations, and potential for carbon reduction can facilitate a rational allocation of resources. Wang et al. (2019) discovered that an optimal distribution plan, which incorporates considerations of both fairness and efficiency, can effectively minimize the national average cost of emission reduction while mitigating regional disparities in development [13]. There have been few articles in previous literature that take sustainability principles into consideration. The principle of sustainability enables the quantification of carbon dioxide absorption capacity and elucidates the intricate interplay between economic development and environmental preservation. Zhou et al. (2021) implemented an inter-provincial allocation of China's carbon quota based on the principles of fairness, efficiency, and sustainability while also evaluating the scheme's carbon intensity efficiency [14].

In general, the research that comprehensively considers the allocation principles to enhance the feasibility of carbon quota allocation scheme has matured. However, there is limited research specifically focusing on the steel industry in different provinces of China, with 2030 carbon peak target as the benchmark for calculation. Moreover, the efficiency of measuring carbon quotas is significantly influenced by the diverse environments in which provinces are situated. Therefore, in this paper, we try to eliminate its influence when constructing the carbon quota allocation model.

## III. Data And Methods

The main industrial product output of each province's steel industry in this paper is identified as crude steel production. Due to factors such as environmental conservation efforts and limited population demand for steel, the production of crude steel in Beijing, Hainan, and Tibet is relatively small, therefore, it will not be analyzed. We selected 28 provincial regions in mainland China for research.

### A. Calculating method

#### 1) Carbon emission calculation of iron and steel industry in each province

The carbon emissions of the steel industry are quantified in this paper, utilizing the methodology proposed by Shang et al. (2010). The energy consumption data pertaining to the "ferrous metal smelting and rolling processing industry" serve as the foundational energy data for calculating carbon dioxide emissions in China's iron and steel sector [15]. These figures are then multiplied by the IPCC2006 carbon emission factors corresponding to different types of energy, resulting in the computation of final carbon emissions. It is expressed as follows:

$$\begin{aligned} &\textit{Iron and steel industry } CO_2 \textit{ emissions} \\ &\quad = \left(\textit{carbon input} - \textit{carbon output}\right) \times \frac{44}{12} \end{aligned} \tag{1}$$

Among them, carbon input includes the consumption of 13 types of energy, such as washed coal, electricity, and other coal washing. Carbon emissions encompass three categories of carbonaceous products, namely crude steel, tar, and coarse coal.

#### 2) Forecast of relevant variables in 2030

Given the absence of official data on provincial crude steel production, GDP, and other indicators for 2030, we employ the GM(1,1) grey model to forecast these variables for all 28 provinces based on relevant data from 2014 to 2020 [16]. The calculation process is as follows:

$$\hat{g}_m^{(0)}\left(k\right) = g_m^{(0)}\left(2014\right) - \frac{b}{a}\left(1-e^{a}\right)e^{-a\left(k-2014\right)} \tag{2}$$

Among them, $a$ is the development coefficient, $b$ is the grey input coefficient of GM (1,1), $g_m^{(0)}$ is the original data of $m\left(m=1,2,\cdots,28\right)$ province in 2014, $\hat{g}_m^{(0)}\left(k\right)$ $\left(k=2014,\cdots,2020\right)$ and $\hat{g}_m^{(0)}\left(k\right)\left(k=2021,\cdots,2030\right)$ represent the fitted and predicted values of the relevant data of $m-th$ provinces, respectively.

Furthermore, following the utilization of the grey model for predicting relevant variables in the steel industry across 28 provinces, a residual test is conducted on the GM(1,1) model to assess the accuracy and reliability of the prediction outcomes. $\varepsilon\left(k\right)=g_m^{(0)}\left(k\right)-\hat{g}_m^{(0)}\left(k\right)$, $\Delta_m\left(k\right)=\left|\frac{\varepsilon_m\left(k\right)}{g_m^{(0)}\left(k\right)}\right|$ is the relative error of $m-th$ province in the $k-th$ year, and $\overline{\Delta}_m = \frac{1}{2020-2013}\sum_{k=2014}^{2020}\Delta_m(k)$ is the average simulation relative error of $m-th$ province. When $\Delta_m(k) < 0.1$ and $\overline{\Delta}_m < 0.1$, it is considered to be a residual qualified model.

*3) Determination of allocation target*

The key to the allocation of carbon quotas for China's provincial steel industry lies in determining the overall carbon quota volume within this sector. Currently, due to the limited availability of certain data pertaining to the provincial steel industry, direct acquisition of accurate carbon emissions for a specific region's steel industry is unattainable. Hence, it is imperative to compute the overall carbon allocation for China's steel industry in accordance with the carbon peak objective. The 'carbon peak by 2030 action plan' proposed in 2021 aims to achieve a minimum reduction of 65% in carbon intensity compared to the levels observed in 2005 by the year 2030. Consequently, in this paper, we postulate that the steel industry in China has the potential to attain a 65% reduction target in emissions by 2030.

$$C_{2030} = g_{2030} \times (1-\alpha) \times \frac{C_{2005}}{g_{2005}} \tag{3}$$

where $\alpha = 65\%$, $C_{2005}$ and $C_{2030}$ represent the $CO_2$ emissions of China's steel industry in 2005 and 2030 respectively, $g_{2005}$ and $g_{2030}$ are China's crude steel production in 2005 and 2030 respectively. The crude steel production data in 2030 are predicted according to the GM(1,1) model.

