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Original Research Paper

Allocation of CO_2 Emissions with Zero Sum Gains Data Envelopment Analysis Models

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ABSTRACT

Along with China's increasing share in global total CO_2 emissions, there is a necessity for China to shoulder large emission mitigating responsibility. The allocation of carbon dioxide emission allowances has become one of the most important global issues. In view of originality, an improved zero sum gains data envelopment analysis optimization model, which could deal with the constant total amount resources allocation, is proposed in this study. This paper contributes to the existing resource allocation method and allocates China's provincial CO_2 emissions in 2013 from the view of technical efficiency. The allocation results reveal that several energy-abundant provinces such as Shanxi and Inner Mongolia need to take more responsibilities in CO_2 emissions reduction. After the ZSG-DEA allocation, all provinces' CO_2 emissions are on ZSG-DEA frontier. The allocation results indicate that different provinces have to shoulder different mitigation burdens in terms of emission intensity reduction.

INTRODUCTION

Climate change has attracted global attention, not only from developed countries, but also from developing countries. As the largest developing country, China has taken various measures for reducing its overall CO_2 emissions. The Chinese government set up a goal of reducing CO_2 emissions per unit gross domestic product (GDP) by 17% until 2015 in 2011, compared to the 2010 level. As a restriction index, this target has been included in the future medium-and-long term plans for national economic and social development. In order to achieve the goal of carbon emission reduction, the choice of carbon dioxide emissions allocation method and initial quotas confirmation, must be solved as an important topic of research.

The aim of this paper is to disaggregate China's national CO_2 emissions intensity reduction target at the regional level, i.e. to allocate China's national CO_2 emission allowance over Chinese provinces in 2013. In this study, we discuss the total emission control problem and analyse the existing emission allowance allocation approach. Then we utilize an improved zero sum gains data envelopment analysis (ZSG-DEA) model, which belongs to the optimization method and could deal with the constant total amount resource allocation problem, to allocate China's CO_2 emission allowance over the provinces. This paper can help facilitate the implementation of this regulation by allocating the appropriate regional CO_2 emissions.

EARLIER STUDIES

Academically, the allocation of CO_2 emissions has been widely studied. Holmberg et al. (2012) used the energy, exergy and market based methods to allocate CO_2 emissions and fuel costs. Wei et al. (2014) presented a systematic and quantitative method to achieve the "common but differentiated responsibility" CO_2 emission allocation principle. Pan et al. (2014) emphasized "equitable access to sustainable development" for per capita cumulative CO_2 emission rights allocation schemes. Morini et al. (2013) raised a method for the optimal demand allocation among combined heat and power (CHP) and renewable energy systems to minimize the primary energy consumption. Hasan et al. (2014) presented a benefit-based allocation method by using a Shapley value approach. Wang et al. (2014) allocated CO_2 emission quotas to major countries using different regimes for a sample period of 2011-2100. Levihn (2014) compared different allocation methods and discussed both advantages and disadvantages of each method.

Different from these previous studies, this paper attempts to employ data envelopment analysis (DEA) to allocate CO_2 emissions. As a non-parametric approach, DEA has been widely used in the resource allocation problem studied by Fang & Zhang (2008), especially the allocation problem with a fixed total amount of input or output. It is considered that Cook & Kress (1999) proposed the first model, under the DEA framework, that deals with the fixed input allocation problem. Cook & Kress's approach was based on outputoriented version of the CCR-DEA model, in which the objective of DEA model is to minimize the weighted combination of input variables with the constraint. Cook & Zhu (2005) extended this method to cases that the input-oriented CCR-DEA model was utilized. Lin (2011) presented several DEA models to solve the same fixed input resource allocation problem. Aparicio & Monge et al. (2012) also conducted research on such problems of the emission permits allocation. In their study, a centralized point of view was adopted in the DEA method to correspond to the three objectives: maximizing aggregated desirable production, minimizing the consumption of input resources, and minimizing undesirable total emissions.

By introducing the zero sum game concepts in to the DEA method, Gomes & Lins (2008) developed a zero sum gains data envelopment analysis (ZSG-DEA) model which was used to reallocate CO_2 emissions allowance among the Annex I parties and Non-Annex I countries of the Kyoto Protocol. Also by using ZSG-DEA model, Serrao (2010) proposed a model to efficiently reallocate agricultural greenhouse gas emissions among the 15 EU countries. Since the DEA based method has been successfully and effectively applied in the resource allocation problem, in this paper we choose a DEA based approach for the CO_2 emission allowance allocation over the provinces in China.

