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Comprehensive Evaluation of Carbon Emission Permits Allocation: Evidence From 30 Provinces in China

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Abstract
The initial allocation of inter-provincial carbon allowances based on total control is a realistic way to achieve carbon emission reduction in China. In order to evaluate different distribution methods, the most important thing is to weigh the fairness and efficiency. This paper focuses on the common carbon allowance allocation methods in the centralized, and then measures from the four dimensions of cost, DEA efficiency, personal will, and fairness. Finally, TOPSIS is used to construct a comprehensive evaluation system to sort the various distribution schemes. The comprehensive evaluation results show that the comprehensive evaluation of the Nash negotiation method is the highest, and the comprehensive evaluation based on the GDP allocation method is the worst.

Key words: Carbon emission quota allocation; Abatement cost; DEA efficiency; Individual willing; Carbon Gini coefficient; Topsis

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INTRODUCTION

Greenhouse gas emissions and other anthropogenic drivers have become the main cause of climate warming since the mid-20th century (IPCC, 2014). Therefore, priority should be given to controlling carbon dioxide emissions to mitigate the effects of global greenhouse gases (Schuur et al.,2015). As the world's largest developing country and the world's largest energy consumer and carbon emitter, China's emission reduction actions are of great significance (Jiang et al. ,2017).

During the "Thirteenth Five-Year Plan" period (2016-2020), China pledged to reduce its carbon dioxide emissions per unit of GDP by 18% by 2020 (The State Council, 2016). A more feasible way to achieve this goal is to convert the intensity target into a total target in stages, and then decompose the total target into each region (Schuur et al.,2015). There are obvious differences in the economic level, technical level, economic structure, and natural environmental conditions of various provinces and cities in China, which leads to different emission reduction potentials that can be achieved by various provinces, municipalities, and autonomous regions. How to allocate carbon emission rights reasonably and effectively in all provinces, municipalities and autonomous regions becomes crucial (An et al.,2017).

The issue of carbon dioxide quota allocation has been widely studied academically. Many scholars have done a lot of research on carbon allocation methods, including index method, optimization method, game theory, and hybrid method (Zhou et al., 2016). Each method has its own advantages and disadvantages, and its selection criteria are not the same. Redistribution, all countries have an efficiency of 1 after allocation. At the national level, Li et al (2017) used the Nash negotiation model to analyze the reduction path of the Pearl River Delta. Pan et al (2014) proposed fairness in global carbon allocation based on the allocation of cumulative emissions per capita. Lin (2011) used the ZSG-DEA model to evaluate the EU's 2009 carbon allowance allocation results. At the provincial level, Zhang (2014) combines Shapley values with information entropy to allocate carbon allowances in different parts of China. The results show that the region has higher GDP and higher carbon allowances, which gives a certain advantage over the benchmark method and grandfather method. Liu (2017) builds a cost-based model that allocates quotas in consideration of marginal abatement costs.

The rest of the paper is organized as follows: Section 2 introduces the single indicator method, the comprehensive indicator method, the minimization of abatement costs and Nash negotiation. Section 3 gives the distribution results of different provinces in China under different distribution schemes. In Section 4, the distribution plan under the comprehensive evaluation index system is ranked. The last section is a summary.

1. METHODOLOGY

1.1 Single indicator Allocation Method

To thinking the imbalance between China's provinces and cities, and better embodying the principle of "common but differentiated responsibility", this study selects the population, GDP, and historical carbon dioxide emissions to represent the principles of equality, efficiency, and feasibility. The specific principles and indicators are shown in Table 1.

Table 1
Allocation Principle and Indicator Selection

Principle	Indicator	Description
Equality	Population	Equal allocation per capita ,so the population lager, the co2 emission quotas greater
Efficiency	GDP	co2 emission quotas are allocated in proportion to GDP
Feasibility	Historical co2 emission	co2 emission quotas are allocated in proportion to the Historical co2 emission

According to the "13th Five-Year Plan" (2016 - 2020), the Chinese government plans to reduce carbon dioxide emissions per unit of GDP by 18% compared to 2015 by 2020.

The carbon intensity CI_t of the t-year is defined as:

$$CI_t = \frac{Q_t}{GDP_t} \quad (1)$$

Among them, Q_t and GDP_t are the carbon dioxide emissions and GDP of t years respectively.

In the study, the carbon intensity of the provinces during the 13th Five-Year Plan period decreased by 18%. Therefore, the national carbon dioxide emission quota $Q_{2020}$and the CO_2 incremental quota ΔQ in 2020 can be calculated as:

$$Q_{2020} = (1-18\%)CI_{2015}GDP_{2020} \quad (2)$$

$$\Delta Q = Q_{2020} - Q_{2015} \quad (3)$$

Therefore, when using the single indicator method, according to the population of a single indicator, GDP or historical carbon dioxide emissions, taking into account the timeliness of the proportion of the corresponding indicators, using the 2005-2015 data for nearly five years (2011- 2015) is measured by the percentage data. Therefore, the incremental carbon dioxide emission quotas for provinces and cities from 2015 to 2020 can be calculated using equations (4) -(6)

$$\Delta Q_{i1} = \frac{\sum_{t=2011}^{2015} P_i(t)}{\sum_{i=1}^{30}\sum_{t=2011}^{2015} P_i(\mathrm{t})} \times \Delta Q \quad (4)$$