*B. Carbon quota allocation model*

A carbon quota allocation model is constructed and optimized with carbon peak as the total target. Firstly, it is imperative to categorize the commonly employed indicators in current research on carbon quotas. Additionally, employing the multi-index decision-making method, the entropy weight technique is utilized to establish the initial carbon quota allocation scheme based on the evaluation index system. The allocation scheme is subsequently adjusted using a three-stage DEA model to eliminate the influence of environmental factors and random noise. Finally, the ZSG-DEA model is employed to refine the initial carbon quota allocation scheme with the aim of enhancing distribution efficiency.

*1) Initial allocation of carbon quotas based on a multi-index approach*

a. Index screening. A clear delineation of responsibilities for emission reduction is a pivotal component of the government's equitable distribution policy. In practical terms, the allocation of quotas is commonly perceived to be a reflection of fairness through the consideration of population size and per capita GDP. Simultaneously, Regions with higher carbon emissions should bear greater responsibility for emission reduction [17, 18]. The principle of efficiency highlights the importance of prioritizing cost-effectiveness in the allocation of limited emission quotas. The carbon intensity of the steel industry is used in this paper as a metric to measure its energy efficiency. Furthermore, the focus of this paper is on the steel industry across 28 provinces in China. The assessment of environmental pollution resulting from the production process also serves as a crucial criterion for carbon quota allocation. Consequently, we incorporated the intensity of air pollutant emissions from the steel industry in each province into the comprehensive evaluation index system [19, 20]. Finally, the measurement index incorporates the crude steel production of each province. The measurement indicators of carbon quota allocation are shown in Table I.

b. Determination of index weight and initial carbon quota. The entropy method is employed to ascertain the weights of the aforementioned six indicators and amalgamate them into a comprehensive indicator [21].

$$Q_m = \sum_{j=1}^{6}\omega_j q_{mj},\ (m = 1,\cdots,28) \tag{4}$$

where $Q_m$ is the comprehensive carbon emission index of $m-th$ province; $q_{mj}$ is the standardized value of the $j-th$ carbon emission related index in $m-th$ province; $w_j$ is the weight of the $j-th$ carbon emission related index, and the index with large dispersion should be given higher weight. GDP per capita, population, and crude steel production serve as positive indicators, while historical cumulative carbon emissions, carbon intensity, and air pollutant emission intensity act as negative indicators.

The calculation formula of the initial carbon quota of $m-th$ province is

$$C_m = \frac{Q_m}{\sum_{k=1}^{28} Q_m} C_{2030} \tag{5}$$

TABLE I
THE MEASUREMENT INDEX OF CARBON QUOTA ALLOCATION

| Index | Indicator description | Allotment principle |
|---|---|---|
| Per capita GDP | The average per capita GDP of each province during the period from 2014 to 2020 | Fairness |
| Population | Average population of provinces from 2014 to 2020 | Fairness |
| Crude steel capacity | The annual average crude steel production of the iron and steel industry in each province from 2014 to 2020 | Fairness |
| Accumulated carbon emissions | Cumulative carbon emissions attributed to the steel industry across provinces during the period spanning from 2014 to 2020 | Fairness |
| Carbon intensity | The steel sector in each province produces 10,000 tons of crude steel, resulting in the production of carbon dioxide. | Efficiency |
| Air pollutant emission intensity | Emissions of air pollutants (sulfur dioxide, nitrogen oxides, soot) resulting from the production of 10,000 tons of crude steel by the steel sector in each province | Sustainability |

*2) Adjustment of initial carbon quota scheme considering environmental factors*

The carbon quota allocation plan of each province will be significantly influenced by variations in policies and environmental conditions across different provinces. Taking into account environmental factors may enhance the equity of carbon quota allocation, but its impact on the efficiency of inter-provincial allocation remains to be empirically tested. Therefore, we employ the three-stage DEA model to account for the impact of environmental factors on the initial allocation scheme, subsequently facilitating optimization and adjustment of the carbon quota scheme.

a. The first stage: opt for the input-oriented DEA-BBC model to conduct an analysis on initial efficiency.

$$\min \theta - \varepsilon(\hat{e}^T S^- + e^T S^+)$$
$$s.t. \quad \begin{cases} \sum_{m=1}^{28} X_m \lambda_m + S^- = \theta X_0 \\ \sum_{m=1}^{28} Y_m \lambda_m - S^+ = Y_0 \\ \lambda_m \quad 0, S^-, S^+ \quad 0 \end{cases} \tag{6}$$

where $m = (1, \cdots, 28)$ denotes $m-th$ decision making units (DMU); $Y$ is the output variable, that is, the GDP of each province in 2030; $X$ is the input variable, that is, the crude steel output of each province in 2030 and the initial carbon quota. If $\theta=1$, $S^+ = S^- = 0$, the decision-making unit DEA is effective; if $\theta=1$, $S^+ \neq 0$ or $S^- \neq 0$, the DMU is weak DEA efficient; if $\theta < 1$, the DMU is not DEA efficient.

