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Industrial carbon abatement allocations and regional collaboration: Re-evaluating China through a modified data envelopment analysis

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Abstract

China’s commitment to significantly reducing carbon emissions faces the twin challenges of focusing costly reduction efforts, whilst preserving the rapid growth that has defined the country’s recent past. However, little work has been able to meaningfully reflect the collaborative way in which provinces are assigned targets on a sub-national regional basis. Suggesting a modified data envelopment analysis (DEA) approach which recognises the two objectives of income maximization and pollution abatement cost minimisation, this paper introduces the potential collaboration between industrial units to the modelling framework. Our theoretical work exposits the roles collectives of industrial decision making units may play in optimising against multiple target functions. Considering the period 2012-2014, we illustrate clearly how China’s three regional collaborations interact with the stated aims of national policy. Developed eastern China may take on greater abatement tasks in the short-term, thus freeing central and western China to pursue the economic growth which will then support later abatement. Policy-makers are thus given a tool through which an extra layer of implementation can be evaluated between the national allocation and setting targets for regional individual decision making units. China’s case perfectly exemplifies the conflicts which must be accounted for if the most economical and efficient outcomes are to be achieved.

Keywords: Data envelopment analysis; Carbon allocation; Carbon abatement cost; Regional collaboration

1. Introduction

China’s emergence as the “global factory” sits firmly at odds with the governmental desire to be a world leader in tackling climate change (Hilton and Kerr, 2017). Since fossil fuel use has been identified as the main cause of carbon emission increases (Wu, Zhu, & Liang, 2016), industrial fossil fuel consumption grew by over 150% between 2000 and 2014, bringing serious ecological damage, and attracting increasing academic attention (Feng, Chu, Ding, Bi, & Liang, 2015; Wu, Zhu, Chu, An, & Liang, 2016). More than 70% of all Chinese energy consumption comes from industry (Wang and Wei, 2014) placing this sector at the centre of climate improvement efforts. At the Copenhagen climate change summit of 2009 the Chinese government committed to reduce carbon intensity, Carbon dioxide (CO_2) emissions per unit gross domestic product, by 45% compared to its 2005 value. Carbon emission abatement is of major national importance (Wang, Wei, & Huang, 2016) and involves collaboration between the central government and the regional governments where polluting factories are located. China has implemented a top down program under which regional abatement tasks are allocated according to ability to produce and in recognition of development needs. Though adjustments have been made to the industrial structure and energy saving regulations have been promulgated (Jiang, Sun, & Liu, 2010), it is in these regional allocations that China places its best hope of meeting the Copenhagen, and subsequent further, commitments.

This paper studies the regional abatement task allocation process through the application of a modified data envelopment analysis (DEA) that is specially calibrated to identify environmental efficiency potential. Environmental efficiency is defined for this purpose as the ability to produce more goods and services whilst simultaneously reducing the negative environmental impact that production generates (Ramli and Munisamy, 2015). Environmental efficiency cannot be readily improved alone as it is a function of the total-factor productive performance of the region and the firms located therein. China's regions have great productive diversity and "opening up" initiatives in regional production are also stretched further inland; an ability to recognise this diversity and dynamism makes the DEA a highly suitable framework upon which to build. By not specifying a particular functional form for production, DEA avoids misspecification (Choi, Zhang, & Zhou, 2012). Unsurprisingly DEA has been increasingly used for environmental tasks (Feng, Chu, Ding, Bi, & Liang, 2015; Wu, Zhu, Chu, An, & Liang, 2016; Wang, Bian, & Xu, 2015).

We make two key contributions to the literature. Firstly our modified DEA offers an improved carbon abatement allocation estimation considering carbon abatement costs at the regional level, thus providing a more robust starting point for policy setting. Through the DEA, we are able to make stronger recommendations for the regional allocation of carbon abatement tasks based on environmental efficiencies. Secondly, we further extend the proposed DEA allocation method to focus on the potential for regional collaboration and the evaluation thereof, an area typically ignored by the literature on regional allocations.

These issues are necessarily addressed within the context of China's rapid development, for which there is a pressing need to increase environmental efficiency, but our approach and results will have resonance for other applications globally. What emerges is a set of recommendations for Chinese policy-makers and a means through which to assess them. We are able to recognise the potential for collaborations, and the approach adopted here can estimate the carbon abatement allocation considering the collaboration relationship among all regions.