Where represents the population of the province in the t-th year

$$\Delta Q_{i2} = \frac{\sum_{t=2011}^{2015} \mathrm{GDP}_i(t)}{\sum_{i=1}^{30}\sum_{t=2011}^{2015} GDP_i(\mathrm{t})} \times \Delta Q \quad (5)$$

represents the gross domestic product of the province in the t-th year

$$\Delta Q_{i3} = \frac{\sum_{t=2011}^{2015} Q_i(t)}{\sum_{i=1}^{30}\sum_{t=2011}^{2015} Q_i(\mathrm{t})} \times \Delta Q \quad (6)$$

Where represents the historical CO_2 emissions of provinces and cities in the t-th year

The gray system model is characterized by less sample, high accuracy, and stability when predicted data(Ren et al, 2016). Therefore, when predicting the carbon emissions of provinces and cities in 2020, the gray prediction model (GM(1,1)) is used for prediction. The specific steps of GM(1,1) can be borrowed from the work (Ye et al2018). The average percentage absolute error $MAPE_i$ of each participant can be calculated by the following formula (7):

$$2MAPE_i = \frac{1}{n}\sum_{j=1}^{n}\left|\frac{Q_i^{(0)}(\mathrm{j}) - Q_i^{(2)}(\mathrm{j})}{Q_i^{(0)}(\mathrm{j})}\right| \times 100\% \quad (7)$$

where and are the original sequence and forecast set, respectively. In addition, when<10%, the prediction has high accuracy (Lewis, 1982).

1.2 Composite Indicator Method

The single indicator approach cannot integrate different allocation criteria, taking into account the different realities of the provinces and cities. Therefore, this study constructs a comprehensive indicator containing the principle of equality (represented by population indicators), efficiency (represented by GDP indicators) and feasibility (represented by historical CO_2 emission indicators), and uses information entropy to assign weights to each single index.

According to information entropy（IE）, this paper firstly determines the decision matrix Z for the distribution of three single indicators in 30 provinces and cities, namely:

$$X = \left(X_{ij}\right)_{30\times 3}, i = 1,2,3,\cdots,30 ,; j = 1,2,3$$

$$Z = \begin{vmatrix} X_{11} & X_{12} & X_{13} \\ X_{21} & X_{22} & X_{23} \\ \vdots & \vdots & \vdots \\ X_{301} & X_{302} & X_{303} \end{vmatrix} \quad (8)$$

The increment represents the indicator value of the 2020 provincial city i of the indicator j of the three single indicator allocations.

In order to facilitate comparison, the decision matrix is standardized. Since the above three indicators are positive indicators, the larger the value, the better. Therefore, the standardized formula is:

$$Y_{ij} = \frac{X_{ij} - minX_{ij}}{maxX_{ij} - minX_{ij}} \quad (9)$$

Y_{ij} represents the normalized value of the province i of the index j of the three single indicator assignments, and max X_{ij} and min X_{ij} represent the maximum and minimum values of the index j, respectively.

Therefore, the matrix Y after standardization is:

$$Y = \begin{vmatrix} Y_{11} & Y_{12} & Y_{13} \\ Y_{21} & Y_{22} & Y_{23} \\ \vdots & \vdots & \vdots \\ Y_{301} & Y_{302} & Y_{303} \end{vmatrix} \quad (10)$$

Thus, the ratio of the indicator j of the province i is:

$$P_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{30} Y_{ij}} \quad (11)$$

The entropy value of the index j can be calculated by the following formula (12):

$$e_j = \frac{1}{\ln n} \sum_{i=1}^{30} P_{ij} \ln P_{ij} \quad (12)$$

Where n is the sum of all provinces and cities, where n=30.

The final information entropy weight value of the index j is calculated by the formula (13)

$$w_j = \frac{1-e_j}{\sum_{j=1}^{3} 1-e_j} \quad (13)$$

Where $0 \ll w_j \leq 1$, $\sum_{j=1}^{3} w_j = 1$, the smaller the information entropy value, the greater the weight of the indicator.

The carbon credits of provinces and cities in 2020 are:

$$Q_{i2020} = \sum_{j=1}^{3} P_{ij}\, w_j \times Q_{2020} \quad (14)$$

1.3 Minimize Abatement Costs (MAC)

The marginal abatement cost of carbon dioxide is the cost of additionally reducing one unit of carbon dioxide. As the proportion of emission reduction increases, the difficulty of reducing emissions increases. Therefore, the marginal abatement cost has an increasing feature, while the marginal abatement cost curve It depicts the marginal abatement costs under different emission reduction ratios. This study selects the classic logarithmic form proposed by the famous economist Nordhaus. As follows:

$$\mathrm{MC(R)} = \alpha + \beta \ln(1 - R) \quad (15)$$

Where MC is the marginal abatement cost, and R is the emission reduction ratio. This paper follows the research of Fan et al. (2016) who estimated the MAC of China in 2020.As follows:

$$MAC_{2020} = -679.63\ln(1 - R) \quad (16)$$

The GDP indices from 2003 to 2005 were 114.8, 114.8 and 113.8 (NBSC, 2017) respectively. The MAC of China's constant price index in 2005 was equation (17):

$$MAC_{i2020} = -453.15\ln(1 - R_{i2020}) \quad (17)$$

Under the condition of satisfying the total carbon quota constraint, this paper selects the appropriate emission reduction quotas of each province and city to minimize the national abatement cost. The model for minimizing abatement costs is as follows:

$$\mathrm{minTC} = \min \sum_i \left\{ -\beta[E_i(1-r_i) - A_i] \ln\left(1 - \frac{A_i}{E_i(1-r_i)}\right) - \beta A_i \right\} \quad \text{s.t.}$$

$$\sum A_i = \bar{A} \quad A_i > 0, i = 1,2,3,\cdots, 30 \quad (18)$$

Where TC is the total cost of national carbon dioxide emission reduction; is the emission reduction of the i-th province, which is the decision-making variable; is the national total emission reduction. By solving the above planning model, the optimal allocation plan of the national emission reduction targets in each province can be obtained, thereby minimizing the national abatement cost.

1.4 Nash Negotiation (NN)

With the implementation of the Tokyo Agreement, carbon emission rights have become a scarce resource that can be traded (Jiang, 2017). Economic growth and emissions are incompatible, and economic growth will inevitably lead to an increase in carbon dioxide. To study the relationship between economic growth and carbon emissions, the environmental Kuznets curve (EKC curve) is widely used in academia (Dinda, 2004). Natural logarithm can reduce volatility and linearize its trend without changing the original integration relationship (Li, 2016), so this paper uses the natural logarithmic form of EKC. From a personal point of view, every participant with high GDP wants to expand its carbon assets through its contribution to the economy (Zhou, 2017). Since promoting economic growth is China's top priority, a rational distribution method should be established on the principle of economic activity. In order to reflect the negotiation process between different participants, this paper uses the Nash negotiation model (Vartiainen, 2007; Zhang, 1995) and chooses GDP as the weight indicator. The Nash negotiation model is a non-union cooperation game that can reflect the fairness of the negotiation process. At the same time, it ensures that each participant's profits are better after negotiation (Yu, 2017) so that each participant is willing to join the negotiations. Since p is an exogenous variable and carbon allowances are risk neutral, maximizing incremental quotas is equivalent to maximizing carbon assets. The asset-oriented model (AM) is expressed as equation (19).

$$.Max\ \prod_{i=1}^{n}(Q_{i2020}-Q_{i2020}^{l})^{w_i} \quad (19)$$

$$s.t.\ \ \sum_{i=1}^{n} Q_{i2020} \le Q_{2020}$$

$$Q_{i2020}^{l} \le Q_{i2020} \le Q_{i2020}^{u}$$

$$\sum_{i=1}^{n} w_i = 1$$

$$w_i = \frac{GDP_{i2020}}{\sum_{i=1}^{n} GDP_{i2020}}$$

where represents the bargaining power (weight) of participant .

2. EMPIRICAL WORK

2.1 Data Description

The GDP, population, carbon dioxide emissions, and energy consumption of the provinces and districts from 2005 to 2015 were selected. The relevant data were obtained from the China Statistical Yearbook and the China Energy Statistics Yearbook. Based on 2005, the GDP of each province is converted into GDP under the constant price of 2005 according to the GDP production index. In addition, the data of carbon dioxide emissions refer to the work (Shan, et al, 2018). Lacking of data in the Tibet Autonomous Region, 30 provinces and autonomous regions in mainland China were selected to participate in the calculation and distribution.

For input and output data of data envelopment analysis, capital stock, population, energy consumption, gross domestic product, and carbon dioxide emissions are selected. The capital stock is calculated by the calculation method of the perpetual inventory method adopted by Zhang Jun et al. (2010), in which the total fixed capital formation of each province comes from the China Statistical Yearbook.

The allocation of carbon emissions in 2020 requires the prediction of relevant data for 2020. According to the 13th Five-Year Plan Document (2016-2020), the Chinese government plans to reduce its carbon dioxide emissions per unit of GDP by 18% from 2015 by 2020.

According to the "13th Five-Year" GDP growth target proposed by the provinces, the GDP in 2020 is predicted. Song Ding (2017) used the gray model's non-gray model to predict China's carbon emissions. The comparative analysis of the two models predicted that the gray model is more suitable for carbon emission prediction. Based on the 2005-2015 CO_2 emissions data, a grayscale model is used to predict CO_2 emissions in each province and region by 2020. This paper assumes that the population, capital stock, energy consumption and other indicators are generally consistent with the previous changes, according to the average growth rate, recursively get the 2020 value.

2.2. Results and Discussion

According to China's "13th Five-Year Plan" goal, the total carbon allowance for 2020 is 13660.97 million tons of standard coal. The distribution results under different allocation schemes are outlined in Table 3.