b. The second stage: the performance of DMU is influenced by management inefficiency, environmental factors, and statistical noise; thus, it becomes imperative to disentangle these three effects. The following input-oriented SFA-like regression function is constructed

$$S_{nm} = f(Z_m; \beta_n) + v_{nm} + \mu_{nm}, \ \mathrm{m} = 1, \cdots, 28; \ n = 1, 2 \tag{7}$$

Among them, $S_{nm}$ is the slack variable; $Z_m$ is the environment variable, $\beta_n$ is the coefficient of the environment variable; $f(Z_m; \beta_n)$ represents the influence of external environment variables on the input slack variable $S_{nm}$; $v_{nm} + \mu_{nm}$ is a mixed error term, $v_{nm}$ denotes random interference, and $\mu_{nm}$ denotes management inefficiency. $v \sim N(0, \sigma_v{}^2)$ ; $\mu$ is management inefficiency; $\mu \sim N^+(0, \sigma_\mu{}^2)$, $v_{nm}$ is independent of $\mu_{nm}$.

Reconfigure the input parameters for each province

$$\begin{aligned} X_{nm}^A = X_{nm} + \ & \max\left(f\left(Z_m; \hat{\beta}_n\right)\right) - f\left(Z_m; \hat{\beta}_n\right) \\ & + \max\left(v_{nm}\right) - v_{nm}, \ \mathrm{m}=1, \cdots, 28; \ n = 1, 2, \cdots, N \end{aligned} \tag{8}$$

Among them, $X_{nm}^A$ is the adjusted input; $X_{nm}$ is the input before adjustment; $\max\left(f\left(Z_m; \hat{\beta}_n\right)\right) - f\left(Z_m; \hat{\beta}_n\right)$ is to adjust the external environmental factors; $\max\left(v_{nm}\right) - v_{nm}$ is to put all decision-making units to the same luck level.

c. The third stage: the adjusted input data of the second stage is utilized as the new input variable, while keeping the output variable unchanged. Subsequently, a reevaluation of each decision-making unit's efficiency is conducted.

*3) The adjustment of initial carbon quota scheme based on efficiency optimization*

The principle of efficiency primarily focuses on safeguarding the interests of provinces with high production efficiency and significant potential for emission reduction, thereby predominantly benefiting developed provinces. Three-stage DEA models may alter the total input quantity, while ZSG-DEA model enables continuous optimization without changing the total input quantity, by constantly adjusting the inputs of each DMU to achieve optimal allocation results [22]. It is extensively employed in the efficiency optimization scheme for allocating provincial carbon quotas in China [23]. Therefore, considering the limited disposability, we employ the input-oriented ZSG-DEA model to adjust resource allocation efficiency values and achieve effective distribution of carbon quotas. The input variable represents the initial carbon emission quota of each province in 2030, while the output variables encompass the GDP and crude steel production of each province in 2030. The carbon emission quotas for each province in 2030 are determined through the ZSG-DEA model.

$$min\theta_0$$
$$s.t. \quad \begin{cases} \sum_{m=1}^{28} \lambda_m X_{nm} \quad 1 + \dfrac{X_{n0}\left(1-\theta_0\right)}{\sum_{m\neq 0} h_{nm}} \leq \theta_0 h_{n0} \quad \left(n = 1, \cdots N\right) \\ \sum_{m=1}^{28} \beta_m Y_{jm} \geq Y_{0j} \quad \left(j = 1, \cdots R\right) \\ \sum_{m=1}^{28} \beta_m = 1 \\ \beta_m \geq 0 \quad \left(m = 1, \cdots, 28\right) \end{cases} \tag{9}$$

Among them, $\theta_0$ is the allocation efficiency of the DMU under evaluation when the sum of carbon quotas is fixed; $\beta_m$ is the weight of the $m-th$ DMU in the whole system; $N$ and $R$ represent the number of input variables and output variables, respectively; $x_{n0}$ is the initial carbon quota of $m-th$ province.

After adjustment, the carbon quota allocation value of $m-th$ province is

$$\begin{aligned} X'_{nm} = & \sum_{m\neq 0} \frac{X_{nm}}{\sum_{m\neq 0} X_{nm}} \times h_{0n}\left(1-\theta_0\right) \\ & - X_{nm}\left(1-\theta_{m0}\right) \quad \left(m = 1, \cdots 28\right) \end{aligned} \tag{10}$$

Among them, $X'_{nm}$ refers to the carbon quota adjustment of the $m-th$ DMU after each iteration; $X_{nm}$ refers to the carbon emission quota of $m-th$ province at the beginning of each iteration; $\theta_{m0}$ is the average efficiency value. When $\theta_{m0}=1$, the province is at the forefront of efficiency and the allocation scheme with the best efficiency is obtained.