The remainder of the paper is organised as follows. First, we take a more detailed look at the literature on carbon abatement, regional allocation, and the DEA process. Second, we outline our DEA approach, introducing the modifications for carbon abatement allocations. Section 4 then presents the Chinese data and our results on potential allocations. Finally, we draw conclusions and provide signposts for future carbon abatement and broader environmental policies.

2. Literature Review

China's central role in global carbon dioxide abatement is the focus of a plethora of academic and policy works approaching the issue from multiple disciplines. China's approach thus far has been to identify targets for provinces (regions) and then to construct carbon trading markets to perfect the allocation at the firm level (Wang, Wei, & Huang, 2016). Though carbon emission abatement is environmentally desirable potential costs must be considered and hence the discussion is extended to the treatment of the issue of income. Our novel model delivers on both objectives, incorporating regional collaboration for the first time.

In the literature, regional carbon emissions cannot be reduced independently, but must be with the consideration of all related production factors (e.g., resource input, economic output, and energy consumption) (Wu, Zhu, & Liang, 2016; Wang, Wei, & Huang, 2016; Zhou, Fan, & Zhou, 2015). Thus, carbon abatement tasks can be allocated in a reasonable way based on a total-factor performance of regional industrial production. Environmental efficiency, as a widely accepted non-parametric total-factor environmental performance evaluation, is adopted here for this purpose. To achieve this, DEA, an important non-parametric method for measuring total-factor performance, is applied to estimate the practical case of regional environmental efficiencies. DEA is widely accepted to present high quality environmental efficiency evaluations (Zhou, Ang, & Poh, 2008). With many related environmental issues having been examined by this method, for example, environmental efficiency estimations (Bian and Yang, 2010), pollutant abatement cost estimations (Wang, Bian, & Xu, 2015) and allocations of carbon emission abatement tasks (Feng, Chu, Ding, Bi, & Liang, 2015; Wu, Zhu, Chu, An, & Liang, 2016), it is a natural choice here.

The identified challenge is to analyse the optimized allocated carbon abatement task for each regional industrial production system. Since the allocation estimation of resources is central to DEA techniques (Feng, Chu, Ding, Bi, & Liang, 2015), the DEA method is widely used in related allocation studies. DEA methods can be used to allocate the resources of input, output, or both (Beasley, 2003). Two primary types of allocations exist within DEA: fixed cost allocation and resource allocation and, representing fixed costs allocated to each decision unit or the process of allocating the resource. Each is based on the DEA efficiency results from the allocation (Du, Cook, Liang, & Zhu, 2014). In DEA, the fixed cost is regarded as a complement of inputs or outputs in allocation, and it forms a single input measure in efficiency evaluation. Meanwhile, resource allocation is assumed to optimize inputs and outputs simultaneously, subjecting the results to corresponding limitations of resources or production possibilities. DEA also offers another mechanism called centralized allocation, which aims to allocate resources by a centralized decision maker controlling over all units (Fang, 2013). There are three objectives of centralized allocation: maximizing desirable outputs, minimizing undesirable outputs, and minimizing inputs (Lozano, Villa, & Brännlund, 2009). An important feature of the centralized allocation is that the optimized target is to consider the overall benefits for all the decision makers (Fang, 2013; Lozano and Villa, 2004), but ignore the benefits of individuals (Feng, Chu, Ding, Bi, & Liang, 2015). A centralized allocation mechanism is proposed in this paper.

DEA allocation approaches have been the basis of many studies of carbon emission allocations. Gomes and Lins (2008) proposed a zero sum gains DEA model to allocate CO_2 emission permits among countries. Lozano, Villa, & Brännlund (2009) provided three levels of centralized models to consider the allocation of emission permits. The application of centralized DEA allocation models to carbon allocations is proposed by Feng, Chu, Ding, Bi, & Liang (2015) and Wu, Zhu, & Liang (2016). Sun, Wu, Liang, Zhong, & Huang (2014) analysed variations of the mechanisms to allocate permits amongst a group of manufacturing companies. Zhou, Sun, & Zhou (2014) introduced spatial, temporal and a joint spatial-temporal allocation strategies for controlling CO_2 emissions at the provincial level in China. Crucially however, the carbon abatement costs of those allocations were omitted, offering us the opportunity to improve thereupon. Unlike the aforementioned studies, this paper uses an improved DEA approach to allocate regional carbon abatement tasks based on carbon abatement costs.