Among the distribution results of single indicators, based on population distribution, Guangdong Province has the highest distribution share, accounting for 7.89%, and Qinghai has the lowest distribution share, only 0.43%. In the distribution based on population indicators, more carbon dioxide quotas are allocated in places with large populations. Among the distribution based on GDP, Jiangsu has the highest distribution share of 9.44% and Qinghai has the lowest share of 0.29%. Among the distribution of historical carbon dioxide emissions, Shanxi Province has the largest share of 11.06%. Shanxi Province is a large coal province with high carbon dioxide emissions. Hainan's distribution ratio is only 0.51%, with the lowest distribution share.

Table 2
Relevant Forecast Data for Various Provinces and Regions in 2020

Province	GDP (billion yuan)	CO_2 emissions (tons)	Capital stock (billion yuan)	Population	Energy consumption (tons of standard coal equivalent)
Beijing	23289.7	91.60	15595.7	23.8	76.3
Tianjin	21037.2	172.19	8228.7	18.3	124.1
Hebei	36959.9	793.79	22979.1	76.6	368.3
Shanxi	13961.8	1398.28	8285.3	37.5	248.5
Inner mongolia	20271.8	935.51	5474.0	25.5	259.3
Liaoning	30016.2	627.81	15938.7	43.8	285.3
Jilin	15515.5	297.69	7371.5	27.6	109.0
Heilongjiang	19360.1	446.63	11833.0	37.8	153.0
Shanghai	30534.1	196.58	22526.6	25.0	132.2
Jiangsu	78267.7	834.66	39312.5	80.7	407.3
Zhejiang	48890.5	452.78	27088.4	56.4	245.2
Anhui	25246.0	468.05	11771.7	63.7	175.3
Fujian	31420.3	289.93	14371.6	39.9	173.8
Jiangxi	18615.3	213.94	7784.6	46.6	119.4
Shandong	76961.2	1252.83	39878.1	101.2	467.1
Henan	45195.1	748.05	20735.0	96.0	290.2
Hubei	32021.0	327.12	17613.3	59.7	216.7
Hunan	30943.4	334.44	18389.7	70.2	202.1
Guangdong	84651.6	730.79	38652.8	112.9	385.6
Guangxi	18129.0	243.06	8058.0	49.9	140.7
Hainan	3693.1	60.60	2574.1	9.5	29.7
Chongqing	18133.5	187.80	5703.9	31.4	124.9
Sichuan	32822.5	421.21	12522.9	84.0	267.9
Guizhou	10402.7	358.04	5623.4	36.1	135.2
Yunnan	15402.2	236.87	9043.6	48.8	149.4
Shaanxi	18230.8	597.18	11103.3	38.6	172.2
Gansu	7797.3	209.00	4160.5	26.4	103.6
Qinghai	2410.6	61.61	2068.2	6.1	68.6
Ningxia	2530.0	206.71	2030.1	7.1	78.5
Xinjiang	10056.2	466.22	8487.2	25.6	293.1

Table 3
Allocation Results Using the Single Indicators Method

Province	Population indicator		GDP indicator		CO_2 emission indicator	
	Q_{2020}	Proportions	Q_{2020}	Proportions	Q_{2020}	Proportions
Beijing	212.65	1.56%	413.74	3.03%	110.58	0.81%
Tianjin	147.57	1.08%	322.38	2.36%	166.02	1.22%
Hebei	740.91	5.42%	641.57	4.70%	783.64	5.74%
Shanxi	366.64	2.68%	262.45	1.92%	1511.55	11.06%
Inner mongolia	252.26	1.85%	337.46	2.47%	1001.83	7.33%
Liaoning	443.21	3.24%	562.84	4.12%	644.44	4.72%
Jilin	277.96	2.03%	275.63	2.02%	300.13	2.20%
Heilongjiang	386.88	2.83%	356.75	2.61%	451.33	3.30%
Shanghai	242.14	1.77%	543.53	3.98%	206.27	1.51%
Jiangsu	802.03	5.87%	1289.75	9.44%	768.75	5.63%
Zhejiang	555.34	4.07%	838.76	6.14%	475.05	3.48%
Anhui	610.44	4.47%	393.51	2.88%	455.56	3.33%
Fujian	381.61	2.79%	486.59	3.56%	266.94	1.95%
Jiangxi	457.09	3.35%	289.39	2.12%	194.02	1.42%
Shandong	983.83	7.20%	1273.42	9.32%	1224.03	8.96%
Henan	952.14	6.97%	729.34	5.34%	710.33	5.20%
Hubei	586.02	4.29%	486.94	3.56%	341.90	2.50%
Hunan	675.77	4.95%	483.32	3.54%	323.98	2.37%
Guangdong	1077.25	7.89%	1448.96	10.61%	621.78	4.55%
Guangxi	476.76	3.49%	298.82	2.19%	224.29	1.64%
Hainan	90.39	0.66%	62.70	0.46%	69.72	0.51%
Chongqing	299.88	2.20%	255.58	1.87%	178.39	1.31%
Sichuan	819.87	6.00%	553.86	4.05%	374.35	2.74%
Guizhou	353.44	2.59%	146.90	1.08%	373.03	2.73%
Yunnan	473.45	3.47%	239.85	1.76%	232.43	1.70%
Shaanxi	380.42	2.78%	290.87	2.13%	623.79	4.57%
Gansu	260.93	1.91%	127.78	0.94%	216.84	1.59%
Qinghai	58.41	0.43%	39.44	0.29%	75.06	0.55%
Ningxia	66.08	0.48%	41.88	0.31%	235.03	1.72%
Xinjiang	229.61	1.68%	166.99	1.22%	499.88	3.66%
Total	13660.97	100%	13660.97	100%	13660.97	100%

