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Forecasting the Allocation Ratio of Carbon Emission Allowance Currency for 2020 and 2030 in China

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Academic Editor: Giuseppe Ioppolo

Received: 5 June 2016; Accepted: 1 July 2016; Published: 9 July 2016

Abstract: Many countries and scholars have used various strategies to improve and optimize the allocation ratios for carbon emission allowances. This issue is more urgent for China due to the uneven development across the country. This paper proposes a new method that divides low-carbon economy development processes into two separate periods: from 2020 to 2029 and from 2030 to 2050. These two periods have unique requirements and emissions reduction potential; therefore, they must involve different allocation methods, so that reduction behaviors do not stall the development of regional low-carbon economies. During the first period, a more deterministic economic development approach for the carbon emission allowance allocation ratio should be used. During the second period, more adaptive and optimized policy guidance should be employed. We developed a low-carbon economy index evaluation system using the entropy weight method to measure information filtering levels. We conducted vector autoregressive correlation tests, consulted 60 experts for the fuzzy analytic hierarchy process, and we conducted max-min standardized data processing tests. This article presents first- and second-period carbon emission allowance models in combination with a low-carbon economy index evaluation system. Finally, we forecast reasonable carbon emission allowance allocation ratios for China for the periods starting in 2020 and 2030. A good allocation ratio for the carbon emission allowance can help boost China's economic development and help the country reach its energy conservation and emissions reduction goals.

Keywords: low-carbon economy; index system; carbon emission allowances; allocation ratio

1. Introduction

Carbon emission allowance currency is considered to be the same as the CO_2 emission allowance in this article. Carbon emission allowance trading schemes represent the most important means of achieving a low-carbon economy, and their allowances have been widely studied.

In September 2003, Directive 2003/87/EC was officially published, and the European Union Allowance (EUA) was in turn regulated by law for the first time. The EUA acts as an authority on carbon emissions. Since its establishment, the EU has formed a formal legislative trading system for carbon emission allowances. This article considers the carbon emission allowance to be the same as the CO_2 emission allowance currency. In the research, the initial modes of carbon emission allowance gradually became the core objectives. Currently, there are several ways of assigning carbon emission allowances.

In recent years, the green or low-carbon economy has captured people's attention as a means of decreasing carbon emissions [1–6].

1.1. The Discussion of the Alternative Methods

1.1.1. Grandfathering Method

The grandfathering method involves using historical records to determine allocation outcomes. This method has been widely used to allocate carbon emissions in the EU aviation industry via free allocation [7]. One advantage of the grandfathering approach is that enterprises are more willing to use this approach than other methods. However, it also has disadvantages. Grandfathering is based on historically-inherited allocation patterns; despite appearing fair in terms of quantity, historical records can neither encourage energy-saving enterprises nor motivate energy-inefficient enterprises to reduce emissions, leading energy-saving enterprises to engage in greater social responsibility efforts while energy-inefficient enterprises assume more allowances. In turn, enterprises will pay less attention to innovation when reducing carbon emissions [8], ultimately resulting in negative effects on the environment.

1.1.2. Baseline Distribution Method

An increasing number of enterprises are entering certain industries. However, because new enterprises have no historical records, they cannot use the grandfathering approach. To address this issue, the benchmarking method (baseline distribution method) was developed [9]. The benchmarking method expands the grandfathering approach in that it does not depend heavily on the use of historical data. This method is mainly used during the third stage of EU carbon emission allowance allocation. The advantage of benchmarking is that it not only involves free allocation, but also addresses the limitations of grandfathering. However, similar to the grandfathering approach, it is limited in terms of allocating allowances. It thus fails to reflect societal equality or to direct enterprises through policy.

1.1.3. Historic Emission and Benchmarking Allocating Method

Historic emission and benchmarking allocating involves combining the historic emission method with the benchmarking approach. This is the primary approach used for carbon emission allowance trading allocation in China. On 18 June 2013, Shenzhen became the first city to use this Emission Trading Scheme (ETS). By 6 May 2016, seven cities and provinces (Shenzhen, Shanghai, Beijing, Tianjin, Chongqing, Guangdong and Hubei) had started to engage in carbon emission scheme trading. Although this method offers the advantages of historic emission allocation and benchmarking, it comes with its own set of disadvantages. Essentially, as the share of carbon emission allowance allocation is normally abundant, the trading market lacks liquidity and fails to allocate carbon emission resources.

1.1.4. Auction Allocation Method

The auction allocation method is an extension of the grandfathering approach. It differs from the benchmarking approach in that it has a different objective: efficient allocation. This method is primarily used in the U.S. carbon trading market. The advantage of auction allocation is that policy information is published prior to auction so that enterprises can plan for their long-term development based on documented data. This facilitates planning adjustments within enterprises. However, enterprises with a monopoly can secure more resources while medium- and small-scale companies struggle to operate and organize [10].

1.1.5. Fixed Pricing Allocation Method

The fixed pricing allocation method, which involves buying carbon emission allowances at fixed prices from the government, was first created in Australia in July 2012 [11]. This approach improves the market to government-determined targets. However, the use of fixed prices comes with several disadvantages. First, this method weakens the effects of resource allocation in the carbon emission allowance market. Second, the establishment of fixed prices may not necessarily fit real trading conditions, and this can have negative effects on the market.

1.1.6. Allocation Method Based on Data Envelopment Analysis

Allocation based on Data Envelopment Analysis (DEA) involves allocating carbon emission allowances across different regions [12,13]. The advantage of this approach is that it can simultaneously consider several different factors. However, it requires an input-output table, making this model analysis approach accurate, but inefficient, as the input-output tables need to be updated. It is thus not suitable for long-term large-scale allocation.

1.1.7. Game Model Allocation Method

The game model allocation method uses mathematical models based on evolutionary game theory to allocate carbon emission allowances [14]. This method can predict conditions of competition and cooperation between enterprises and can thus effectively simulate reality. However, the wealth of data needed renders this model demanding in terms of statistics and calculations. This model can also be affected by subjective factors. The carbon emission allowance game model thus needs to be further developed and refined.

1.1.8. Mixed Integer Programming Allocation Method

The allocation method based on Mixed Integer Programming (MIP) uses MIP to allocate allowances and minimize costs. The benefit of this method is that it allocates carbon emission allowances based on a new factor: the supply chain. However, this method has not yet been perfected, and measures that enterprises take may be ignored when simulating reality.

Several other studies have examined carbon emission allowance allocation methods (e.g., Chipman and Tian's study on externality [15]); only those methods that have been recently developed or that are used frequently are listed above. Although these methods are usable, they each present weaknesses. The grandfathering and benchmarking methods are based on historical data, thus disregarding enterprises that have effectively saved energy. The auction allocation method disadvantages small companies. The fixed price method limits the market's resource allocation function. Allocation based on DEA in operations research is inefficient and cannot make timely adjustments in allocation quantities based on changes. The game model allocation method over-relies on subjective settings. Finally, the MIP allocation method fails to take enterprise emissions reductions into consideration.

We thus cite two common issues. First, current methods do not consider ways to improve carbon emission allowance allocation to better suit developing societies. Second, carbon emission reductions have negative effects on the economy [16], and ways to mitigate such negative effects have not yet been addressed. These two issues are of significance for China. China is a developing country that generates high levels of carbon emissions. Due to the close relationship between carbon emissions and the economy, if carbon emissions are not carefully controlled, they will inevitably have negative effects on the domestic economy.

In addressing these two issues, we divide the carbon emission reduction process into two periods.

The first period of the carbon emission reduction economy involves joint carbon emission reduction. The second period follows and involves adapting to emissions reduction policies.

We assume that the period from 2020 to 2029 is the first period, and the period from 2030 to 2050 is the second period.

These two periods present different demands and unique sources of potential. Different allocation methods should be applied to prevent negative effects on regional economic development [17].

1.2. Literature Review on the Low-Carbon Economy Valuation Index

A low-carbon economy evaluation index system involves using a series of evaluation indexes to quantify economic development and to then measure it. Several scholars have conducted research in this area. For example, Zhuang [18] proposed an evaluation index system that involves a standard hierarchy: low carbon output, low carbon consumption, low-carbon resources and low-carbon policies. This system can be used to accurately measure low-carbon economic development patterns for particular regions. However, most scholars have focused on constructing evaluation index systems and analyzing their results. Thus, few studies have focused on the principles of the evaluation index system construction and related connections.

Several limitations to evaluation index system construction remain.

For example, Fu et al. [19] argued that low-carbon economic development can be measured based on the following hierarchy: low carbon output, low carbon consumption, low-carbon resources, low-carbon policies and low-carbon environment. This system can generate complete data on a particular region. However, the logical connections in the system are ambiguous, creating additional problems. Lin et al. [20] noted this issue and established a new evaluation system that now includes Xiamen city in the research as a sample.

Pan et al. [21] argue that as an economic form, the low-carbon economy is at a different stage. Their research explores resource endowments, techniques and consumption models. This index system can generate economic information on a particular region. However, the principle hierarchy is overlapped, thus increasing the ratios of some indexes and ultimately producing inaccuracies.

Ren et al. [22] developed an innovative method that determines carbon emissions indexes based on industry chains and that uses the horizontal path to evaluate the outside factor. While this index system is new, it is inadequate in terms of carbon absorption. Yang and Li [23] describe the source and sink clearly. Carbon production and carbon absorption patterns are thus listed clearly, rendering the system complete.