## IV. Result Analysis

### A. Outcomes of initial carbon quota allocation grounded on the principles of equity, efficiency, and sustainability

In this paper, we employ six indicators, namely per capita GDP, population, crude steel production, historical cumulative carbon emissions, carbon intensity, and air pollutant emission intensity to establish an initial allocation index system for carbon quotas. The weights of the aforementioned six indicators were determined using the entropy method, yielding values of 22.23%, 17.87%, 45.23%, 4.40%, 4.26%, and 6.02% correspondingly. It can be seen that the production of crude steel is the main factor influencing carbon emissions in the steel industry across provinces, while the weights of the latter three indicators are relatively small.

The initial carbon quota of each province is determined based on the total carbon quota in 2030 and the corresponding allocation weight assigned to each province. The GM(1,1) model is utilized to predict the total GDP and crude steel production data for 2030. The simulation relative error and average simulation relative error of most provinces are found to be below 0.1, indicating a high level of accuracy in the predictions within an acceptable range. The estimated total carbon emissions of the steel industry in 2030, based on the overarching objective of achieving carbon peaking, amount to approximately 1,656,711.438 thousand tons as calculated by using (3). Therefore, based on (4) and (5), the initial allocation of carbon quotas for each province can be derived as presented in the second column of Table II. The distribution of initial carbon quotas among provinces is illustrated in Fig. 1, revealing a gradual decline from southeastern to northwestern regions. Notably, Hebei and Jiangsu exhibit the highest initial carbon quotas, surpassing 100 million tons each, aligning with their status as major annual crude steel producers. In order to ensure the stability of future economic development in economically developed areas (such as Guangdong, Shanghai, Zhejiang) and densely populated regions (such as Shandong, Henan), a relatively higher proportion of carbon quotas is allocated. Conversely, sparsely populated areas like Ningxia and Qinghai with lower steel demand and crude steel output receive fewer carbon quotas.

### B. Revising the initial carbon quota allocation through a three-stage DEA model

#### 1) The first stage involves utilizing the traditional DEA model to analyze the initial allocation efficiency

In order to ensure a more equitable distribution of carbon quotas among provinces, we employ a three-stage DEA model to mitigate the influence of environmental factors and random noise on carbon emission efficiency, thereby establishing a level playing field for all provinces within the same external context. initial efficiency values for carbon quota allocation in the first stage across 28 provinces are presented in Table III. According to Table III, only three provinces in China-Zhejiang, Guangdong, and Guizhou - exhibit an initial carbon quota allocation efficiency value of 1. These provinces are positioned on the technological efficiency frontier. The inefficiency of comprehensive technology in various provinces primarily arises from pure technical inefficiencies, while the issue of scale inefficiency is relatively moderate.

#### 2) The second stage involves a SFA-like regression analysis to eliminate confounding environmental factors and statistical noise

The competition among local governments has been recognized as a significant factor in fostering China's economy for long-term, sustained, and rapid growth. The local government's emphasis on the ecological environment during the process of economic development also determines whether China can achieve its goal of carbon peak. In addition, The development trend of urbanization in China's provinces holds significant practical implications for advancing socialist modernization. Hence, we selected local government competition and urbanization level as environmental variable indicators. Among them, the urbanization rate of each province serves as an indicator of the degree of urban development. Additionally, drawing on the research conducted by Miao et al. (2017), the level of economic catch-up is considered a proxy variable for local government competition, implying that provinces strive to surpass neighboring regions and those with higher levels of national economic advancement [24]. The calculation method of the province's economic catch-up level is as follows:

$$LGC=\frac{GDP_1}{GDP}\times\frac{GDP_2}{GDP} \tag{11}$$

Among them, LGC represents the level of economic catch-up; $GDP_1$ represents the highest per capita GDP of neighboring provinces except for this province; $GDP_2$ represents the maximum per capita GDP among provinces in China; GDP represents the per capita GDP of the province.