Table 4
Allocation Results Using the Latter Three Method

Province	IE		MAC		NN	
	Q_{2020}	Proportions	Q_{2020}	Proportions	Q_{2020}	Proportions
Beijing	211.26	1.5%	89.96	0.7%	91.60	0.7%
Tianjin	180.19	1.3%	223.28	1.6%	172.19	1.3%
Hebei	761.58	5.6%	754.49	5.5%	793.79	5.8%
Shanxi	820.98	6.0%	1229.66	9.0%	1398.28	10.2%
Inner mongolia	588.83	4.3%	931.44	6.8%	935.51	6.8%
Liaoning	577.13	4.2%	556.91	4.1%	627.81	4.6%
Jilin	261.83	1.9%	275.38	2.0%	297.69	2.2%
Heilongjiang	394.06	2.9%	440.47	3.2%	446.63	3.3%
Shanghai	313.20	2.3%	189.74	1.4%	196.58	1.4%
Jiangsu	1025.68	7.5%	812.98	6.0%	834.66	6.1%
Zhejiang	643.97	4.7%	430.14	3.1%	452.78	3.3%
Anhui	479.44	3.5%	559.91	4.1%	468.05	3.4%
Fujian	361.16	2.6%	336.60	2.5%	289.93	2.1%
Jiangxi	275.62	2.0%	221.45	1.6%	213.94	1.6%
Shandong	1277.38	9.4%	1153.99	8.4%	1252.83	9.2%
Henan	828.59	6.1%	717.78	5.3%	748.05	5.5%
Hubei	457.81	3.4%	309.08	2.3%	327.12	2.4%
Hunan	476.25	3.5%	314.92	2.3%	334.44	2.4%
Guangdong	1107.62	8.1%	705.71	5.2%	730.79	5.3%
Guangxi	298.78	2.2%	359.01	2.6%	243.06	1.8%
Hainan	18.94	0.1%	92.03	0.7%	60.60	0.4%
Chongqing	206.88	1.5%	187.00	1.4%	187.80	1.4%
Sichuan	570.59	4.2%	420.95	3.1%	421.21	3.1%
Guizhou	267.50	2.0%	378.77	2.8%	358.04	2.6%
Yunnan	278.46	2.0%	217.22	1.6%	236.87	1.7%
Shaanxi	442.90	3.2%	816.84	6.0%	597.18	4.4%
Gansu	162.22	1.2%	211.59	1.5%	209.00	1.5%
Qinghai	2.36	0.0%	109.69	0.8%	61.61	0.5%
Ningxia	76.57	0.6%	191.20	1.4%	206.71	1.5%
Xinjiang	293.17	2.1%	422.80	3.1%	466.22	3.4%
Total	13660.97	100%	13660.97	100%	13660.97	100%