Xiao and Tang [24] present a low-carbon economy evaluation system for cities with seven principle hierarchies and 51 indexes as an example. While it is a comprehensive system, it fails to consider causalities between indexes. This can generate auto-correlative variables and can thus render outcomes inaccurate.

Overall, works on index systems have been written by authoritative scholars. Each system can comprehensively measure regional economic development patterns. The primary shortcomings of the index system are as follows: the logic between indexes is ambiguous; auto-correlative variables have not been tested; relationships between indexes and the low-carbon economy present weak levels of causality, and carbon emission sources and sinks have not been considered fully.

In addressing these problems, we conduct an auto-correlative test to exclude the relative hierarchy, and we use the entropy weight and the Fuzzy Analytic Hierarchy Process (FAHP) to make integrated assessments. We thus simplify existing methods and address the subjectivities of the FAHP.

The carbon emission intensity level for 2010 and 2011 reached 1.085271 (tons CO_2)/10,000 CNY in China according to the World Bank [25]. At this carbon emission intensity level, we forecast that total carbon emissions will reach 9.249 billion tons in 2020. In 2015, China's carbon emission intensity level was 80% of 2010 levels [26]. China's 2020 carbon emission intensity level should reach 82% of the 2015 level [27]. Thus, the carbon emission intensity for 2020 should reach 0.711938 (tons CO_2)/10,000 CNY.

Carbon emission intensity, energy intensity and total carbon emission forecast valuations for 2020 in China vary across studies [12,13,28–32].

Actual carbon emission intensity and total carbon emission amount may be as low as possible for 2020 in China in terms of the Paris agreement [33]. We are more concerned with the allocation of carbon emission proportions in each region of China.

The contribution of the research is as the follows. This paper developed a low-carbon economy index evaluation system by the entropy weight method to measure information filtering levels. This paper conducted vector autoregressive correlation tests, consulted 60 experts for the fuzzy analytic hierarchy process and conducted max-min standardized data processing tests. This article built first- and second-period carbon emission allowance models in combination with a low-carbon economy index evaluation system.

The remainder of this paper is organized as follows. The next section presents carbon emissions calculations for 2012; then, using the entropy weight method, we combine autocorrelation tests and select 12 from 21 possible variables. The third section presents a basic and advanced low-carbon economy evaluation index system based on the FAHP and based on input from 60 experts. We then present carbon emissions proportion models for the first and second periods for each region in China. In the fourth section, we forecast allocation ratio for carbon emission allowances for the first and second periods beginning in 2020 and 2030, respectively, for China. Finally, we present a summary of the paper.

2. Data and Variable Selection for Carbon Emission Allowance Allocation

2.1. Carbon Emission Data and Calibration

It is necessary to understand actual carbon emission conditions before researching the CO_2 emission allowance ratio for 2020 and 2030 in China. As actual data on carbon emissions are not clearly recorded on official statistics websites or in the yearbook, we must calculate these values. Annual carbon dioxide emissions for 2012 were determined using the Intergovernmental Panel on Climate Change (IPCC) data combined with the 2013 China Energy Statistics Yearbook [34]. The accounting methods used in this paper were established in consultation with IPCC records.

2.1.1. Scope Definition

In terms of carbon emissions, we study total carbon dioxide emissions for terminal energy consumption. In accordance with the International Energy Agency's approach, terminal energy consumption pertains to the following sectors: industry, transport and other (residential), agriculture/forestry, commercial and public services, fishing and unspecified.

2.1.2. Methods

The IPCC created a simple means of estimating emissions that combines information on human activities (Activity Data (AD)) with emissions or coefficients (Emission Factor (EF)), as shown in the "2006 IPCC country listing guidelines on greenhouse gases" [35].

The above-mentioned equation is Equation (1).

$$E = AD \times EF \tag{1}$$

E: greenhouse gas emissions level

AD: activity data

EF: emission factor

There are three ways of determining the *EF* that involve different degrees of complexity. When using the basic method, the *EF* is determined via the default data method using existing domestic or international statistical data and combining these data with the default emission factor and other parameters ("IPCC Method 1"); the second approach, the intermediate method, involves using national statistical data to identify key categories with a strong impact on emissions to establish a database of *EF* ("IPCC Method 2"); the third approach, the senior method, involves using the *EF* model or measured values under different environments. IPCC Methods 1 and 2 are available as a compiled approach to China's 2011 provincial emissions accounting in the "Provincial greenhouse gas list preparation guidelines".

As IPCC Method 2 involves technological, industry and energy classification, too many data must be classified, thus rendering emission factor determination difficult and computationally unfeasible. We thus use IPCC Method 1 to measure carbon dioxide emissions.

We summarize IPCC Method 1 in Equation (2).

$$Eco_{2_i} = ((P_k + I_k - E_k - B_k - R_k) \times CF_k \times Qc_k - FP_k \times Mc_k \times Fc_k)\, OF_k \times M \quad (2)$$

2.1.3. Data Sources

Variable designations in Equation (2) and data sources are shown in Table 1.

Table 1. Variables.

Variable Name	Variable Symbol	Unit	Variable Data Source
fuel k production level	P_k	ton	China Energy Statistical Yearbook 2013 [34] China Energy Statistical Yearbook 2014 [36]
fuel k import level	I_k	ton	
fuel k export level	E_k	ton	
the number of aircraft or ships using fuel k	B_k	ton	
fuel k reserve change	R_k	ton	
the heat value of each fuel k unit	CF_k	TJ/Gg· Mm^3	China Statistical Yearbook [37–40]
fuel k carbon content	Qc_k	kg/TJ	Provincial Greenhouse Gas List Preparation Guidelines [35]
fuel k unit carbon content	Mc_k	kg/ton	Value of 72.43%
fuel k carbon fixation rate	Fc_k	%	
fuel k oxygenation rate	OF_k	%	Provincial Greenhouse Gas List Preparation Guidelines [35]
relative quality	M	N.A	Value of 44/12

2.1.4. Method Calibration and Calculation

The 2005 carbon dioxide emissions accounting level, which can be found on the official ERI (Energy Research Institute of National Development and Reform Commission in China) website, is 5.166 billion tons. A Chinese carbon dioxide emission level of 5.193 billion tons for 2005 was calculated using the method above combined with 2006 China Energy Statistics Yearbook data [41]. The difference between them is only 0.53%. This accounting method is therefore feasible and accurate.

According to the above-listed official data, from Equation (2), we can calculate 2012 carbon dioxide emissions levels for each province in China. Due to statistical constraints, some data for Hong Kong, Macao, Taiwan and Tibet are unavailable. We thus only account for carbon dioxide emissions for 30 provinces in Table 2. Total 2012 carbon emissions derived from Equation (2) amount to 8.21788 billion tons, as shown in Table 2. The Gross Domestic Product (GDP) level was 57,585 billion CNY in 2012. The carbon emission intensity level is thus 8.21788 billion tons (tons CO_2)/57,585 billion CNY or 1.43 (tons CO_2)/10,000 CNY.

Table 2. 2012 carbon dioxide emissions for Chinese provinces and cities.

Province	Carbon Dioxide Emissions (10^8 tons)	Province	Carbon Dioxide Emissions (10^8 tons)
Beijing	0.67	Henan	3.29
Tianjin	1.19	Hubei	2.61
Hebei	5.27	Hunan	1.9
Shanxi	14.00	Guangdong	3.80
Inner Mongolia	5.42	Guangxi	1.36
Liaoning	4.02	Hainan	0.27
Jilin	1.90	Chongqing	1.07
Heilongjiang	2.34	Sichuan	2.07

Table 2. *Cont.*

Province	Carbon Dioxide Emissions (10^8 tons)	Province	Carbon Dioxide Emissions (10^8 tons)
Shanghai	1.56	Guizhou	1.81
Jingsu	4.78	Yunnan	1.67
Zhejiang	2.68	Shaanxi	2.08
Anhui	2.48	Gansu	1.12
Fujian	1.63	Qinghai	0.27
Jiangxi	1.12	Ningxia	1.51
Shandong	6.46	Xinjiang	1.81
Total 82.18			

2.2. *Variable Selection for Establishing a Low-Carbon Economy Evaluation Index System*

The low-carbon economy approach involves an economic form of energy conservation and emissions reduction. To achieve energy conservation and emissions reduction targets, variable selection methods should first follow a set of low-carbon economic development model principles.

2.2.1. Variables Selection Principles

(1) Fair principles on common, but differentiated duties

The goal of low-carbon economic development is equity. As an international phenomenon, carbon emissions influence the economies of all countries. The evaluation variable should be fair in terms of the constraints on each region. However, people have different understandings of "fairness" across interest groups. Our view of "fairness" is based on the Kyoto Protocol, which upholds principles of common, but differentiated duty. We use Gross Domestic Product (GDP) as the variable representing historical responsibility, an approach that is supported in Zhang [42]. We describe additional relations between carbon dioxide emissions and economic development by analyzing carbon emission in detail.

(2) Unified principles combining per capita and total values

Combining per capita and total carbon emissions is also essential to upholding equitable historical responsibility. This principle emphasizes the comprehensive evaluation of regional conditions, including indices such as GDP, carbon emissions and green space. We compare these variables not only by measuring total values, but also by examining per capita values. We use per capita and unit area data as our variables to improve the credibility of our evaluations.