One of the key issues related to the CO_2 emission allowance allocation under the DEA framework is how to deal with the CO_2 should be minimized. There are several approaches to modelling such types of undesirable outputs in the DEA context; for instance, dealing the undesirable outputs through a weak disposability reference technology by assuming the undesirable outputs and desirable outputs are generated in the same production process proposed by Färe et al. (1989) and Arita Duasa et al. (2013). Feng (2014), Färe et al. (2007), Lozano & Gutierrez (2008) applied the directional distance function to simultaneously increase the desirable outputs and decrease the undesirable outputs. Cheng & Liu (2009) translated the undesirable outputs into desirable outputs mathematically under the classification in variance and Zhou et al. (2015) and Zhang et al. (2008) treated the undesirable outputs as inputs. Furthermore, Sueyoshi et al. (2010, 2011, 2012) proposed a DEA model using the range adjusted measure which combined the undesirable and desirable outputs in a unified treatment. Since the regional CO_2 emission allowance is a sub-divided quota of the total emission control target of China, which can essentially be considered as a distribution of the resource to each region, the approach proposed in this paper, therefore, realistically treats the undesirable outputs of the CO_2 emissions allowance as inputs.

MATERIALS AND METHODS

CCR-DEA model and zero sum gains DEA (ZSG-DEA) model: The classic input-oriented CCR model which was proposed by Charnes et al. (1978) for calculating the technical efficiency of DMU can be expressed in equation (1).

$$\begin{aligned} & E_{CCR} = \min \theta \\ & s.t. \quad \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{ik}, \quad i = 1, \ldots, m, \\ & \qquad \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rk,} \; j = 1, \ldots, s, \\ & \qquad \lambda_g \ge 0, \quad j = 1, \ldots, n \end{aligned} \qquad \ldots(1)$$

In model (1), θ is the CCR-DEA efficiency measure of the kth DMU under evaluation, and E_{CCR} is the optimized efficiency score for DMU_k. x_{ij} and y_{rj} are the input and output values, respectively, of each DMU_j, and x_{ik} and y_{rk} are the input and output values for the under evaluation DMU_k. λ_j is the intensity variable associated with each DMU_j for connecting the inputs and outputs. In model (1), there are n DMUs, and each of them has s inputs and m outputs.

The ZSG-DEA model was first proposed by Lins et al. (2003) in order to estimate the winning efficiency of different countries in the Olympics. The idea is that the total amount of an input (output) is fixed so that a decrease in the input (output) for one decision making unit (DMU) can lead to an increase in the input (output) for another DMU. It suggests that in ZSG-DEA, the resource allocation is highly effective. After the reallocation of resources by using the ZSG-DEA model, the DMUs with lower technical efficiency scores can reach the frontier of best practice. In the ZSG-DEA model, two allocation principles, including average allocation and linear allocation, are often adopted. The linear allocation is more often used, such as the two ZSG-DEA application cases conducted by Gomes & Lins (2008). In the following part we present how to develop such a ZSG-DEA model.

$$\begin{aligned} & E_{zsg} = \min \sum_{i=1}^{m} w_i \theta_i \\ & s.t. \quad \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rk,} \; r = 1, \ldots, s, \\ & \qquad \sum_{j=1}^{n} \lambda_j x_{ij} \left(1 + \frac{x_{ik}(1-\theta_i)}{\sum_{j=1, j \ne k}^{n} x_{ij}} \right) \le \theta_i x_{jg}, \; i = 1, \ldots, m, \end{aligned} \qquad \ldots(2)$$

$$\sum_{i=1}^{m} w_i = 1, \quad w_i \geq 0, \quad i = 1, \ldots, m,$$
$$\lambda_j \geq 0, \; j = 1, \ldots, n$$

In model (2), θ_i is the ith input related ZSG-DEA efficiency measure of DMU_k under the constraint that the sum of the ith input must be fixed, w_i is the normalized user-specified weight for θ_i, and E_{ZSG} is the unified weighted average efficiency for DMU_k. x_{ij} and y_{rk} are the input and output values, respectively, and x_{ik} and y_{rk} are the input and output values for the under evaluation DMU_k. λ_j is the contribution of DMU_j to the efficient projection.

The under evaluated DMU_k in model (2) is the object unit that is attempting to decrease its inputs, thus y_i is the decrease rate for its ith input. Therefore, x_{ik} (1-θ_i) is the decrease on the ith input for DMU_k, and the amount of the decrease needs to be distributed to the other n-1 DMUs so that their ith input will increase. This process makes sure that the decrease of DMU_k equals to the increase of the other DMU_j ($j \neq k$), and the sum of the ith input is constant. One strategy to distribute x_{ik} (1-θ_i) to other DMUs is that, the increase on the ith input for the other DMUs are proportional to their levels of the initial ith input, and the proportion for DMU_j is $x_{ij} / \sum_{j=1, j\neq k}^{n} x_{ij}$. Thus, after the redistribution, the ith input of DMU_j becomes

$$x_{ij}\left(1 + \left(x_{ik}\left(1-\theta_i\right)\right) / \sum_{j=1, j\neq k}^{n} x_{ij}\right).$$

The above ZSG-DEA model is formulated to promote the allocation of the input with a constant total amount, when the inefficient DMUs are searching for efficiency. After this input redistribution process, all the DMUs will be projected to a new efficient frontier and therefore all DMUs will become efficient.