Carbon emission abatement in regional industrial productions generates corresponding costs. China's regions have significant disparities of resources, economic well-being and technological capabilities for carbon abatement. In this circumstance, carbon abatement costs, such as the costs of industrial structure modification, costs of energy consumption structure modification, or technological updating costs, may vary wildly among different regions (Wang, Wei, & Huang, 2016; Cui, Fan, Zhu, & Bi, 2014). Failure to account for this within the allocation process is liable to bring unreasonable and inequitable outcomes. Wang, Wei, & Huang (2016) identified that larger carbon abatement tasks would be allocated to regions with the lowest cost; either the financial or opportunity cost of production reduction. There is then a circle to this, with those allocated most tasks becoming more incentivised to further reduce their costs of pollution.

Acquiring the actual abatement costs for pollutants is hard, and hence the shadow prices of pollutants are commonly accepted as proxies. Estimation of these shadow prices can be done in a number of ways, but with the DEA approach nesting their evaluation, this efficiency analysis can be treated as an accepted approach (Zhou, Zhou, & Fan, 2014). Wang and Wei (2014) and Wang and He (2017) are amongst the recent examples of works seeking to estimate the prices of carbon abatement tasks for China's different industrial sectors. However, to the best of our knowledge, studies of carbon allocations based on abatement costs are still scarce. This paper speaks to that gap, first estimating the allocation of carbon abatement tasks with the presence of corresponding carbon abatement costs by employing a modified DEA method.

Existing DEA carbon allocation estimations primarily aim to either maximize the potential gross domestic product (GDP) gains or minimize the carbon emissions solely; costs generated from the abatement processes are always ignored. A notable exception is Wu, Zhu, Chu, An, & Liang (2016), which estimated carbon allocations considering corresponding costs. However, Wu, Zhu, Chu, An, & Liang (2016) incorporated the simplifying assumption that the price of the carbon emission allowance is equal to the cost of allocation. For whole China this would mean a single value, which is unrepresentative.

Another major contribution of this paper lays in its investigation of potential regional collaborations on carbon abatement allocations. Asked to consider such possibilities the centralized allocation scheme would suffer implementation difficulties arising from the inconsistency between the interests of individuals and the overall economy (Feng, Chu, Ding, Bi, & Liang, 2015). Inherent conflicts exist between coalitions and the national interest. China's 13th five-year-plan puts such regional co-operations as a keystone of carbon abatement and hence "regional collaborations" have national resonance. In the extant literature regional collaborations have been applied focusing on the issues of political challenges on energy transfer, climate change mitigation, resources sharing and energy security (Uddin and Taplin, 2015; Huda and Mcdonald, 2016; Srivastava and Misra, 2007).

We propose that regional collaborations may derive from geographical proximity, similarities in economic and industrial make up, and pre-existing arrangements on permit trading. Geographical arguments are clear: pollution from a neighbouring province can easily drift into the air and create negative externalities that the province would want to prevent that neighbour from imposing upon it. An evident spatial diffusion (Burnett, Bergstrom, & Dorfman, 2013) emerges. To deal with the cross-regional CO_2 diffusion, regional collaboration activities for carbon abatement have huge potential. Neighbouring regions are liable to have more closely associated economic development modes and industrial structures (Hao, Liu, Weng, & Gao, 2016). In turn these similarities form the basis of working together on joint interests and are a platform for agreed abatement task allocations. Provinces are more likely to accept costs if they see that their neighbours are also taking their perceived fair share as well. An existing case is the joint air pollution control among Beijing–Tianjin–Hebei and surrounding regions decided by China's National Development and Reform Commission and their relative ministries (Zhang, Wang, & Da, 2014).