(3) Balanced principles on equilibrating economies and cultures

Economy and culture, especially for low-carbon economies, are two inseparable factors in social development because the degree of economic development is based on social and cultural knowledge and on technological levels. If we simply measure economies, we may overvalue the effects of economic benefits while neglecting the essential significance of social development (cultural progress), thus misleading the public. We thus separate social development standards into two categories: economic and cultural standards.

(4) Comprehensive principles for describing carbon production and absorption progress

Ren et al. [22] uses the carbon industry chain as an innovative index to analyze low-carbon economies by only taking carbon emissions and solutions into account while neglecting descriptions of carbon absorption. Variables such as carbon absorption, carbon sinks, green space areas and harmless treatment rates play a small but important role in comprehensive descriptions of low-carbon economies. We thus use the carbon industry chain as one of our standards.

2.2.2. Variable Screening Method

The entropy method, as an indicator in the information screening method, has been widely used in many scientific fields. As a means of studying low-carbon economies, the entropy method is used less frequently based on a small collection of relatively simple features. In initiating low-carbon economies based on entropy theory studies, the primary role of the entropy method is to use the relevant evaluation variables. However, entropy weight methods rely too heavily on variable data, and current conditions with no clear market mechanisms can easily result in data over superstition, causing results to be biased. In this paper, to avoid these problems, we use the entropy detection variable. We select more meaningful variables in the next round of empowerment after obtaining different variables through operation.

The entropy method is described as follows:

(1) Entropy matrix evaluation

The entropy weight is based on an evaluation matrix, and so, before performing entropy calculations, we first create the entropy matrix. The entropy method for establishing the matrix is evaluated through a system with m evaluation objects and n evaluation variables. The evaluation matrix of m evaluation objects and n evaluation variables is shown in Equation (3) [43].

$$A = \begin{vmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \ldots & a_{nm} \end{vmatrix} \tag{3}$$

According to Equation (3), it is necessary to establish five packets for the entropy evaluation matrix, as different indicators have different meanings, and units are occasionally too similar to the indicator percentage values in this section with unified decimal points reserved to the fifth place.

(2) Standardization

As each variable has different dimensions and units, to determine more convincing indicators, we apply the normalized non-unit treatment.

When standardizing data, standardization is generally performed via two methods. The first method involves the conventional standardization process, whereby upcoming data are combined into a matrix with no average valuation and with a standard deviation of one. The second method involves min-max standardization treatment, whereby upcoming data are placed in the [0, 1] interval of the matrix. The first method can be understood as the use of data means and standard deviations based on raw data linear transformations with data normalized to a value of zero. While it is thus possible to retain the fluctuation characteristics of the original data, negative transformation data will emerge. The second method involves the use of maximums and minimums from the raw data linear transformation with data normalized to the [0, 1] interval matrix. This method also can retain fluctuation characteristics for the original data that are not negative.

Subsequent data operations include logarithmic and other operations, and thus, negative data indicators are not accepted in this section. We thus use the second method in this section.

(3) Entropy valuation computation

Entropy valuations were computed after data were normalized with the entropy valuation of the j variable defined as shown in Equation (4).

$$H_j = -\frac{1}{\ln m}\sum_{i=1}^{m} a'_{ji}\ln a'_{ji} \quad (\mathrm{j} = 1, 2, \cdots, n) \tag{4}$$

When $a'_{ji} = 0$, $a'_{ji} ln a'_{ji} = 0$.

(4) The entropy weight

The entropy weight of the j evaluation variable is defined as shown in Equation (5).

$$\omega_j = \frac{1-H_j}{m-\sum_{j=1}^{n} H_j} \quad (j = 1, 2, \cdots, n) \tag{5}$$

When the entropy weight is close to a value of zero, which denotes that the variable information provided is not sufficient, consider removing the indicator.

2.2.3. Variable Definitions

According to the four basic principles on which this thesis is based, we conduct a comprehensive analysis based on the existing literature [34,36–40]. Twenty-one variables were selected. Our low-carbon economy evaluation system was created by screening variable information via the entropy weight method and by then screening related variables through vector autoregression tests. The low-carbon economy evaluation system includes a social development index, an economic foundation index and a carbon industrial chain index.

The social development index includes the urbanization rate, consumer spending levels, vehicles per capita and government environmental inputs. The economic foundation index includes GDP per capita levels and primary, secondary and tertiary industry GDP values. The carbon industrial chain index includes carbon productivity levels, resident carbon dioxide emissions, carbon sinks and garbage treatment rates.

We discuss the significance of the 21 variables next.

(1) Social development index

① Urbanization

The urbanization rate is the proportion of the urban population to the total population. The urbanization rate is considered to be one manifestation of the social development index, as it can reflect resident living conditions based on work and living patterns in different provinces and cities, and land utilization also directly affects regional carbon dioxide emissions levels. Lin and Sun [44] demonstrated that urbanization is indeed a significant factor affecting carbon emissions through the decomposition of carbon emissions factors, although it is a secondary determinant of carbon emissions. Urbanization is the only path to development and should not be interrupted. Lin and Sun [44] set the urbanization rate as an evaluation variable for the low-carbon index.

② Consumer spending

Consumer spending is defined as consumption per capita. Consumption per capita can reflect both resident ideological and living standards. Moreover, Chen et al. [45] indicated that consumption includes embodied energy, which also represents a large proportion of carbon emissions. Pan et al. [21] showed that consumption affects carbon emissions, as all economic activities ultimately drive present or future consumption. In conclusion, consumption generates carbon emissions and affects carbon emissions growth, and as a form of human development, consumption embodies social and individual development potential. Consumption per capita must therefore be given considerable attention [46].

The relationship between provincial consumption per capita and the low-carbon economy is as follows: the higher the consumption level per capita, the better the outcomes of economic development. First, high consumption per capita supports high income per capita in a region. Second, high consumption levels per capita show that people can endure some level of carbon emission burden.

③ Vehicles per capita

The vehicles per capita value denotes the average number of vehicles per person. This value reflects social development, as per capita vehicles may reflect higher levels of cultural literacy among residents in different provinces. When cultural appreciation among residents reaches a certain level, demand for cars drops, and to protect the environment, more people opt for public transportation or for other low-carbon modes of transport.

④ Government environmental inputs

Government environmental inputs are used as a variable in this article. Government environmental inputs denote the ratio of government environmental investment to total government expenditure. This variable reflects a government's environmental attitudes. Attitudes constitute an important feature of social progress. When a provincial government pays sufficient attention to environmental issues, the ratio of government environmental investment to total government expenditures is high.

As the degree of provincial and municipal government environmental investment increases, governmental emphasis on regional environmental conditions increases, thus improving the basis for current and future environmental conditions. Therefore, the greater the value of this variable is, the stronger the foundation for a low-carbon economy.

⑤ Government environmental inputs per unit area

Government environmental inputs per unit area is a social development index variable with a significant effect on different provinces. If we evaluate government environmental investments separately and ignore regional features, we would decrease the evaluation's reliability.

The greater the environmental investments made by provincial and municipal government, the higher the government's emphasis on regional environmental conditions and the better the foundation for current and future environmental conditions. Thus, as the values increase, low-carbon economic foundations improve.

⑥ Government environmental inputs per capita

Government environmental inputs per capita refers to environmental accounting investments that the government dedicates to one person as a variable of social development. Due to major differences between provinces in terms of population, if we evaluate total government environmental investments separately and ignore regional features, we would decrease the reliability of our evaluations.

The higher the level of provincial and municipal government environmental investment per capita, the greater the government's emphasis on regional environmental conditions and the stronger the basis of current and future environmental conditions. Therefore, the higher the value is, the stronger the foundations of the low-carbon economy.

(2) Economic foundation index

① GDP per capita

The GDP per capita of different provinces is one variable of the economic foundation index and reflects economic fundamentals. Zhuang [47] highlights that the relationship between GDP per capita and carbon dioxide emissions per capita needs to be measured constantly and that per capita introduces populations into carbon allowances, complementing Fan [48] (final consumption should capture emissions reduction responsibilities), Pan and Chen [49] (use population as the final distribution principle) and the Development Research Center of the State Council of China [50] (use per capita to measure the available balance of global carbon emissions).

The higher the provincial and municipal GDP is, the stronger societal development becomes. Therefore, the higher the variable is, the stronger the foundations for the low-carbon economy.

② Income per capita

Income per capita refers to disposable income per capita and is one variable of the economic foundation index. Income per capita can reflect standard living conditions, and incomes constitute an important factor in carbon emission decomposition [51].

③ Primary industry GDP

The primary industry GDP variable is equal to primary industry GDP/total GDP. The greater the variable's value is, the weaker the foundations of the low-carbon economy.

④ Secondary industry GDP

The secondary industry GDP variable is equal to secondary industry GDP/total GDP.

China's total GDP increase is primarily based on secondary industries, which are mostly influenced by carbon dioxide emission limitations [52]. At the same time, secondary industries, as major production sectors, have significant effects on carbon emissions [53].

The higher that provincial and municipal secondary industry GDP becomes, the more that regional economic development depends on secondary industries. The carbon dioxide emissions of secondary industries constitute the most important part of the three industrial structures and is the most easily affected by carbon dioxide emission limitations. When a region relies heavily on one secondary industry, mitigation policies will surely affect regional economic conditions. Therefore, the greater the variable is, the weaker the foundations of the low-carbon economy.