TABLE II
RESULTS OF THREE CARBON QUOTA ALLOCATION SCHEMES

| Province | Initial carbon quota | Carbon quota adjustment based on three-stage DEA | Initial allocation efficiency | Allocation efficiency after three iterations | Carbon quotas adjustment based on ZSG-DEA model |
|---|---|---|---|---|---|
| Tianjin | 7039.37 | 8027.58 | 0.3098 | 0.9999 | 2921.48 |
| Hebei | 13000.20 | 14056.66 | 1 | 1 | 17949.95 |
| Shanxi | 5644.78 | 6383.63 | 1 | 1 | 7793.99 |
| Inner Mongolia | 4953.41 | 5454.31 | 0.6907 | 0.9999 | 4679.56 |
| Liaoning | 7287.82 | 7942.36 | 0.5519 | 0.9999 | 5441.27 |
| Jilin | 4332.43 | 4633.57 | 0.4608 | 0.9999 | 2717.36 |
| Heilongjiang | 3316.52 | 4042.50 | 0.7827 | 0.9999 | 3568.20 |
| Shanghai | 8016.44 | 9127.92 | 0.4865 | 0.9999 | 5247.82 |
| Jiangsu | 12066.25 | 12993.00 | 0.7388 | 0.9999 | 12061.67 |
| Zhejiang | 7014.53 | 7930.45 | 0.8197 | 0.9999 | 7876.27 |
| Anhui | 5848.25 | 6576.99 | 0.7816 | 0.9999 | 6261.60 |
| Fujian | 6561.79 | 7180.56 | 0.7629 | 0.9999 | 6845.30 |
| Jiangxi | 5186.09 | 6147.49 | 0.6301 | 0.9999 | 4458.33 |
| Shandong | 9239.02 | 9617.34 | 0.5979 | 0.9999 | 7450.61 |
| Henan | 6792.93 | 7365.90 | 0.7412 | 0.9999 | 6876.08 |
| Hubei | 6587.09 | 6897.50 | 0.6483 | 0.9999 | 5811.39 |
| Hunan | 5858.68 | 6504.04 | 0.6931 | 0.9999 | 5544.51 |
| Guangdong | 8713.23 | 9465.30 | 1 | 1 | 12030.73 |
| Guangxi | 5045.39 | 5335.81 | 0.6952 | 0.9999 | 4797.38 |
| Chongqing | 4609.85 | 5713.67 | 0.6874 | 0.9999 | 4336.28 |
| Sichuan | 6107.30 | 6755.19 | 0.8484 | 0.9999 | 7113.01 |
| Guizhou | 2985.49 | 3936.79 | 0.9746 | 0.9999 | 4015.75 |
| Yunnan | 4487.43 | 4487.43 | 0.8081 | 0.9999 | 4980.61 |
| Shaanxi | 4730.11 | 5497.87 | 0.6676 | 0.9999 | 4317.88 |
| Gansu | 3094.43 | 3899.19 | 0.6239 | 0.9999 | 2646.88 |
| Qinghai | 1940.61 | 2679.47 | 0.8663 | 0.9999 | 2317.53 |
| Ningxia | 1678.47 | 2649.65 | 1 | 1 | 2317.53 |
| Xinjiang | 3533.23 | 3965.89 | 0.6796 | 0.9999 | 3292.19 |
| Total | 165671.14 | 185268.09 | / | / | 165671.14 |

Note: The unit of carbon quota is ten thousand tons.

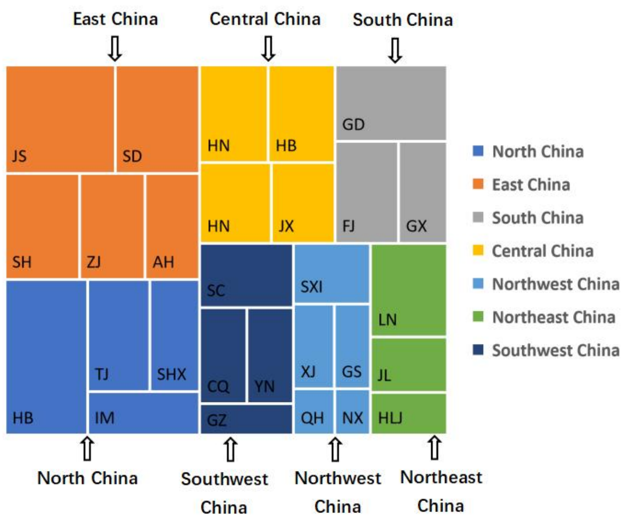


Fig. 1. The proportion of initial carbon quotas in each province (Utilize acronyms to represent the names of each province)

An SFA model is established, with the crude steel production and relaxation variables of initial carbon quotas in 2030 as dependent variables, and local government competition levels and urbanization levels as independent variables. The local government competition levels for each. province in 2030 are calculated based on the average values of this indicator from 2014 to 2020. The urbanization levels are predicted using a GM(1,1) model based on the urbanization rates from 2014 to 2020 for each province. All prediction results have successfully passed residual tests.The verification results of environmental indicators in the second stage SFA model are presented in Table IV, incorporating adjustments to input factors such as crude steel production and carbon emission quotas. Table IV shows that the regression coefficients of the two slack variables of crude steel production and initial carbon quota are significant with the two environmental variables of local government competition and urbanization level. The LR values of the two models are greater than the critical value of the unilateral generalized likelihood ratio test at the 1% level (8.273). These two environmental variables should be considered when adjusting the input value.

Further analysis of the impact of various environmental factors on the coefficients of two types of input redundancy reveals that an increase in urbanization levels and local governments' implementation of policies to outperform neighboring cities in terms of GDP competition will result in an augmentation in crude steel production inputs, while initial carbon quota inputs decrease. This enables provinces to swiftly achieve emission reduction targets while sustaining the development of the steel industry, thereby attaining carbon peak levels.

According to the separation formula proposed by Luo (2012), we have derived the adjusted crude steel output and carbon quota allocation value [25]. The adjusted allocation of carbon quotas can be found in the third column of Table II. The distribution results altered the total amount of original crude steel production and carbon quota.