Furthermore, China has launched pilot markets for carbon emissions trading in seven provinces or municipalities in 2003, that is, in Shenzhen, Beijing, Tianjin, Shanghai, Guangdong, Hubei and Chongqing (Wang, Wei, & Huang, 2016). China's government enacted a policy to create a carbon emission trading market for the whole country in 2017. The establishment of local carbon trading markets could be helpful in forming potential regional carbon abatement allocations (Jiang, Yang, Chen, & Nie, 2016) and collaborations. Ultimately, however, the carbon intensity reduction target is decided by the central government and allocated for each local government to implement in China. For example, the provincial carbon intensity abatement ratio is set in the range of [0.100, 0.195] for each province during the 12th five-year plan by China State Council[1]. In this circumstance, the cities included in one province could be regarded as a regional collaboration by achieving the same carbon reduction target. The potential regional collaboration is thus viewed as an important consideration to decide the local carbon reduction target for the central government in the future. Meanwhile, the local carbon reduction target from the central government could also help to form the regional collaboration. Consequently, regional collaborations still represent a valuable alternative to the allocation both in the

[1] The website of "work plan of controlling greenhouse emissions during 12th five-year plan period for China State Council": http://www.gov.cn/zwgk/2012-01/13/content_2043645.htm.

study of China and also in the wider application of DEA, which is valuable in the policy context and for theoretical development.

Consequently, in ignoring regional disparities of carbon abatement costs, past works have thus missed important geographical elements that have been demonstrated to be relevant elsewhere in the literature. Removing this over-simplification our paper first proposes a nonlinear DEA approach to allocate the regional industrial carbon abatement tasks considering corresponding carbon abatement costs. The carbon abatement costs are calculated by estimating shadow prices in DEA model recognizing regional variation. Furthermore, we adjust the aforementioned allocation model into an improved meta-frontier one to analyse impacts of different regional collaborations on the optimized regional carbon allocations.

3. Methodology

A modified DEA model is proposed to allocate carbon emission abatement tasks for regional industrial systems. To obtain effective allocation results, we treat the minimized total carbon abatement costs as a part of the allocation target; an estimation thereof is also derived. To analyse impacts of regional collaborations on carbon allocations, the aforementioned carbon allocation model is extended to incorporate regional collaborations and their impacts.

3.1. The efficiency evaluation model

There are n independent regions in China, denoted by decision making unit j (i.e., DMU j, j = 1, 2,..., n). In common with past work in process of regional industrial production each region employs labour, capital and energy as inputs and produces both desirable and undesirable outputs. We consider labour (L), capital stock (K) and energy consumption (E) as the three inputs. Gross Domestic Product (Y) and CO_2 emissions (C) play the role of desirable and undesirable outputs, respectively.

Regional economic developments depend on energy consumption, and CO_2 emission abatement is costly. Following Wang, Wei, & Zhang (2012), this paper considers that CO_2 emissions are subjected by an equal constraint, which indicates a null-joint relationship between carbon emission and GDP (Sueyoshi and Goto, 2012). The relationship means the joint-production process between GDP and CO_2 emissions. In an environmental vision, our initial model focuses on carbon emissions and the consumption of energy resources with an equal target weight setting (i.e., 0.5). The equal weights mean that the targets of energy saving and carbon abatement are treated as equally important. This equality follows the approach in Wang, Wei, & Zhang (2012) and Wu, Zhu, & Liang (2016); equation (1) provides the model.

The intensity of production within DMU_i is given a λ_i .When evaluating DMU_i we are interested in the energy efficiency θ_{ei} and the environmental efficiency θ_{ci} . c is used in the environment efficiency subscript since our focus is on carbon abatement. Efficiency values are all in the range of [0, 1]. Note that model (1) decreases the amounts of energy and undesirable outputs as much as possible with given non-energy inputs and desirable outputs. When evaluating DMU i's efficiency, the target function contains mixed effects of energy consumption and carbon emission. This model setting measures the environmental performance in relation to input and output simultaneously.

$$
\begin{aligned}
& \min \frac{1}{2}(\theta_{ei}+\theta_{ci}) \\
\text{s.t.}\quad & \sum_{j=1}^{n}\lambda_j E_j \le \theta_{ei} E_i, \\
& \sum_{j=1}^{n}\lambda_j K_j \le K_i, \\
& \sum_{j=1}^{n}\lambda_j L_j \le L_i, \\
& \sum_{j=1}^{n}\lambda_j Y_j \ge Y_i \ , \\
& \sum_{j=1}^{n}\lambda_j C_j = \theta_{ci} C_i, \\
& \lambda_j \ge 0,\ j=1,2,...,n.
\end{aligned}
\tag{1}
$$

It is noteworthy that, model (1) is a CRS (constant returns to scale) model, which can capture the overall technical efficiency (pure technical efficiency and scale efficiency) of the evaluated DMU, and can satisfy all relevant production technologies (Zhou and Ang, 2008). Thus we proceed with CRS for rationality of exposition (1).