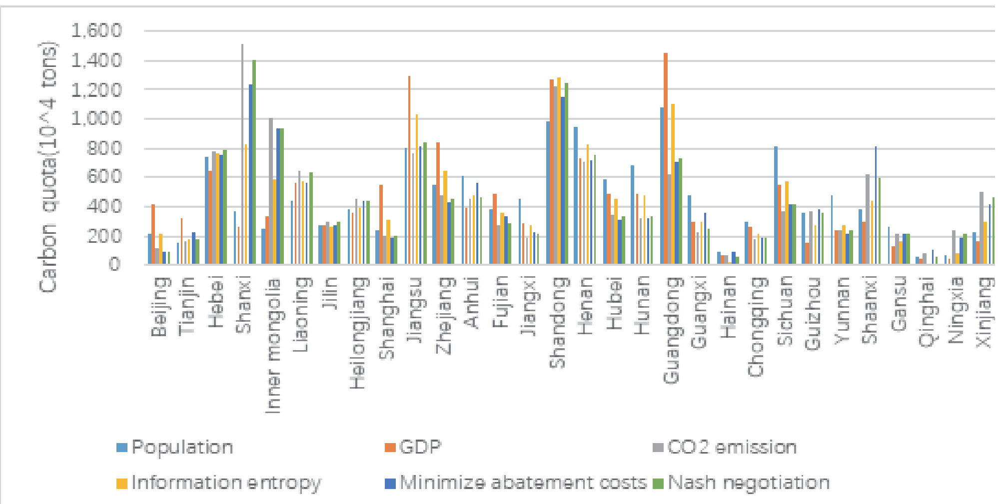

Figure 1
Distribution results under six distribution methods

In the distribution based on information entropy, this paper weights the three indicators (population, GDP, historical carbon dioxide emissions) in the single indicator allocation, and then implements the distribution. The distribution results show that the distribution of Shandong Province and Guangdong Province ranks first and second, and the distribution of Qinghai is the least. The distribution based on information entropy is different from the distribution result of a single indicator because it takes into account various factors. Among the cost-based allocations, Shanxi Province has the most quotas, accounting for 9.0%. Hainan and Beijing accounted for the least, at 0.7%. Due to the large emission reductions in Shanxi Province, the cost of abatement is large. In order to ensure the country's total abatement costs are the smallest, provinces and cities with larger abatement costs allocate more shares. According to calculations, Shanxi Province has the largest abatement cost, which is 51,766.40yuan / ton, so Shanxi Province has the most carbon allowance. In the distribution based on Nash negotiations, Shanxi and Shandong provinces have more carbon allowances, and Hainan Qinghai has fewer carbon allowances.

The final results of the distribution based on the six distribution methods are shown in Figure 1. There are significant differences in carbon allowances among the six provinces and cities under the six allocation schemes. Taking Beijing as an example, it allocates more according to the GDP indicator, and the carbon allowance based on the optimal cost and Nash negotiation is less.

3. COMPREHENSIVE EVALUATION

In this part, the four indicators of abatement cost, efficiency, individual will, and fairness are selected to measure the results of the above scheme. The TOPSIS method is used to sort the schemes, and the advantages and disadvantages are compared.

3.1. Indicator Measure

In order to measure the cost of abatement and personal will, it is only necessary to bring the final allocation result to the relevant abatement cost equation and the Nash negotiation model.

The initial generation of the Lorenz curve was developed by scholars based on the question of whether the distribution between population and income was fair, and the curve was drawn according to the corresponding rules. Compared to the absolute fair line, observe the degree of curvature of the curve to determine whether the income distribution relationship is equal. The Gini coefficient is defined as: the area between the plotted income distribution curve and the assigned absolute fairness curve is A, and the area of the lower right area of the plotted income distribution curve is B. The quotient of dividing A by (A+B) indicates the degree of unfairness. For the Gini coefficient measurement, the value is: the value of the Gini coefficient is less than 0.2, indicating that the income is absolutely fair, 0.2-0.3 means the income is relatively average, 0.3-0.4 means the income is relatively fair, 0.4-0.5 means the income gap is larger, more than 0.5 Explain that the income gap is very different

In order to examine the inter-provincial fairness of the distribution results, the Gini coefficient is used for measurement. The Gini coefficient is an indicator of the fairness of income distribution according to the Lorenz curve. This paper uses the Carbon-Gini coefficient to measure the fairness of carbon quota allocation. In this paper, the per capita carbon emissions are used as the basis for the Lorenz curve. The cumulative population ratio and cumulative carbon emissions ratio are taken as the horizontal and vertical coordinates, and the Lorentz curve of the initial allocation and redistribution of carbon emissions in each province in 2020 is obtained（figure 2）.

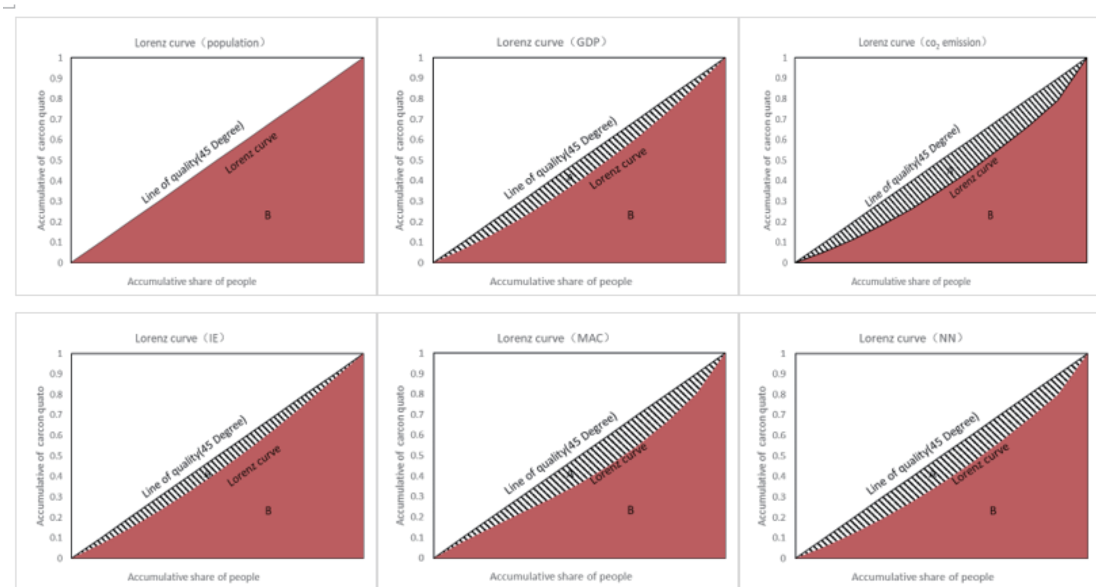

Figure2
Lorenz curves under six distribution methods

according to the formula of the carbon Gini coefficient, the carbon Gini coefficients of the six distribution method are, 0, 0.1360, 0.2146, 0.1035, 0.1919, 0.2028, respectively. According to the basis of the Gini coefficient classification, the method based on historical emissions, population、GDP、 information entropy、cost optimization、Nash negotiation are relatively average, especially the method based on population distribution is absolute average