TABLE III
CARBON QUOTA ALLOCATION EFFICIENCY BASED ON THREE-STAGE DEA MODEL

| Province | The frist stage | | | | The third stage | | | |
|---|---|---|---|---|---|---|---|---|
| | TE | PTE | SE | RS | TE | PTE | SE | RS |
| Tianjin | 0.153 | 0.329 | 0.465 | ris | 0.15 | 0.438 | 0.343 | ris |
| Hebei | 0.181 | 0.259 | 0.696 | ris | 0.182 | 0.305 | 0.595 | ris |
| Shanxi | 0.27 | 0.475 | 0.568 | ris | 0.259 | 0.567 | 0.457 | ris |
| Inner Mongolia | 0.226 | 0.473 | 0.478 | ris | 0.223 | 0.604 | 0.37 | ris |
| Liaoning | 0.197 | 0.358 | 0.55 | ris | 0.196 | 0.447 | 0.439 | ris |
| Jilin | 0.151 | 0.473 | 0.319 | ris | 0.146 | 0.624 | 0.235 | ris |
| Heilongjiang | 0.201 | 0.591 | 0.34 | ris | 0.179 | 0.723 | 0.248 | ris |
| Shanghai | 0.515 | 0.531 | 0.968 | ris | 0.603 | 0.627 | 0.962 | ris |
| Jiangsu | 0.622 | 0.638 | 0.974 | ris | 0.678 | 0.68 | 0.997 | ris |
| Zhejiang | 1 | 1 | 1 | — | 1 | 1 | 1 | — |
| Anhui | 0.603 | 0.748 | 0.806 | ris | 0.618 | 0.804 | 0.769 | ris |
| Fujian | 0.661 | 0.756 | 0.874 | ris | 0.636 | 0.808 | 0.787 | ris |
| Jiangxi | 0.475 | 0.632 | 0.752 | ris | 0.515 | 0.688 | 0.749 | ris |
| Shandong | 0.511 | 0.557 | 0.917 | ris | 0.504 | 0.624 | 0.807 | ris |
| Henan | 0.704 | 0.741 | 0.95 | ris | 0.684 | 0.8 | 0.856 | ris |
| Hubei | 0.553 | 0.645 | 0.858 | ris | 0.527 | 0.74 | 0.712 | ris |
| Hunan | 0.569 | 0.692 | 0.823 | ris | 0.536 | 0.761 | 0.704 | ris |
| Guangdong | 1 | 1 | 1 | — | 1 | 1 | 1 | — |
| Guangxi | 0.349 | 0.571 | 0.611 | ris | 0.358 | 0.714 | 0.501 | ris |
| Chongqing | 0.51 | 0.692 | 0.737 | ris | 0.463 | 0.722 | 0.641 | ris |
| Sichuan | 0.756 | 0.848 | 0.892 | ris | 0.719 | 0.893 | 0.804 | ris |
| Guizhou | 1 | 1 | 1 | — | 0.915 | 1 | 0.915 | ris |
| Yunnan | 0.533 | 0.761 | 0.7 | ris | 0.579 | 0.964 | 0.6 | ris |
| Shaanxi | 0.481 | 0.67 | 0.717 | ris | 0.414 | 0.744 | 0.556 | ris |
| Gansu | 0.228 | 0.68 | 0.335 | ris | 0.36 | 1 | 0.36 | ris |
| Qinghai | 0.159 | 1 | 0.159 | ris | 0.096 | 1 | 0.096 | ris |
| Ningxia | 0.196 | 1 | 0.196 | ris | 0.135 | 1 | 0.135 | ris |
| Xinjiang | 0.343 | 0.684 | 0.502 | ris | 0.321 | 0.841 | 0.382 | ris |
| Mean | 0.470 | 0.672 | 0.685 | / | 0.464 | 0.754 | 0.608 | / |

Note: TE, PTE, SE and SR represent the comprehensive efficiency, pure technical efficiency, scale efficiency and scale return of carbon quota allocation, respectively. $TE = PTE * SE$ . '—' represents constant returns to scale, 'ris' represents increasing returns to scale.

TABLE IV
THE REGRESSION RESULTS OF THE SECOND STAGE SFA MODEL

| | Relaxation variable of input index | |
|---|---|---|
| | The output of crude steel | Initial allocated carbon allowance |
| Intercept | -13475.534** | 1043.4423** |
| | (-249.870) | (76.142) |
| LGC | 12128.572** | -800.50628** |
| | (21.477) | (-38.107) |
| Urbanization level | 9352.3531** | -1416.6628** |
| | (90.556) | (-179.362) |
| Sigma-squared | 154464480** | 3763210.7** |
| | (154449390) | (3763168.3) |
| Gamma | 0.99999999** | 0.99999999** |
| | (357626.71) | (19830771) |
| Log likelihood | -283.06466 | -236.62032 |
| LR test | 15.739 | 8.736 |

** denote statistical significance at the 5% levels.

*3) The third stage involves conducting a DEA efficiency analysis on the adjusted input variables*

Conducting an input-oriented BBC model analysis, utilizing adjusted crude steel production and carbon quota allocation values as independent variables while maintaining a constant dependent variable. Environmental and random factors are eliminated to ensure equal external conditions and luck among all provinces. The results are presented in Table III. Following adjustment, only Zhejiang and Guangdong remain on the efficiency frontier when compared to the DEA efficiency in the first stage. Guizhou's scale efficiency has experienced a slight decline, resulting in its comprehensive efficiency falling short of reaching the efficiency frontier. From the perspective of other provinces, it is commonly observed that there is an increase in pure technical efficiency and a decrease in scale efficiency. This indicates that the pure technical efficiency values of provinces are often underestimated, while the scale efficiency values are frequently overestimated.