A non-radial ZSG-DEA model for CO_2 emission allowance allocation in China: In this study, we aim to obtain a ZSG-DEA efficient frontier which could appropriately represent an efficient regional allocation of CO_2 emissions (undesirable output) in the context of CO_2 emission intensity reductions and energy intensity reduction in China.

Using the ZSG-DEA model, we aim to achieve an efficient allocation, which means that all regions which lie on the new ZSG-DEA frontier will become DEA efficient by adjusting the amounts of CO_2 emissions among different regions of China. In order to reflect the demographic and economic characteristics of each region during allocation, the output variables we used in the modified ZSG-DEA model are the gross domestic product (GDP in billion RMB) based on the price of 2005, total energy consumption (TE in million tonnes of coal equivalent, i.e. tce), and population (POP in millions of inhabitants). The input variables used are CO_2 emissions (CO_2 in million tonnes). Here, the term of coal equivalent is a reference unit for the energetic evaluation of various energy carriers. All two inputs have constant total amounts which need to be reallocated among China's regions. The associated ZSG-DEA allocation model (3) is shown below:

$$\begin{aligned}
& E'_{ZSG} = \min \; \theta^{CO_2} \\
& s.t. \sum_{j=1}^{n} \lambda_j y_j^{GDP} \geq y_k^{GDP}, \\
& \sum_{j=1}^{n} \lambda_j y_j^{POP} \geq y_k^{POP}, \\
& \sum_{j=1}^{n} \lambda_j y_j^{TE} \geq y_k^{TE}, \\
& \sum_{j=1}^{n} \lambda_j x_j^{CO_2}\left(1 + \frac{x_k^{CO_2}\left(1-\theta^{CO_2}\right)}{\sum_{j=1, j\neq k}^{n} x_j^{CO_2}}\right) \leq \theta^{CO_2} x_k^{CO_2}, \qquad \ldots(3) \\
& \lambda_j \geq 0, \; j = 1, \ldots, n.
\end{aligned}$$

RESULTS

Variables and data description: We apply the ZSG-DEA model by using Eq. (3) to investigate how to efficiently allocate China's CO_2 emissions to different provinces in 2013. The values of China's GDP, population, and total energy consumption in 2013, collected from the China Statistical Yearbook and the China Energy Statistical Yearbook.

The data on CO_2 emissions at the province level are not available. With reference to the 2006 IPCC National Greenhouse Gas Inventories, energy-related CO_2 emissions can be calculated as Eq. (8),

$$I = \sum_{i=1}^{4} E_i \times K_i \times \frac{44}{12} \qquad \ldots(4)$$

where I denotes total CO_2 emissions, K_i is the carbon emission coefficient of the i_{th} kind of primary energy, E_i refers to the i_{th} kind of primary energy consumption, and 44/12 is the ratio of molecular weights of CO_2 and C. Primary energy carbon emission coefficients are recommended by the Energy Research Institute of Chinese National Development and Reform Commission. Coefficients for coal, fossil oil, natural gas, and nonfossil energy are 0.7476, 0.5825, 0.4435 and 0 respectively (ton C/ton standard coal). Unfortunately, due to the lack of data, Tibet, Hong Kong, Macau and Taiwan were not included in this study, while other 30 provinces, autonomous regions and provincial municipalities

Table 1 : Descriptive statistics of input and output variables for 30 provinces in 2013.

Variable	Unit	Maximum	Minimum	Mean	Standard deviation
GDP	10^8 yuan	62474.79	2122.06	21117.66	15280.71
Population	10^4 persons	10644.00	578.00	4506.80	2681.90
Energy consumption	10^4 tons (standard coal)	41655.00	1886.00	16137.90	9591.59
CO_2 emission	10^6 tons	1271.23	58.97	465.31	297.56

(such as Beijing, Shanghai, Tianjin and Chongqing) were included.

Empirical results: The DMUs considered in this study are 30 administrative regions of China, and the initial CCR-DEA efficiency of each region calculated through model (1). In Table 2, four DMUs were efficient in the CCR DEA model: Beijing, Jiangxi, Sichuan, Qinghai. The average efficiency is 70.7%. Inefficient DMUs are in the cooperation group in the ZSG-DEA paradigm.