⑤ Tertiary industry GDP

Tertiary industry GDP is one variable of the economic foundation index and is equal to tertiary industry GDP/total GDP. It reflects economic fundamentals.

The prosperity of tertiary industries can also represent the prosperity of the commercial and financial industry. Vendor supply models and fuzzy hierarchy analysis methods have been applied to the low-carbon economy [54]. Therefore, the prosperity and development of tertiary industry and of the low-carbon economy are closely linked. The higher provincial and municipal tertiary industry GDP is, the more regional economic development depends on tertiary industry.

The tertiary industry represents a more favorable industry structure that can adapt to low-carbon economy emission reductions. While emission reduction policies do not have a significant impact on industries, an increase in the proportion of tertiary industry activity is inevitable in a developed country. Thus, to some extent, a high proportion of tertiary industry activity reflects a strong regional economic foundation. Therefore, the higher this variable is, the stronger the foundations of the low-carbon economy.

(3) Carbon industrial Chain index

① Carbon productivity

Carbon productivity is a variable in the carbon industrial chain index. The variable represents the conditions of carbon usage. As provincial and municipal carbon productivity improves, regional carbon usage becomes more effective, technological development advances and fewer carbon emissions are generated to produce the same products. Therefore, the greater the variable is, the stronger the low-carbon economy.

② GDP energy consumption

GDP energy consumption is defined as energy consumption/GDP and is one variable in the carbon industrial chain index. As provincial and municipal GDP energy consumption increases, carbon dioxide and carbon-based technology usage decreases, and products requiring the same level of economic wealth require more carbon consumption. Therefore, the greater the variable is, the weaker the low-carbon economy.

③ Carbon dioxide emissions per capita

The carbon dioxide emissions per capita forms one variable in the carbon industrial chain index and represents carbon emissions conditions.

As carbon dioxide emissions per capita at the provincial and municipal levels increase, reliance on carbon dioxide increases, and overall carbon dioxide emissions increase. Therefore, the greater this variable is, the weaker the low-carbon economy.

④ Resident carbon dioxide emissions consumption

Carbon dioxide emissions consumption by residents is defined as carbon dioxide emissions/consumer spending. The greater this variable is, the weaker the low-carbon economy.

⑤ Carbon dioxide emissions per unit of GDP

Carbon dioxide emissions per unit of GDP forms one variable of the carbon industrial chain index.

As provincial and municipal carbon dioxide emissions per unit of GDP increase, reliance on carbon dioxide increases, and carbon dioxide emissions increase. Therefore, the greater this variable is, the weaker the low-carbon economy.

⑥ Carbon dioxide emissions per unit area

Carbon dioxide emissions per unit area forms one variable in the carbon industrial chain index.

As provincial and municipal carbon dioxide emissions per unit of area increase, regional development relies more heavily on carbon dioxide use, and more carbon dioxide emissions are generated. Therefore, the greater the variable is, the weaker the low-carbon economy.

⑦ Forest green rate

The forest green rate is one variable in the carbon industrial chain index. The forest green rate has a significant effect on fixed carbon, and so, the forest green rate represents carbon emission absorption levels. As the provincial and municipal green rate increases, environmental conditions in an area improve, and more carbon emissions are absorbed. Therefore, the greater this variable is, the stronger the low-carbon economy.

⑧ Green area per capita

Green area per capita forms one variable in the carbon industrial chain index. Provincial and municipal green areas per capita represent carbon emission absorption levels. At the same time, as the calculation excludes population effects, the variable can reflect provincial environmental conditions. As the provincial and municipal green area per capita increases, environmental conditions improve, and carbon emission absorption levels increase. Therefore, the greater this variable is, the stronger the low-carbon economy.

⑨ Carbon sinks

We use the definition of carbon sinks presented in Tan and Chen [55]. Carbon sinks constitute the net result of carbon exchange and involve net absorption of outside carbon in the carbon cycle. Carbon sinks form one variable in the carbon industrial chain index and represent the carbon fixation condition.

TAs' provincial and municipal carbon sinks increase; regional environmental conditions improve; and carbon emissions absorption and fixation levels increase. Therefore, the higher the value is, the stronger the foundations of the low-carbon economy.

⑩ Garbage treatment rate

The garbage treatment rate is one variable in the carbon industrial chain index. The garbage treatment rate represents the absorption of carbon emissions and the prevention of secondary carbon dioxide generation after garbage treatment. As the provincial and municipal garbage treatment rate increases, regional garbage treatment conditions, technological resources and carbon emission absorption and fixation levels improve. Therefore, the higher the value is, the stronger the low-carbon economy.

Twelve variables are retained and nine variables excluded through the entropy weight method and via vector autoregressive correlation test screening. The specific content is shown in Table 3.

Table 3. Low-carbon economy index evaluation system content.

	Criterion	Letters	Variables	Formulas or Origins	Letters
Index Evaluation System	**Social Development Index**	B_1	Urbanization rate	Urban population/population	C_{11}
			Consumer spending per capita	Consumer spending/population	C_{12}
			Vehicles per capita	Total vehicles/population	C_{13}
			Government environmental inputs	1	C_{14}
			Government environmental inputs per unit area	2	Excluded
			Government environmental inputs per capita	3	Excluded
	Economic Foundation Index	B_2	GDP per capita	GDP/population	C_{21}
			Primary industry GDP	Primary industry GDP/GDP	C_{22}
			Secondary industry GDP	Secondary industry GDP/GDP	C_{23}
			Tertiary industry GDP	Tertiary industry GDP/GDP	C_{24}
			Income per capita	Total Income/population	Excluded
	Carbon Industrial Chain Index	B_3	Carbon productivity	Total GDP/carbon dioxide emissions	C_{31}
			4	5	C_{32}
			Carbon sinks	Carbon sequestration × green area	C_{33}
			Garbage treatment rate	Direct access	C_{34}
			GDP energy consumption	Energy consumption/GDP	Excluded
			Carbon dioxide emissions per unit of GDP	Carbon dioxide emissions/GDP	Excluded
			Carbon dioxide emissions per unit area	Carbon dioxide emissions/area	Excluded
			Carbon dioxide emissions per capita	Carbon dioxide emissions/population	Excluded
			Forest green rate	Direct access	Excluded
			Green area per capita	Forest green rate × area/population	Excluded

Notes: 1, government environmental input/government spending; 2, government environmental input/area; 3, government environmental input/population; 4, consumption of carbon dioxide emissions by residents; 5, carbon dioxide emissions/consumer spending.

3. Model

3.1. The First-Period Carbon Allowance Currency Allocation Model

The first period of the carbon emission reduction economy involves those regions initially involved in carbon emission reduction planning. The following phases form the first period of the carbon allowance allocation model.

3.1.1. Basic Low-Carbon Economy Evaluation Index System Construction

We present an evaluation index system based on the FAHP. The FAHP is normally used when employing a weighting method and is also frequently used when generating an integrated assessment model. The aforementioned entropy method is used to select variables in combination with expert knowledge and objective data; this was considered to be a more convincing evaluation index system for us to apply in regards to the low-carbon economy.

A fuzzy judgment matrix scale must also be established when using the FAHP. A matrix scale is the fuzzy relationship that x_{ij} represents when comparing i and j in a precedence matrix. Such a quantitative measure of fuzzy relationships can use the following scale (see Table 4).

Table 4. Fuzzy judgment matrix (precedence relation matrix) scale.

Scale from 0 to 1	Meaning
0	The latter is more important than the former
0.5	The former and the latter are equally important
1	The former is more important than the latter

Sixty Chinese specialists employed in relevant fields were invited to weight FAHP factors based on Tables 3 and 4. We obtained three rule hierarchies and a corresponding fuzzy judgment matrix X (precedence relation matrix) with 12 indicators. See Tables 5–8.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1r} \\ \vdots & \ddots & \vdots \\ x_{r1} & \cdots & x_{rr} \end{bmatrix}$$

Table 5. Fuzzy judgment matrix of the objective hierarchy (precedence relation matrix).

A	B_1	B_2	B_3
B_1	0.5	0.5	1
B_2	0.5	0.5	1
B_3	0	0	0.5

Table 6. Fuzzy judgment matrix of the social development indicators (precedence relation matrix).

B_1	C_{11}	C_{12}	C_{13}	C_{14}
C_{11}	0.5	0	1	0
C_{12}	1	0.5	1	1
C_{13}	0	0	0.5	0
C_{14}	1	0	1	0.5

Table 7. Fuzzy judgment matrix of the economic foundation indicators (precedence relation matrix).

B_2	C_{21}	C_{22}	C_{23}	C_{24}
C_{21}	0.5	1	1	1
C_{22}	0	0.5	0	0
C_{23}	0	1	0.5	0.5
C_{24}	0	1	0.5	0.5

Table 8. Fuzzy judgment matrix of the carbon industry chain indicators (precedence relation matrix).

B_3	C_{31}	C_{32}	C_{33}	C_{34}
C_{31}	0.5	0	0.5	0.5
C_{32}	1	0.5	1	1
C_{33}	0.5	0	0.5	0.5
C_{34}	0.5	0	0.5	0.5

As shown in Table 5, in regard to low-carbon economic development in China, most of the 60 invited specialists consulted believe that social development indicators are as important as economic foundation indicators, followed by indicators on low-carbon technologies.