### C. The efficiency optimization results of ZSG-DEA model

Utilizing (9), we computed the initial carbon quota allocation efficiency for each province employing the entropy method. The provinces of Hebei, Shanxi, Guangdong, and Ningxia have been identified as the leading regions in terms of DEA efficiency, exhibiting an allocation efficiency score of 1. The initial distribution efficiency of most provinces is relatively low, with Tianjin, Jilin, and Shanghai exhibiting an efficiency level below 0.5. The ZSG-DEA model is employed in this paper to adjust carbon quotas for 28 provinces and regions, aiming to enhance the allocation efficiency of each province towards a value close to 1 while maintaining the total amount of carbon quotas unchanged throughout the iterative process. After three iterations, the carbon quota allocation results for 28 provinces have reached a relatively optimal state, as evidenced in the sixth column of Table II. According to the findings presented in Table II, there has been an increase in the carbon quota allocation for the steel industry in 13 regions with higher initial efficiency of allocation, such as Hebei, Shanxi, and Heilongjiang. Conversely, a decrease in the carbon quota allocation has been observed for 15 regions with lower initial efficiency of allocation, including Tianjin, Inner Mongolia, and Liaoning. The ZSG-DEA model enhances allocation efficiency by allocating more carbon quotas to regions with higher initial allocation efficiency, particularly the four regions with an initial allocation efficiency of 1, which receive additional increments in carbon quotas. Conversely, regions with lower initial allocation efficiency experience a reduction in their carbon quotas.

### *D. The outcomes of three carbon quota allocation schemes*

According to the findings from Table II, the carbon quota allocation schemes reveal that steel industries in Hebei, Jiangsu, and Guangdong regions have been allocated a larger proportion of carbon quotas compared to Qinghai, Ningxia, and other regions. Hebei and Jiangsu provinces, as the largest steel producers in China, have been allocated a larger carbon quota. However, their steel industry also ranks high in terms of carbon dioxide emissions, which inevitably places greater responsibility on them for reducing carbon emissions. The average carbon quotas for the steel industry in the eastern, central, and western regions under the three scenarios are illustrated in Fig. 2. It is evident that there is a gradual decrease in carbon quotas for the steel industry from east to west. In addition, the distribution results of Qinghai and Ningxia under the three schemes are similar.

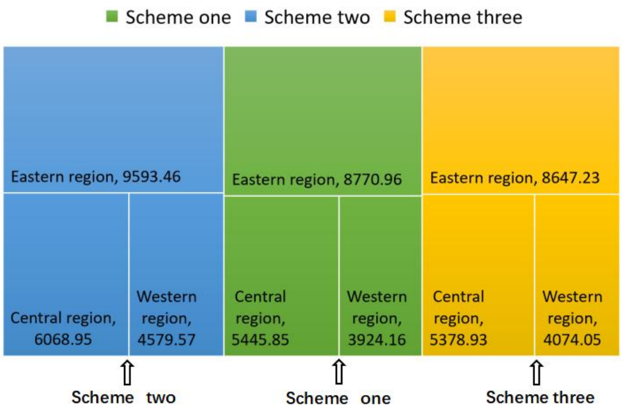


Fig. 2. The average carbon quotas under the three allocation schemes in the eastern, central, and western regions

The target carbon emission reductions for the steel industry in each province under three different carbon quota allocation schemes are presented in Table V. Additionally, a GM(1,1) model is employed to predict the carbon emissions of the steel industry in each province for 2030, with residual tests confirming the accuracy of these predictions. If the target carbon emission reduction in Table V is a positive value, it indicates the necessity to mitigate an equivalent amount of carbon emissions; conversely, if the target carbon emission reduction is a negative value, it implies the potential for increasing the corresponding amount of carbon emissions. The three allocation schemes collectively indicate that the steel industry of Hebei and Inner Mongolia exhibits the highest target carbon emission reductions, followed by Jiangsu, Shandong, and Guangdong. In the event that these provinces' steel industry fails to attain a harmonious balance between economy and environment, they may need to procure carbon quotas from other provinces with surplus quotas, thereby assuming the role of buyers in the carbon trading market. Conversely, regions such as Shanghai and Henan, which possess negative target values for carbon reduction, indicate that their steel industry is more likely to easily accomplish the 2030 emission reduction target and potentially become sellers of carbon quotas in the carbon trading market.