Data Envelopment Analysis (DEA) is a technique for evaluating the efficiency of input and output. This paper selects population, capital stock, energy consumption as input variables, and GDP and CO_2 emissions as output indicators. It tries to maximize the efficiency of a service unit by comparing the efficiency of a particular unit with the performance of a group of similar units that provide the same service. This paper analyzes the input and output of 30 provinces and cities through DEAP software and obtains the relative efficiency value. At the same time, we chose to use the average efficiency value of 30 provinces and cities as the DEA efficient value of the six schemes （Table 5）.

Table 5
DEA Efficient Value Under Six Distribution Methods

Province Population	DEA efficient value					
	GDP	Carbon emission	IE	MAC	NN	
Beijing	1	1	1	1	1	1
Tianjin	1	1	1	1	1	1
Hebei	0.948	0.674	0.691	0.722	0.692	0.695
Shanxi	0.975	0.628	1	1	1	1
Inner mongolia	1	1	1	1	1	1
Liaoning	1	0.847	0.785	0.814	0.746	0.783
Jilin	1	0.921	0.925	0.897	0.911	0.922
Heilongjiang	1	0.765	0.827	0.841	0.831	0.831
Shanghai	1	1	1	1	1	1
Jiangsu	1	0.965	0.999	1	0.995	1
Zhejiang	1	0.941	0.963	0.975	0.94	0.948
Anhui	0.972	0.826	0.923	0.961	0.992	0.927
Fujian	0.984	0.932	0.939	0.933	0.952	0.938
Jiangxi	1	0.911	0.926	0.959	0.937	0.93
Shandong	0.971	0.854	0.959	0.97	0.947	0.961
Henan	1	0.88	0.942	0.99	0.946	0.948
Hubei	0.978	0.763	0.788	0.789	0.771	0.774
Hunan	0.975	0.74	0.768	0.799	0.756	0.76
Guangdong	1	1	1	1	1	1
Guangxi	0.975	0.877	0.831	0.879	0.907	0.837
Hainan	0.954	0.633	0.733	0.619	0.825	0.7
Chongqing	1	1	1	1	1	1
Sichuan	1	0.986	0.852	0.943	0.863	0.862
Guizhou	0.993	0.574	0.726	0.742	0.758	0.728
Yunnan	0.982	0.638	0.669	0.708	0.66	0.668
Shaanxi	0.969	0.643	0.846	0.825	1	0.845
Gansu	1	0.652	0.659	0.662	0.663	0.659
Qinghai	0.935	0.416	0.428	0.402	0.495	0.413
Ningxia	0.915	0.405	0.824	0.467	0.737	0.783
Xinjiang	0.876	0.423	0.497	0.496	0.477	0.496
Mean	0.98	0.797	0.85	0.846	0.86	0.847

The above allocation scheme is analyzed from four perspectives of cost, efficiency (DEA), individual will, and fairness. The individual will represent the expected income (displayed by GDP) between the provinces during the game. Thereby obtaining indicators under different allocation schemes, see Table 6.

Table 6
Indicator Measurement Under Six Distribution Methods

Method	Cost(Billion yuan)	Efficient	Individual will	Fairness
Population	1007125.79	0.98	39.57	0.00
GDP	1580566.65	0.797	52.81	0.136
Carbon emission	262328.64	0.85	100.05	0.2146
IE	648178.60	0.846	64.22	0.1035
MAC	166414.71	0.86	12.93	0.1919
NN	221148.41	0.847	101.96	0.2028

As can be seen from the above table, different schemes have advantages in the measurement values of the four indicators. In terms of a single population-based allocation indicator, it has the greatest advantage in efficiency and fairness, and has obvious disadvantages in terms of abatement costs.

3.2. Sorting of Allocation Schemes

Due to the different criteria considered in the allocation scheme, it is not possible to clearly compare the type of the scheme to be more dominant. This paper uses TOPSIS as a comprehensive evaluation method to obtain a comprehensive weight from four indicators.