3.2. Carbon abatement cost estimation

Data on the abatement costs of pollutants is difficult to obtain so we use the shadow prices of carbon emissions to represent the real ones. This paper aims to use the DEA method to estimate the shadow price of carbon emission as Wang, Lv, Bian, & Cheng (2017) and Wang and Wei (2014). Then the shadow price estimation and carbon abatement allocation could be estimated with similar model settings; and forbidding any presenting of production functions to avoid the inherent misspecification risk present in the parametric method (Choi, Zhang, & Zhou, 2012).We firstly present the dual programming of model (1):

$$
\begin{aligned}
& \max\ (-K_i w_k - L_i w_l + Y_i w_y) \\
\text{s.t.}\quad & E_i w_e = 1/2, \\
& C_i w_c = 1/2, \\
& Y_j w_y - E_j w_e - K_j w_k - L_j w_l - C_j w_c \le 0,\quad j=1,2...,n, \\
& w_e \ge 0, w_k \ge 0, w_l \ge 0, w_y \ge 0, w_c \ \textit{is free}.
\end{aligned}
\tag{2}
$$

In model (2), w_e, w_k, w_l, w_y, w_c are dual variables corresponding to the constraints of energy, capital, labour, GDP and carbon emissions respectively. The target function is the efficiency of DMU$_i$. As

Wang, Bian, & Xu (2015) and Wang and He (2017) we assume that the absolute shadow price of our marketable desirable output (GDP) is equal to its market price. The shadow prices of carbon emission with respect to the desirable output can be transformed as:

$$p_{ci} = p_{yi}\frac{w_c}{w_y} = \frac{w_c}{w_y} * 1\text{CNY}, \tag{3}$$

Here p_{ci} and p_{yi} are the relative shadow prices of carbon emission and GDP for region i, respectively. These shadow prices reflect the trade-off between desirable and undesirable outputs (Wang, Bian, & Xu, 2015). The shadow price of CO_2 denotes the marginal rate of transformation between CO_2 and GDP, which could be regarded as being a price proxy of carbon abatement cost for China's regions. For instance, the shadow price can be derived from the technology expenditure and production reduction loss for carbon abatement in practice. Based on the target function in model (1), the proposed shadow price is exogenous for the following allocation, which aims to achieve maximized carbon abatement and energy savings. This setting is in agreement with the carbon abatement objective, which is from the environmental perspective.

3.3. A modified DEA approach for carbon abatement allocations

The allocation goal for China's central government is to achieve the given CO_2 abatement task with minimized carbon abatement costs and maximized regional economic output from industrial production. DEA allocation analysis has three traits: (1) The efficiency is formed by all the DMUs and output targets may not be achievable in the short term; (2) after the certain amounts of permits or resources are allocated, there must be changes in DMU production (Wu, Zhu, & Liang, 2016); (3) the ex-ante planning is adopted in DEA allocation, and the allocation results are used to forecast the performance of resource utilization in the next period (Feng, Chu, Ding, Bi, & Liang, 2015). However such adopted practice does not preclude the analysis of alternatives.

This paper departs from these three traits to consider that the allocation process includes two possible scenarios. The first is the allocation process affected by national collaboration, termed national allocation for short. This indicates that the industrial production system of each region has a higher level of involvement in the handling of its emission abatement target. Each region is treated as a co-operator in the national platform of carbon abatement allocation, the central government then setting levels. The national allocation also assumes that each region uses all efforts to reduce its allocated carbon abatement cost to minimize the total national abatement costs. This could be regarded as a centralized resource allocation problem (Lozano and Villa, 2004) and derives from Wang, Wei, & Huang (2016) and Wu, Zhu, Chu, An, & Liang (2016) amongst others.