As shown in Table 6, consumer spending is the most important indicator in terms of the development of China's low-carbon economy. Government investment environments constitute the next most important indicator, and the low urbanization indicator ranks third. The per capita share of vehicles is the least important indicator, supporting Zhang et al.'s [56] view that most carbon emissions are not created through heavy industry, but are generated by urban consumers.

As shown in Table 7, the social development indicator weighting results show that most of the experts believe that GDP per capita is the most important indicator in terms of low-carbon economic development in China. Secondary and tertiary GDP are equally important, while primary industry GDP is the least important indicator.

As shown in Table 8, most of the experts consulted believe that carbon dioxide emissions consumption per capita is the most important indicator, while carbon productivity, carbon sink and garbage treatment rate indicators are equally important.

In this paper, the fuzzy matrix is first converted into a fuzzy consistent matrix to avoid conducting consistency tests for the fuzzy matrix itself (precedence relation matrix). Assume that the fuzzy matrix is X (the results of expert evaluations), as shown in Tables 5–8.

The fuzzy consistency matrix is denoted as Y. Y is expressed in Equation (6).

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1r} \\ y_{21} & y_{22} & \cdots & y_{2r} \\ \vdots & \vdots & \vdots & \vdots \\ y_{r1} & y_{r2} & \cdots & y_{rr} \end{bmatrix} \tag{6}$$

Y is expressed in Equations (7) and (8).

$$\begin{gathered} y_i = \sum_{j=1}^{r} x_{ij} \\ i = 1, 2, \cdots, r \end{gathered} \tag{7}$$

$$y_{ij} = \frac{y_i - y_j}{2r} + 0.5 \tag{8}$$

To determine the weight of a low-carbon economy index system, we must first calculate the sum of the fuzzy consistent matrix without diagonal elements for each row, as expressed in Equation (9).

$$\begin{gathered} l_i = \sum_{j=1}^{r} y_{ij} - 0.5 \\ i = 1, 2, \cdots, r \end{gathered} \tag{9}$$

y_{ij} denotes the diagonal elements of Y excluding (i is not equal to j).

The sum of the diagonal elements is expressed through Equation (10).

$$\sum_i l_i = \frac{r(r-1)}{2} \tag{10}$$

The weight of the index is expressed through Equation (11).

$$w_i = \frac{l_i}{\sum_i l_i} = 2\frac{l_i}{r(r-1)} \tag{11}$$

The total scheduling weight scale can be produced after calculation (see Table 9).

Table 9. Total scheduling weight scale.

Index Hierarchy	Standard Hierarchy			Ultimate Weight
	B_1	B_2	B_3	
	0.4166	**0.4166**	**0.1666**	
C_{11}	0.1944			0.0810
C_{12}	0.4166			0.1736
C_{13}	0.0833			0.0347
C_{14}	0.3055			0.1273
C_{21}		0.4166		0.1736
C_{22}		0.0833		0.0347
C_{23}		0.2500		0.1041
C_{24}		0.2500		0.1041
C_{31}			0.1944	0.0324
C_{32}			0.4166	0.0694
C_{33}			0.1944	0.0324

Comprehensive evaluation Equation (12) can be produced following Table 9.

$$\begin{aligned} U_{1i} = {} & 0.08102\,C_{11} + 0.17361\,C_{12} - 0.03472\,C_{13} + 0.12731\,C_{14} + 0.17361\,C_{21} - 0.03472\,C_{22} \\ & - 0.10417\,C_{23} + 0.10417\,C_{24} + 0.03241\,C_{31} - 0.06944\,C_{32} + 0.03241\,C_{33} + 0.03241\,C_{34} \end{aligned} \tag{12}$$

3.1.2. Provincial Evaluation Score Calculation

Data collected from 30 provinces nationwide (except for Hong Kong, Macau, Taiwan and Tibet) are used herein. We use a min-max standardization to first standardize the data. From Equation (12) and Tables 2 and 3, we obtain comprehensive evaluation results on the low-carbon economic development for 30 provinces in China for 2012.

For example, C_{31} shown in Table 3 is the carbon productivity of one region and is equal to the total GDP/total carbon dioxide emissions for that region. The valuation scores of low-carbon economic development for one region in 2012 can be determined based on Equation (12) when C_{31} is included. All parameters can be solved from Tables 2 and 3, and the results are shown in Table 10.

Table 10. Evaluation of low-carbon economic development in various provinces of China for 2012.

Provinces	Evaluation Scores	Provinces	Evaluation Scores
Beijing	0.3445110	Henan	0.2308976
Tianjin	0.2972748	Hubei	0.2480530
Hebei	0.2384506	Hunan	0.2548442
Shanxi	0.2273866	Guangdong	0.2819445
Inner Mongolia	0.2682990	Guangxi	0.2451672
Liaoning	0.2691645	Hainan	0.2737197
Jilin	0.2545505	Chongqing	0.2731518
Heilongjiang	0.2522145	Sichuan	0.2472006
Shanghai	0.3321558	Guizhou	0.2501424
Jiangsu	0.2775995	Yunnan	0.2498491
Zhejiang	0.2785171	Shaanxi	0.2461821
Anhui	0.2406266	Gansu	0.2386316
Fujian	0.2637339	Qinghai	0.2562230
Jiangxi	0.2421416	Ningxia	0.2529227
Shandong	0.2555405	Xinjiang	0.2405634

3.1.3. Carbon Allowance Currency Allocation Proportions

According to Equation (12), the carbon allowance proportion for region i is expressed by Equation (13).

$$t_{1,i} = \frac{U_{1i}}{\sum_{i=1}^{m} U_{1i}}, i = 1, 2, \cdots, m, m = 30 \tag{13}$$

The carbon allowance proportion for 30 provinces in China can be determined from Equation (13).

3.1.4. Provincial Carbon Allowance Currency Allocation Determination

The carbon allowance proportion for region i is $t_{1,i}$ according to Equation (13), and the total carbon emissions level for the same period is d for China. Carbon allowances for region i are expressed by Equation (14).

$$d_{1,i} = t_{1,i} \times d, i = 1, 2, \cdots, m, m = 30 \tag{14}$$

We can calculate the carbon allowance system of China's 30 provinces for 2012 based on Equation (14).

3.1.5. The Final First-Period Carbon Allowance Currency Allocation Rational Model

We can compute the ratio of the CO_2 emission allowance currency from Equation (13) for the first period for China to consider historical emission proportions per capita and other factors cited by previous studies. We determine the CO_2 emission allowance currency ratio by averaging Equation (13), the fifth iteration of 2020 in China based on Zeng et al. [12], the fifth iteration for 2020 in China based on Wang et al. [13] and the CO_2 emission allowance currency ratio for 2020 in China according to Yu et al. [28]. The final first-period carbon allowance currency allocation rational model is shown in Equation (15).

$$\text{FRCEAC(e, 1)} = [\text{FRCEAC(a)} + \text{FRCEAC(b)} + \text{FRCEAC(c)} + \text{FRCEAC(d)}]/4 \tag{15}$$

FRCEAC(e) denotes the final first-period carbon allowance allocation rational model.

FRCEAC(a) denotes the forecasted ratio of CO_2 emission allowance currency based on Equation (13) for 2020 in China according to the present article. FRCEAC(b) denotes the forecasted ratio of CO_2 emission allowance currency based on Zeng et al. [12]. FRCEAC(c) denotes the forecasted ratio of CO_2 emission allowance currency based on Wang et al. [13]. FRCEAC(d) denotes the forecasted ratio of CO_2 emission allowance currency based on Yu et al. [28].

3.2. The Second-Period Carbon Allowance Currency Allocation Model

The regions included in the second period have already completed the first period. These regions have adapted to emission reduction policies. The two periods present different demands and unique sources of potential. The following tasks are used to develop the second-period carbon allowances allocation model.

3.2.1. Advanced Low-Carbon Economy Evaluation Index System Construction

The advanced low-carbon economy index system improves the evaluations of the importance of energy savings and emission reduction outcomes. The advanced low-carbon economy index system is based on the basic low-carbon economy evaluation index system.

From the hierarchical model of the new index system, we obtain Figure 1.

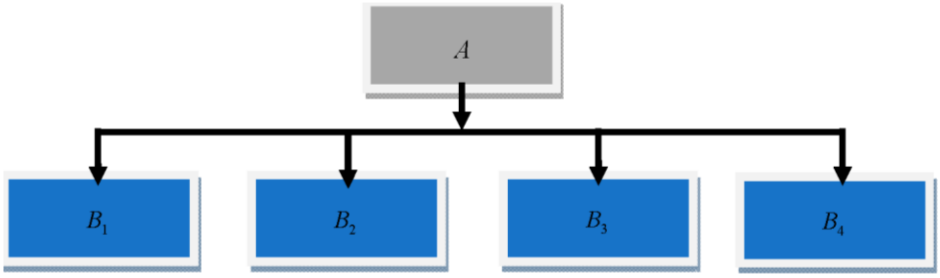

Figure 1. The advanced low-carbon economy evaluation system.

In Figure 1, A is regarded as the advanced low-carbon economy evaluation system. B_1, B_2, B_3 and B_4 are defined as the social development index, economic foundation index, carbon industry chain and basic low-carbon economy evaluation result index, respectively. The relationships between these symbols are as follows.