The TOPSIS method is an effective multi-index evaluation method (Lee, et al, 2018). The specific ideas are as follows:

(1) Let the decision matrix $A = (a_{ij})_{m\times n}$, in order to avoid the decision type and the difference in the size of the attribute value, normalize the attribute value. Normalized decision matrix B= $(b_{ij})_{m\times n}$, 其中

$$b_{ij} = \frac{a_{ij}}{\sqrt{\sum_i^m a_{ij}^2}}, i = 1,2,\dots,m; j = 1,2,\dots,n$$

$C = (c_{ij})_{m\times n}$ uct a weighted canonical matrix $C = (c_{ij})_{m\times n}$. Let the weight vector given by the decision maker $w = [w_1, w_2, \dots, w_n]^T$, then

$$c_{ij} = w_j \cdot b_{ij}, i = 1,2,\dots,m; j = 1,2,\dots,n$$

(3) Determine the positive ideal solution C^* and the negative ideal solution C^0.

$$C_j^* = \begin{Bmatrix} max_i c_{ij}, j \text{ is a benifit attribute} \\ min_i c_{ij}, j \text{ is a cost attribute} \end{Bmatrix}$$

$$C_j^0 = \begin{Bmatrix} max_i c_{ij}, j \text{ is a cost attribute} \\ min_i c_{ij}, j \text{ is a benifit attribute} \end{Bmatrix}$$

Where the benefit attribute means the bigger the better, the cost type attribute means the smaller the better.

(4) Calculate the distance from each scheme to the positive (negative) ideal solution

$$s_i^* = \sqrt{\sum_{j=1}^{n} \left(c_{ij} - C_j^*\right)^2}, i = 1,2,\dots,m$$

(5) Calculate the comprehensive evaluation value

$$f_i^* = \frac{s_i^0}{s_i^0 + s_i^*}, i = 1,2,\dots,m$$

The above four indicators are measured in a certain sense. In this paper, the same weights are given to the four indicators, and the distribution results under the four principles are weighted by the same weight 1/4, so that the comprehensive evaluation value is obtained.

Among the four indicators, abatement costs and fairness are cost-based indicators, meaning that the smaller the value, the better. Efficiency and personal willingness are efficiency indicators, meaning that the bigger the better. In order to ensure the consistency of the data, the data is homogenized and standardized. According to the comprehensive evaluation method of TOPSIS, the comprehensive evaluation values under the six distribution schemes were 0.3380, 0.2826, 0.6137, 0.4007, 0.5138, and 0.6717, respectively. It can be seen from the comprehensive evaluation value that the Nash negotiation method ranks first, followed by historical emissions, cost optimization, information entropy, and population-based, while the GDP-based allocation scheme ranks the worst.

4. CONCLUSIONS AND POLICY IMPLICATIONS

4.1 Main Conclusions

In the long-term goal of addressing climate change, there is a series of carbon emission rights allocation programs. In order to achieve the participation of Chinese provinces, equity and efficiency are of paramount importance. In the study of carbon allocation, there are distribution schemes under different standards. In order to achieve the carbon emission reduction targets of China's 13th Five-Year Plan, the decomposition of the total target is crucial. In the literature review, this paper includes equality (represented by population indicators), including benefits (represented by GDP), including feasibility (represented by historical CO_2 emissions) in the single indicator method. In the composite index method, information entropy is represented. At the same time, in the optimization method, the cost is selected as the best. In addition, due to the importance of game theory among the subjects of carbon allocation, the Nash negotiation method is chosen.

The process of selecting four evaluation indicators takes into account efficiency, fairness, feasibility and individual will. The results show that the six distribution methods selected do not dominate the different index values. After applying the TOPSIS comprehensive evaluation method, it can be seen that the Nash negotiation distribution method has the highest score, which means that Nash negotiation has a greater advantage in comprehensively showing the cost of abatement, efficiency, fairness and personal will. The distribution method based on the single indicator of GDP has the lowest score. Since this indicator is too different from other schemes in the indicator of abatement cost, it affects its comprehensive score.

4.2 Policy Implications

Based on the above conclusions, this study has a certain impact on Chinese policy makers in order to achieve carbon emission reduction targets.

First, when Chinese policy makers allocate carbon allowances among different entities, using a single indicator (such as population, GDP, and historical carbon dioxide emissions), it may be difficult to reach consensus among different entities. Because there are large differences in the quotas allocated by different indicators for different entities. Individual entities tend to choose distribution indicators that are beneficial to them.

Secondly, compared with a single indicator, the comprehensive evaluation index can more comprehensively reflect the multiple negative standards, and is more easily accepted by various entities. Because under the comprehensive indicator allocation, the quota difference of each entity is relatively small. Therefore, according to the actual situation of different provinces and regions, choose the appropriate composite indicators for distribution

Third, whether it is a region with good economic development or a region with poor economic development, in order to achieve the national emission reduction targets, there will inevitably be certain emission reduction costs. The generation of abatement costs will cause some provinces and cities to have some pressure to use clean production technology. In order to alleviate this pressure, policy makers must provide a good environment for production technology innovation, and provide corresponding policy concessions and corresponding laws and regulations.

Finally, the allocation of carbon credits involves bargaining between participating entities, and Nash negotiations consider whether the allocation is acceptable to each participating entity. Among the comprehensive evaluation indicators, the Nash negotiation model has the highest score, indicating that the allocation method can better consider various indicators. Therefore, policy makers should consider the ability of each participant to bargain in the initial allocation of carbon allowances so that the distribution plan can be more easily implemented.

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