TABLE V
THE TARGET CARBON EMISSION REDUCTIONS OF PROVINCES IN THE THREE ALLOCATION SCHEMES

| Province | Carbon emissions in 2030 | Target carbon emissions reduction | | |
|---|---|---|---|---|
| | | Initial carbon quota | Carbon quota adjustment based on three-stage DEA | Carbon quotas adjustment based on ZSG-DEA model |
| Tianjin | 3206.53 | -3832.74 | -4820.96 | 285.15 |
| Hebei | 43349.32 | 30349.11 | 29292.66 | 25399.37 |
| Shanxi | 11890.57 | 6245.79 | 5506.94 | 4096.59 |
| Inner Mongolia | 39825.99 | 34872.58 | 34371.68 | 35146.43 |
| Liaoning | 15372.04 | 8084.21 | 7429.67 | 9930.77 |
| Jilin | 2373.05 | -1959.39 | -2260.52 | -344.32 |
| Heilongjiang | 5119.77 | 1803.24 | 1077.26 | 1551.57 |
| Shanghai | 2312.19 | -5704.25 | -6815.73 | -2935.63 |
| Jiangsu | 25941.23 | 13874.97 | 12948.23 | 13879.56 |
| Zhejiang | 5748.81 | -1265.71 | -2181.64 | -2127.46 |
| Anhui | 7540.04 | 1691.79 | 963.05 | 1278.45 |
| Fujian | 7208.57 | 646.79 | 28.01 | 363.27 |
| Jiangxi | 4989.93 | -196.16 | -1157.56 | 531.60 |
| Shandong | 22317.52 | 13078.51 | 12700.18 | 14866.91 |
| Henan | 3522.96 | -3269.97 | -3842.94 | -3353.12 |
| Hubei | 4610.29 | -1976.80 | -2287.22 | -1201.10 |
| Hunan | 4449.52 | -1409.16 | -2054.53 | -1095.00 |
| Guangdong | 21925.60 | 13212.37 | 12460.30 | 9894.87 |
| Guangxi | 8892.62 | 3847.23 | 3556.81 | 4095.24 |
| Chongqing | 2401.05 | -2208.80 | -3312.61 | -1935.23 |
| Sichuan | 4653.41 | -1453.90 | -2101.79 | -2459.60 |
| Guizhou | 2814.57 | -170.92 | -1122.22 | -1201.18 |
| Yunnan | 10613.12 | 6125.69 | 6125.69 | 5632.51 |
| Shaanxi | 3722.58 | -1007.53 | -1775.30 | -595.30 |
| Gansu | 2718.69 | -375.74 | -1180.50 | 71.82 |
| Qinghai | 1399.57 | -541.05 | -1279.91 | -917.97 |
| Ningxia | 10336.58 | 8658.11 | 7686.93 | 8019.05 |
| Xinjiang | 11013.33 | 7480.10 | 7047.44 | 7721.13 |

Note: The unit of carbon quota is ten thousand tons.

## V. CONCLUSION AND SUGGESTIONS

In this paper,We address the research gap by proposing three carbon quota allocation schemes for the steel industry in different provinces of China, aligned with the 2030 carbon peak target. Firstly, an initial carbon quota allocation scheme is derived using the entropy method, considering fairness, efficiency, and sustainability principles. Secondly, a three-stage DEA model is employed to eliminate environmental factors and random noise from the initial allocation scheme. Lastly, by utilizing the ZSG-DEA model, each province's steel industry can improve its carbon quota allocation efficiency to reach the efficiency frontier based on the initial allocation scheme. The study found that：

1) The initial carbon quota allocation scheme assigns the initial carbon quotas for each province based primarily on crude steel production. The allocation of carbon quotas is higher for the steel industry in economically developed and densely populated regions. Carbon quotas gradually decreased from the southeast to the northwest.
2) Considering the competition among local governments and the level of urbanization can effectively optimize the initial allocation scheme for carbon quotas. The level of urbanization and the improvement of provinces' awareness of competition for neighboring provinces will lead to an increase in crude steel production input, while the initial carbon quota input will be reduced.
3) The allocation scheme based on the ZSG-DEA model can be summarized as follows: regions with higher initial allocation efficiency in the steel industry will receive a greater number of carbon quotas, while regions with lower initial allocation efficiency will receive a reduced number of carbon quotas.
4) The three allocation schemes all demonstrate a decreasing trend in the average carbon quota of the steel industry from the eastern region to the western region. This suggests that in the process of carbon quota allocation in each province, crude steel production, economic development trend, historical emission responsibility and so on will have an appropriate impact.
5) The results of the three allocation schemes indicate that provinces with larger carbon reduction targets, such as Hebei, Inner Mongolia, and Jiangsu, may purchase carbon quotas from other provinces that have a surplus. On the other hand, industries like steel in Shanghai and Henan are predicted to have lower carbon emissions than their allocated quotas, potentially becoming sources of carbon quota outflow in the future.

The three allocation schemes each possess their own respective advantages in general. Although the initial allocation scheme can equitably distribute carbon quotas for China's steel industry among provinces, it rigidly constrains their economic development trajectories and capacities, thereby impeding the impetus for growth in certain underdeveloped regions. Moreover, a majority of regions have not yet attained the efficiency frontier with regards to allocation effectiveness. By excluding environmental variables and random noise from the initial allocation schemes, it is shown that the carbon quota allocation results for each province no longer solely depend on their current level of development. This encourages provinces to strive for economic catch-up. However, the allocation scheme based on the three-stage DEA model will modify the initial input of crude steel production and carbon quotas for each province, potentially leading to an increase in costs associated with emission reduction. The allocation scheme based on the ZSG-DEA model can enhance the efficiency of carbon quota distribution among provinces while maintaining the total amount of crude steel production and carbon quotas unchanged. However, this distribution plan exhibits greater advantages for regions with higher levels of economic development. Therefore, the Chinese government can promptly adjust the carbon quota allocation scheme for the steel industry based on factors such as the anticipated development trends of each province.

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