$A = \{B_1, B_2, B_3, B_4\}$ = {social development index, economic foundation index, carbon industry chain, basic low-carbon economy evaluation result index}. In the same way, the other variables can be defined as follows. $B_1 = \{C_{11}, C_{12}, C_{13}, C_{14}\}$ = {urbanization rate, resident consumption expenditure, per capita occupancy vehicles, the proportion of government expenditures on the environment};

$B_2 = \{C_{21}, C_{22}, C_{23}, C_{24}\}$ = {per capita GDP, first industry proportion, second industry proportion, third industry proportion};

$B_3 = \{C_{31}, C_{32}, C_{33}, C_{34}\}$ = {carbon productivity, carbon dioxide emissions from household unit consumption, carbon sink, innocuous refuse treatment efficiency};

$B_4 = \{C_{41}\}$ = {basic low-carbon economy evaluation results}.

The fuzzy judgment matrix (precedence relation matrix) of evaluation system rule hierarchy A and the comprehensive evaluation index are built as shown in Tables 11 and 12.

Table 11. The fuzzy judgment matrix (precedence relation matrix) of the evaluation system hierarchy A.

A	B_1	B_2	B_3	B_4
B_1	0.5	0.5	1	1
B_2	0.5	0.5	1	1
B_3	0	0	0.5	1
B_4	0	0	0	0.5

Table 12. The fuzzy judgment matrix (precedence relation matrix) of the comprehensive evaluation index.

B_4	C_{41}
C_{41}	0.5

By calculating the numerical results from Tables 6–8, a new weight table can be presented as shown in Table 13.

According to Table 13, the advanced low-carbon economy evaluation index can be written as shown in Equation (16).

$$U_{2i} = 0.07022\,C_{11} + 0.15046\,C_{12} - 0.03009\,C_{13} + 0.11034\,C_{14} + 0.15046\,C_{21} - 0.03009\,C_{22} - 0.09028\,C_{23} + 0.09028\,C_{24} + 0.03781\,C_{31} - 0.08102\,C_{32} + 0.03781\,C_{33} + 0.03781\,C_{34} + 0.08333\,C_{41} \quad (16)$$

Table 13. The new weight table.

Indicator	B_1, B_2, B_3 or B_4				Final Weight
	B_1	B_2	B_3	B_4	
	0.36111	**0.36111**	**0.19444**	**0.08333**	
C_{11}	0.19444				0.07022
C_{12}	0.41667				0.15046
C_{13}	0.08333				0.03009
C_{14}	0.30556				0.11034
C_{21}		0.41667			0.15046
C_{22}		0.08333			0.03009
C_{23}		0.25000			0.09028
C_{24}		0.25000			0.09028
C_{31}			0.19444		0.03781
C_{32}			0.41667		0.08102
C_{33}			0.19444		0.03781
C_{34}			0.19444		0.03781
C_{41}				1.00000	0.08333

3.2.2. Provincial Evaluation Score Calculation

According to Equation (16), the comprehensive evaluation results for low-carbon economic development in the 30 Chinese provinces for 2012 can be determined as shown in Table 14.

Table 14. The comprehensive evaluation results of low-carbon economic development in China for 2012.

Province	Final Score	Province	Final Score
Beijing	0.3578685	Henan	0.2499058
Tianjin	0.3120544	Hubei	0.2653433
Hebei	0.2559804	Hunan	0.2732842
Shanxi	0.2410199	Guangdong	0.2982154
Inner Mongolia	0.2848430	Guangxi	0.264338
Liaoning	0.2851161	Hainan	0.2903751
Jilin	0.2698661	Chongqing	0.2899427
Heilongjiang	0.2685016	Sichuan	0.2665246
Shanghai	0.3443232	Guizhou	0.2673254
Jiangsu	0.2937926	Yunnan	0.2681576
Zhejiang	0.2953515	Shaanxi	0.2642108
Anhui	0.2588689	Gansu	0.2549083
Fujian	0.2814690	Qinghai	0.2733016
Jiangxi	0.2611579	Ningxia	0.2665476
Shandong	0.2729516	Xinjiang	0.2578254

3.2.3. The Carbon Allowance Currency Allocation Proportion

The advanced low-carbon economy evaluation index for region i is U_{2i}. The proportion of carbon allowance currency allocation can be written as shown in Equation (17).

$$t_{2,i} = \frac{U_{2i}}{\sum_{i=1}^{m} U_{2i}}, i = 1, 2, \cdots, m, m = 30 \quad (17)$$

The forecasted ratio difference of CO_2 emission allowance currency based on Equations (17) minus (13) in China as determined in the present article is shown in Figure 2. Beijing, Tianjin and Shanghai will decrease the CO_2 emission allowance currency ratio more (0.05%) through Equation (17) than through Equation (13) according to Figure 2.

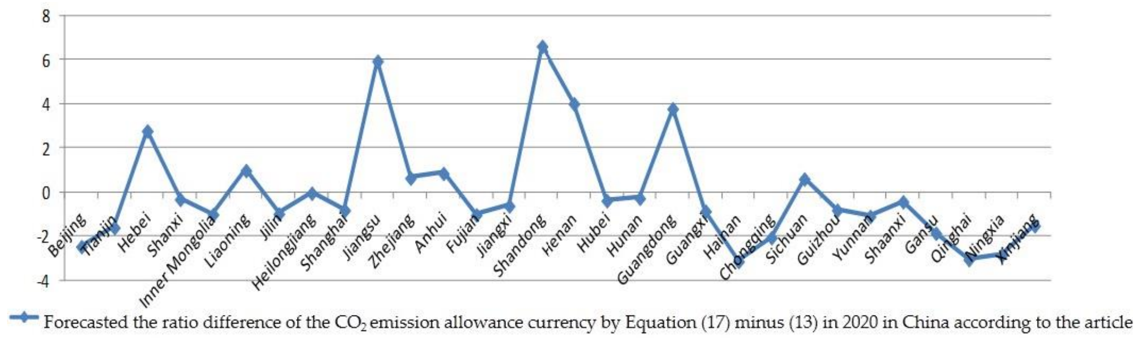

Figure 2. The forecasted 2020 ratio difference of CO_2 emission allowance currency from Equations (17) minus (13) for China.

3.2.4. Carbon Dioxide Emission Allowances Based on the Advanced Low-Carbon Economy Evaluation Index System

According to Equation (17), the total carbon emission quantum is d, and so, the allowance of region i can be defined as shown in Equation (18).

$$d_{2,i} = t_{2,i} \times d, i = 1, 2, \cdots, m, m = 30 \quad (18)$$

3.2.5. The Final Second-Period Carbon Allowance Currency Allocation Rational Model

We can compute the CO_2 emission allowance currency ratio from Equations (13) and (17) for 2030 for the second period in China to consider the proportion of historic emissions per capita and other factors cited in previous studies. We allocate the CO_2 emission allowance currency ratio by averaging Equations (13) and (17), the fifth 2020 iteration for China according to Zeng et al. [12], the fifth 2020 iteration for China according to Wang et al. [13] and the CO_2 emission allowance currency ratio for 2020 in China according to Yu et al. [28]. The average CO_2 emission allowance currency ratio for the second period in China should be rational.

The final form of the second-period carbon allowance currency allocation rational model is shown in Equation (19).

$$\text{FRCEAC(e, 2)} = [\text{FRCEAC(a1)} + \text{FRCEAC(b)} + \text{FRCEAC(c)} + \text{FRCEAC(d)} + \text{FRCEAC(a2)}]/5 \quad (19)$$

FRCEAC(e) denotes the final form of the first-period carbon allowances allocation rational model.

FRCEAC(a1) denotes the forecasted ratio of CO_2 emission allowance currency based on Equation (13) in China according to this article.

FRCEAC(b) denotes the forecasted ratio of CO_2 emission allowance currency based on Zeng et al. [12]. FRCEAC(c) denotes the forecasted ratio of CO_2 emission allowance currency based on Wang et al. [13]. FRCEAC(d) denotes the forecasted ratio of CO_2 emission allowance currency based on Yu et al. [28]. FRCEAC(a2) denotes the forecasted ratio of CO_2 emission allowance currency based on Equation (17) for China according to this article.

4. The Results and Discussions of Carbon Emission Allowance Allocation for 2020 and 2030

4.1. 2020 CO_2 Emission Allowance Currency Ratio Forecasting Results for China

We assume that the period from 2020 to 2029 is the first period. Thus, 2020 is the first year of the first period. The forecasted ratio of CO_2 emission allowance currency for 2020 in China according to Equation (15) is denoted as FRCEAC(e,1) in Table 15 and as the blue line in Figure 3.

Table 15. FRCEAC(e,1) is the forecasted ratio of CO_2 emissions allowance currency for 2020 in China according to Equation (15).