A comparative analysis can be made through Table 2. Analysing, for instance, the DMUs of Beijing and Ningxia, it can be found that, although these two regions have approximately the same quantities of CO_2 emissions, Beijing is more efficient than Ningxia, since its GDP is seven times as much of Ningxia.

Using the CCR efficiency scores, we determine new targets for the ZSG-DEA (Eq. 3), with the reallocation of the undesirable output CO_2 emissions for the constant returns to scale case. A uniform CCR DEA frontier is built, where all DMUs are 100% efficient.

ZSG-DEA CCR model benefits the countries that work at the optimal scale operation and punishes the ones that are not operating on the optimal scale. From this model, it can be seen that Hebei must decrease its emissions and should search for partners that want or can reduce their emissions, in order to keep the global emission unchanged.

Beijing and Jiangxi, according to ZSG-DEA, may increase their CO_2 emissions, and still remain efficient; therefore they can trade their excess quota. So, it is possible to propose a carbon quota trade process, as provinces that can increase their emissions must negotiate the emissions reduction with the others.

DISCUSSION

Along with the China's status of being the greatest energy consumer and CO_2 emitter in the world, there is a huge necessity for China to achieve emission-cutting target through regional allocation of emission allowance equally. In addition, the energy intensity reduction target was also proposed as part of China's National Plan during both the 11th and 12th Five-Year Plans. In this study, we point out that China's CO_2 emissions intensity reduction target is essentially a total emission control and emission allowance allocation problem.

This paper developed a modified ZSG-DEA model to allocate the constant total amount of CO_2 emissions allowance over China's 30 provinces in 2013. Through the efficiency measure, iteration and adjustment process of ZSG-DEA model, a new ideally efficient CO_2 emissions allowance allocation scheme at the provincial level for China is proposed.

The allocation result first shows that the ZSG-DEA model can be seen as an effective method for the CO_2 emission allowance allocation, in that it benefits the high-performing regions and punishes the regions far from the optimal scale of operation. Furthermore, our results have a certain strategic significance for policy making. The level of ZSG-CO_2 emissions may be used as an indicator for monitoring the harmony between CO_2 emissions and other factors such as capital investment and economic development.

The inconsistency between CO_2 emissions after reallocation and the actual CO_2 emissions in different regions shows that the regions react quite differently to this "dilemma" problem (to achieve both economic development and energy conservation and emission reduction). In order to achieve the proposed national emission reduction targets, different regions should collaborate through innovative efforts, such as the use of effective economic instruments, capacity building and technology transfer.

The conclusion drawn from this study is important for the government to adopt relative strategies and enrich the low-carbon-economy system in China. However, the research is still preliminary and worthy of further study, such as method improvement and in-depth analysis of variable relationships.

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Table 2: CCR-DEA efficiency and reallocation promoted by ZSG-DEA CCR model.

Provinces	CO_2 emissions (10^6 tons)	CCR-DEA efficiency	CO_2 emissions (10^6 tons) after reallocation	CCR-DEA efficiency after reallocation
Beijing	146.18	1.000	222.78	1.000
Tianjin	213.03	0.739	239.86	1.000
Hebei	1045.60	0.550	875.80	1.000
Shanxi	775.68	0.427	504.43	1.000
Inner Mongolia	867.26	0.428	566.10	1.000
Liaoning	800.56	0.527	643.47	1.000
Jilin	325.68	0.579	287.28	1.000
Heilongjiang	404.96	0.618	381.60	1.000
Shanghai	291.79	0.733	325.78	1.000
Jiangsu	885.35	0.643	867.73	1.000
Zhejiang	525.03	0.696	556.51	1.000
Anhui	402.71	0.804	493.32	1.000
Fujian	314.35	0.755	361.56	1.000
Jiangxi	238.62	1.000	363.66	1.000
Shandong	1271.23	0.574	1111.67	1.000
Henan	828.36	0.637	803.92	1.000
Hubei	497.54	0.729	552.70	1.000
Hunan	394.76	0.960	577.26	1.000
Guangdong	750.76	0.866	990.51	1.000
Guangxi	271.43	0.939	388.43	1.000
Hainan	83.13	0.587	74.32	1.000
Chongqing	223.49	0.850	289.55	1.000
Sichuan	453.84	1.000	691.66	1.000
Guizhou	295.76	0.704	317.10	1.000
Yunnan	314.30	0.815	390.53	1.000
Shanxi	484.94	0.466	344.48	1.000
Gansu	224.09	0.651	222.40	1.000
Qinghai	58.97	1.000	89.87	1.000
Ningxia	182.50	0.416	115.79	1.000
Xinjiang	387.27	0.524	309.09	1.000
Total	13959.17		13959.17	

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