Current studies of centralized carbon allocation, to the best of our knowledge, always focus on the target of maximized economic output or minimized carbon emission solely (Feng, Chu, Ding, Bi, & Liang, 2015; Wu, Zhu, & Liang, 2016). This paper proposes a DEA allocation model, which aims to obtain the maximized GDP outputs and minimized carbon abatement costs simultaneously after the carbon abatement tasks are allocated. In model (4), T is the target function ratio post allocation of each regions total carbon abatement task. The corresponding carbon abatement cost for region i is p_{ci} and $\hat{Y}_i$ indicates the maximized post allocation GDP output for region i. Notably, $\hat{Y}_i$ is affected by all the factors in the carbon allocation, including the expenditure of carbon abatement. ΔC_i denotes the abatement task of CO_2 for region i, and is decided by the central government. B_p is the total future CO_2 abatement task and thus the constraint $\sum_{i=1}^{n} \Delta C_i = B_p$ thus means that the sum of CO_2 abatement tasks of all the regions should be equal to the national total. An upper limit on the size of the task to be given to any region is set at C_i^u .

We assume that each region participates in the carbon abatement processes. Thus $0 \le \Delta C_i \le C_i$ implies that the most any region can be asked to do is eliminate its current output C_i and the lower limit of doing nothing. All the other variables and constraints have identical meanings to those in models (1) and (3). We aim to obtain the optimal solutions of λ_{ij}^*, ΔC_i^* , and $\hat{Y}_i^*$ by solving model (4). To this end, $(C_i - \Delta C_i^*)$ denotes the optimal allocated carbon emission quota for region i in next period at the current production level. As in Wang, Wei, & Huang (2016) and Wu, Zhu, & Liang (2016), $\hat{Y}_i^*$ here represents the maximized GDP. Note that, the basic optimization targets between model (1) and model (4) are different. The carbon abatement cost p_{ci} from model (1) could be regarded as an exogenous variable for the following models. Moreover, the optimal GDP output and carbon emission in model (4) could be replaced by $\hat{Y}_i$ and $C_i - \Delta C_i$, the maximised GDP output and remaining carbon emission, in the allocation process, but not by the same proposition as the weak disposability. This indicates that the potential technology improvement could be assumed in the regional carbon abatement to reduce the loss of GDP output.

$$
\begin{aligned}
&\text{Min } T = \frac{\sum_{i=1}^{n} p_{ic} * \Delta C_i}{\sum_{i=1}^{n} \hat{Y}_i} \\
\text{s.t.}\quad & \sum_{j=1}^{n} \lambda_{ij} E_j \le E_i,\ i = 1,2,\ldots,n, \\
& \sum_{j=1}^{n} \lambda_{ij} K_j \le K_i,\ i = 1,2,\ldots,n, \\
& \sum_{j=1}^{n} \lambda_{ij} L_j \le L_i,\ i = 1,2,\ldots,n, \\
& \sum_{j=1}^{n} \lambda_{ij} Y_j \ge \hat{Y}_i,\ i = 1,2,\ldots,n, \\
& \sum_{j=1}^{n} \lambda_{ij} C_j = C_i - \Delta C_i,\ i = 1,2,\ldots,n, \\
& \sum_{i=1}^{n} \Delta C_i = B_p, \\
& 0 \le \Delta C_i \le C_i^u, \\
& \hat{Y}_i, \lambda_j \ge 0,\ j = 1,2,\ldots,n.
\end{aligned}
\tag{4}
$$

Definition 1. The economical level of total national carbon abatement is defined as:

$$
EL = \frac{\sum_{i=1}^{n} \hat{Y}_i}{\sum_{i=1}^{n} p_{ic} * \Delta C_i},\ i = 1,2,\ldots,n \tag{5}
$$

The economical level is the reciprocal of national target function, which is the ratio of maximized industrial GDP output to total carbon abatement costs for the country. The economic level can reflect the ratio of carbon abatement cost to the total economic output. Hence this ratio can measure if the national carbon abatement allocation cost is economical for its economic gain. The economical level is adopted to compare the national economic performance derived from different allocation plans.