Province	FRCEAC(a1)	FRCEAC(b)	FRCEAC(c)	FRCEAC(d)	FRCEAC(e,1)
Beijing	4.3989604	2.6126062	1.9709608	1.5631040	2.6364079
Tianjin	3.7958086	1.8611990	2.2273459	1.6549379	2.3848229
Hebei	3.0447002	4.7710240	5.8514568	7.6800655	5.3368116
Shanxi	2.9034282	2.5004716	2.6145943	4.6895877	3.1770205
Inner Mongolia	3.4258259	3.5791062	2.4499025	5.7551360	3.8024927
Liaoning	3.4368764	4.4652101	4.4520212	5.7012295	4.5138343
Jilin	3.2502745	1.7509169	2.3047956	2.6412335	2.4868051
Heilongjiang	3.2204480	2.4238785	3.2101557	2.8343601	2.9222106
Shanghai	4.2411920	3.1467566	3.4576385	2.4681267	3.3284285
Jiangsu	3.5445806	7.8968557	9.5111767	6.3596783	6.8280728
Zhejiang	3.5562968	4.7517501	4.2303549	4.0453732	4.1459437
Anhui	3.0724858	3.6865887	3.9579457	3.2432045	3.4900562
Fujian	3.3675353	2.9315431	2.3760137	2.2607659	2.7339645
Jiangxi	3.0918296	2.5433197	2.5059867	1.8731351	2.5035678
Shandong	3.2629155	8.4627411	9.9019860	8.2999440	7.4818967
Henan	2.9482588	5.7398982	6.9864952	5.2899057	5.2411395
Hubei	3.1673102	3.5256372	2.8202366	4.1278400	3.4102560
Hunan	3.2540253	3.8379347	3.0160863	3.3335690	3.3604038
Guangdong	3.6000608	7.9394463	7.4102429	6.1496542	6.2748511
Guangxi	3.1304625	2.8138669	2.3047956	2.0793940	2.5821298
Hainan	3.4950404	0.6638219	0.3970408	0.3711924	1.2317739
Chongqing	3.4877895	1.7628387	1.4662025	1.7354762	2.1130767
Sichuan	3.1564262	4.8070172	3.7896929	3.6199988	3.8432838
Guizhou	3.1939891	2.2918275	2.4160739	2.2248588	2.5316873
Yunnan	3.1902441	2.7178353	2.1285308	2.2702248	2.5767087
Shaanxi	3.1434216	2.4476418	2.7463478	2.6833853	2.7551991
Gansu	3.0470118	1.6050582	1.2240610	1.5215033	1.8494086
Qinghai	3.2716314	0.3668046	0.2581656	0.3702741	1.0667189
Ningxia	3.2294903	0.5626462	0.4237476	1.0822620	1.3245365
Xinjiang	3.0716784	1.5337563	1.5899440	2.0705779	2.0664892
Total	100	100	100	100	100

Notes: FRCEAC(a1): forecasted ratio of CO_2 emission allowance currency based on Equation (13) in China according to the present article; FRCEAC(b): forecasted ratio of CO_2 emission allowance currency for the 5th iteration in 2020 in China according to Zeng et al. (b) [12]; FRCEAC(c): forecasted ratio of CO_2 emission allowance currency for the 5th iteration in 2020 in China according to Wang et al. (c) [13]; FRCEAC(d): forecasted ratio of CO_2 emission allowance currency for 2020 in China according to Yu et al. (d) [28]; FRCEAC(e,1): forecasted ratio of CO_2 emission allowance currency from Equation (15) according to the present article (for 2020 in China).

Each method presents advantages and disadvantages as stated in Clò [57]. We found that fluctuations in the forecasted CO_2 emission allowance currency ratio in China for the second period were the smallest for Equation (15) as shown in [12,13] and Yu et al. [28]. On the other hand, there exists a short- and long-run causality running from energy consumption to GDP growth and pollutant emission [58–60]. We would like to seek a balance among energy consumption, GDP growth and pollutant emission. Therefore, we would like to use Equation (15) as the carbon allowance currency allocation rational model for the first period.

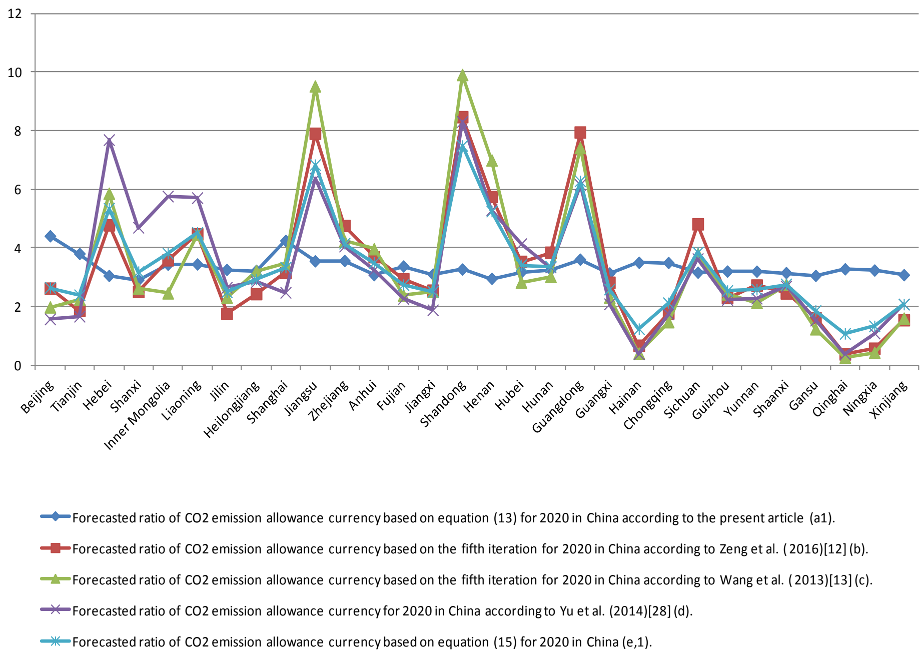

Figure 3. Forecasted ratio of CO_2 emission allowance currency for 2020 according to Equation (15). Notes: (a1) means forecasted ratio of CO_2 emission allowance currency based on Equation (13) for 2020 in China according to the present article; (b) means forecasted ratio of CO2 emission allowance currency based on the fifth iteration for 2020 in China according to Zeng et al. (2016) [12]; (c) means forecasted ratio of CO_2 emission allowance currency based on the fifth iteration for 2020 in China according to Wang et al. (2013 [13]; (d) means forecasted ratio of CO_2 emission allowance currency for 2020 in China according to Yu et al. (2014) [28]; (e,1) means forecasted ratio of CO_2 emission allowance currency based on Equation (15) for 2020 in China.

4.2. 2030 CO_2 Emission Allowance Currency Ratio for China

We assume that the second period will run from 2030 to 2050. Hence, 2030 is first year of the second period.

The forecasted ratio of CO_2 emission allowance currency for 2030 in China according to Equation (19) is denoted as $FRCEAC^{(e,2)}$ in Table 16 and is the yellow line in Figure 4.

Table 16. FRCEAC(e,2) is the forecasted ratio of CO_2 emission allowance currency for 2030 in China according to Equation (19).

Province	FRCEAC(a1)	FRCEAC(a2)	FRCEAC(b)	FRCEAC(c)	FRCEAC(d)	FRCEAC(e,2)
Beijing	4.398960	4.294594	2.612606	1.970960	1.563104	2.968045
Tianjin	3.795808	3.744803	1.861199	2.227345	1.654937	2.656819
Hebei	3.044700	3.071888	4.771024	5.851456	7.680065	4.883827
Shanxi	2.903428	2.892355	2.500471	2.614594	4.689587	3.120087
Inner Mongolia	3.425825	3.418253	3.579106	2.449902	5.755136	3.725644
Liaoning	3.436876	3.421531	4.465210	4.452021	5.701229	4.295373
Jilin	3.250274	3.238523	1.750916	2.304795	2.641233	2.637148
Heilongjiang	3.220448	3.222149	2.423878	3.210155	2.834360	2.982198
Shanghai	4.241192	4.132044	3.146756	3.457638	2.468126	3.489151
Jiangsu	3.544580	3.525653	7.896855	9.511176	6.359678	6.167588
Zhejiang	3.556296	3.544360	4.751750	4.230354	4.045373	4.025627
Anhui	3.072485	3.106551	3.686588	3.957945	3.243204	3.413355
Fujian	3.367535	3.377763	2.931543	2.376013	2.260765	2.862724
Jiangxi	3.091829	3.134020	2.543319	2.505986	1.873135	2.629658
Shandong	3.262915	3.275550	8.462741	9.901986	8.299944	6.640627
Henan	2.948258	2.998989	5.739898	6.986495	5.289905	4.792709

Table 16. *Cont.*

Province	FRCEAC(a1)	FRCEAC(a2)	FRCEAC(b)	FRCEAC(c)	FRCEAC(d)	FRCEAC(e,2)
Hubei	3.167310	3.184247	3.525637	2.820236	4.127840	3.365054
Hunan	3.254025	3.279542	3.837934	3.016086	3.333569	3.344231
Guangdong	3.600060	3.578728	7.939446	7.410242	6.149654	5.735626
Guangxi	3.130462	3.172187	2.813866	2.304795	2.079394	2.700141
Hainan	3.495040	3.484640	0.663821	0.397040	0.371192	1.682347
Chongqing	3.487789	3.479452	1.762838	1.466202	1.735476	2.386351
Sichuan	3.156426	3.198424	4.807017	3.789692	3.619998	3.714311
Guizhou	3.193989	3.208033	2.291827	2.416073	2.224858	2.666956
Yunnan	3.190244	3.218020	2.717835	2.128530	2.270224	2.704971
Shaanxi	3.143421	3.170656	2.447641	2.746347	2.683385	2.838290
Gansu	3.047011	3.059022	1.605058	1.224061	1.521503	2.091331
Qinghai	3.271631	3.279750	0.366804	0.258165	0.370274	1.509325
Ningxia	3.229490	3.198699	0.562646	0.423747	1.082262	1.699369
Xinjiang	3.071678	3.094029	1.533756	1.589944	2.070577	2.271997
Total	100	100		100	100	100

Notes: FRCEAC(a1): forecasted CO_2 emission allowance currency ratio based on Equation (13) for China according to the present article; FRCEAC(a2): forecasted CO_2 emission allowance currency ratio based on Equation (15) for China according to the present article; FRCEAC(b): forecasted CO_2 emission allowance currency ratio for the 5th iteration in 2020 in China according to Zeng et al. (b) [12]; FRCEAC(c): forecasted CO_2 emission allowance currency ratio for the 5th iteration in 2020 in China according to Wang et al. (c) [13]; FRCEAC(d): forecasted CO_2 emission allowance currency ratio for 2020 in China according to Yu et al. (d) [28]; FRCEAC(e,2): forecasted CO_2 emission allowance currency ratio for 2030 based on Equation (19) in China according to the present article.

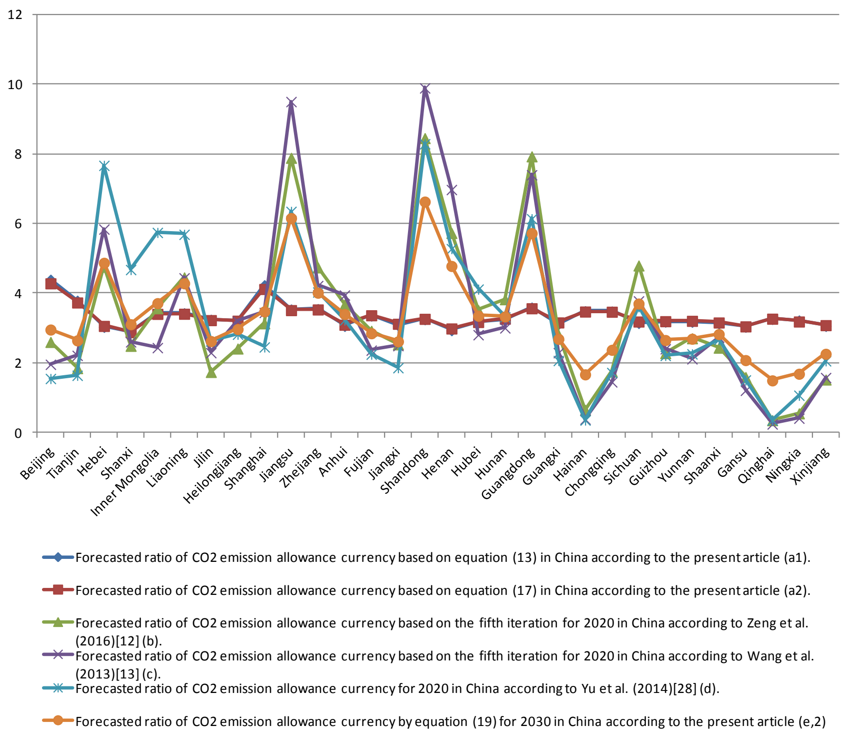

Figure 4. The yellow line (e,2) denotes the forecasted CO_2 emission allowance currency ratio for 2030 in China according to Equation (19). Notes: (a1) Forecasted CO_2 emission allowance currency ratio based on Equation (13) for 2020 in China according to the present article; (a2) forecasted CO_2 emission allowance currency ratio based on Equation (17) for 2020 in China according to the present article; (b) forecasted CO_2 emission allowance currency ratio for the fifth iteration for 2020 in China according to Zeng et al. (b) [12]; (c) forecasted CO_2 emission allowance currency ratio for the fifth iteration for 2020 in China according to Wang et al. (c) [13]; (d) forecasted CO_2 emission allowance currency ratio for 2020 in China according to Yu et al. (d) [28]; (e,2) forecasted CO_2 emission allowance currency ratio based on Equation (19) for 2020 in China according to the present article.

We found that fluctuations in the forecasted CO_2 emission allowance currency ratio for China for the second period to be smallest in Equation (19) in this paper [12,13], as stated in Yu et al. [28].

4.3. Forecasted Chinese CO_2 Emission Allowance Currency Ratio Differences between the First and Second Periods

Figure 5 presents forecasted Chinese CO_2 emission allowance currency ratio differences between the first and second periods. The difference is equal to Equation (19) minus Equation (15).

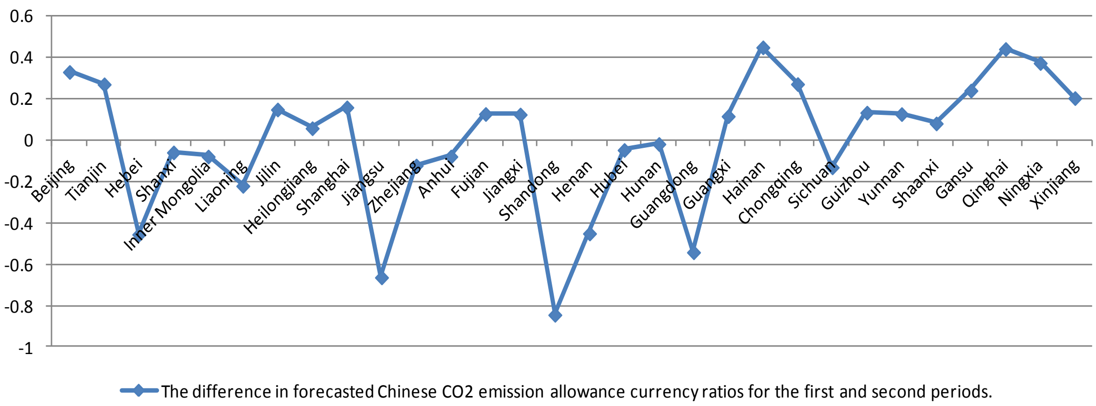

Figure 5. The difference in forecasted Chinese CO_2 emission allowance currency ratios for the first and second periods.

Figure 5 shows that Hebei, Jiangsu, Shandong and Guangdong will decrease the CO_2 emission allowance currency ratio in the second period 0.4% over the first period.

5. Conclusions

Carbon emission intensity, energy intensity and total carbon emission forecast valuations for 2020 in China vary across studies [12,13,28–32]. We are more concerned with the allocation and the methods of carbon emission allocation ratios in each region of China. The methods [1–16] emphasize one factor of the carbon emission proportions allocation.

This article examines carbon emission allowance currency allocation ratios based on first- and second-period allocation models involving a basic low-carbon economy evaluation system for the first period and an advanced low-carbon economy evaluation system for the second period.

To improve our evaluations, we use weighting information provided by 60 industry experts, conduct a vector autoregression correlation test and employ the entropy weight method to measure degrees of information filtering when constructing basic and advanced low-carbon economy evaluation index systems.

Carbon emissions reduction targets are divided into two periods from 2020 to 2050. While historical carbon emissions are considered more during the first period, technology innovations in terms of carbon emissions are more considered in the second period. The two phases come with different emissions reduction potentials and policies, and different allocation methods can separate carbon reduction behaviors from regional economic development outcomes.

The basic and advanced low-carbon economy evaluation index system for carbon emission allowance currency allocation is efficient and straightforward and can quickly determine regional carbon allowance currency allocation proportions. The basic low-carbon economy evaluation index system for regional carbon emission allowance currency allocation may result in poor adaptations to carbon emission reduction policies.

For the first period, we average the basic low-carbon economy evaluation index system carbon allowance allocation proportion with existing results for each region. The average proportion can be treated as the final allocation proportion for the first period of each region. Each region presents greater levels of certainty and reduced levels of volatility, thereby reducing regional economic development risks.

For the second period, we average the advanced low-carbon economy evaluation index system carbon allowance allocation proportion with the existing results for each region. The average proportion can be treated as the final allocation proportion for the second period for each region. Each region presents greater levels of certainty and reduced levels of volatility, thereby reducing regional economic development risks.

The allocation results for the second period will improve energy conservation and regional emissions reduction outcomes. At the same time, differences between the carbon allowance allocation proportion and actual carbon allowance demand proportion can promote carbon allowance currency market circulation, improving the role of market allocation resources.

All in all, this article put the low carbon economy development index system as an important factor of carbon allowance allocation ratios, considering both energy conservation, emissions reduction and considering the adaptability of policy from the first and second period. The new approach can make people and policy designers more adapted to the different stages of development.

Acknowledgments: The authors acknowledge the valuable comments and suggestions from our colleagues, especially Professor Tang Ke in academy of social sciences of Tsinghua University. The authors are grateful to the anonymous reviewers, whose comments have helped to improve the manuscript. The research is funded jointly by the National Natural Science Foundation of China (71473010; 71573186); the Chinese philosophy & social science research program (11 & ZD140; 12BJY060); the National Bureau of Statistics research project (2014LY113); the Beijing education committee fund (PXM2015_014204_500026; SZ201510005002); Beijing modern manufacturing base of Beijing philosophy and social sciences and the scientific research incentive fund of economic and management school and graduate students key science and technology fund (ykj-2014-10620) in the Beijing University of Technology; the Beijing natural science fund (9142001); and the Specialized Research Fund of Higher Education in China (20131103110004).

Author Contributions: Shihong Zeng and Jiuying Chen conceived of, designed and performed the experiments; Shihong Zeng and Jiuying Chen analyzed the data and contributed materials. All authors wrote the paper.

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

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