Model (4) is nonlinear but it can be transformed into the following linear model (6). In model (6), T' denotes the adjusted linear target function, and $\eta_{ij} = t\lambda_{ij}$ denotes the transformed intensity variable corresponding to λ_{ij}. $\hat{y}_i = t\hat{Y}_i$ and $\Delta c_i = t\Delta C_i$ represent the transformed values for $\hat{Y}_i$ and ΔC_i, respectively. By solving model (6), we can obtain the optimal values of $\hat{y}_i^*$, Δc_i^*, η^* and t^*. Based on these results, regional optimal outputs of industrial GDP and carbon abatement tasks can be acquired, $\hat{Y}_i^* = \hat{y}_i^* / t^*$, $\Delta C_i^* = \Delta c_i^* / t^*$, respectively.

$$
\begin{aligned}
& \operatorname{Min} T' = \sum_{i=1}^{n} p_{ic} * \Delta c_i \\
\text{s.t.} \quad & \sum_{i=1}^{n} \hat{y}_i = 1,\ i = 1, 2, ..., n, \\
& \sum_{j=1}^{n} \eta_{ij} E_j \le tE_i,\ i = 1, 2, ..., n, \\
& \sum_{j=1}^{n} \eta_{ij} K_j \le tK_i,\ i = 1, 2, ..., n, \\
& \sum_{j=1}^{n} \eta_{ij} L_j \le tL_i,\ i = 1, 2, ..., n, \\
& \sum_{j=1}^{n} \eta_{ij} Y_j \ge \hat{y}_i,\ i = 1, 2, ..., n, \\
& \sum_{j=1}^{n} \eta_{ij} C_j = tC_i - \Delta c_i,\ i = 1, 2, ..., n, \\
& \sum_{i=1}^{n} \Delta c_i = tB_p, \\
& 0 \le \Delta c_i \le tC_i^u, \\
& \hat{y}_i, \eta_j \ge 0,\ j = 1, 2, ..., n.
\end{aligned} \tag{6}
$$

Proposition 1. National collaboration produces an outcome which weakly dominates other independent regional allocations.

Proof. It is readily apparent that the optimal solution of carbon abatement task allocation in model (6) is a feasible solution to that in model (4). Thus the target function value obtained from model (6) is less than or equal to that from model (4).

In practice the national collaboration may be hard to achieve as it requires the maximum possible levels of trust and involvement for the collaborators. In scenario 2 a region can achieve limited collaborations with its neighbours to pursue the most economical carbon allocation for that grouping. In this circumstance, regions may jointly plan their allocated carbon reduction amounts and reassess their practical carbon emission abatement tasks. A regional collaboration is thus a coalition in the game theoretic sense. The corresponding DEA allocation model is as follows:

$$\text{Min } T_2 = \frac{\sum_{i=1}^{n} p_{ic} * \Delta C_i}{\sum_{i=1}^{n} \hat{Y}_i}$$

$$\begin{aligned}
\text{s.t.} \quad & \sum_{j \in D(p)} \lambda_{ij} E_j \le E_i, \ i = 1,2,...,n, \ p = 1,2,...,P, \forall i \in D(p) \\
& \sum_{j \in D(p)} \lambda_{ij} K_j \le K_i, \ i = 1,2,...,n, \ p = 1,2,...,P, \forall i \in D(p) \\
& \sum_{j \in D(p)} \lambda_{ij} L_j \le L_i, \ i = 1,2,...,n, \ p = 1,2,...,P, \forall i \in D(p) \\
& \sum_{j \in D(p)} \lambda_{ij} Y_j \ge \hat{Y}_i, \ i = 1,2,...,n, \ p = 1,2,...,P, \forall i \in D(p) \\
& \sum_{j \in D(p)} \lambda_{ij} C_j = C_i - \Delta C_i, \ i = 1,2,...,n, \ p = 1,2,...,P, \forall i \in D(p) \\
& \sum_{j \in D(p)} \Delta C_j = B_p, \ p = 1,2,...,P, \forall j \in D(p), \\
& 0 \le \Delta C_i \le C_i^u, \\
& \hat{Y}_i, \lambda_j \ge 0, \ j = 1,2,...,n.
\end{aligned} \tag{7}$$

Once again the model is non-linear and so model (7) is transformed into the linear model (8). T_2 indicates the adjusted target function. *D(p)* denotes the subset of observed DMU belonging to the regional coalition *p*. A coalition of size *Q* is made up of multiple DMU_q (q = 1, 2,..., Q). All the other variables and constraints in model (7) and (8) have the similar interpretations as those in models (4) and (6), respectively. The main difference between the models (6) and (8) is the participators of allocation. In scenario 1, model (6) aims to reach the national optimal carbon abatement cost by CO_2 abatement allocation at the national level. In scenario 2, model (8) aims to reach the national allocation target by allocating carbon abatement tasks across the local collaboration region. DMUs only aim to obtain the optimal allocation solution to their own *D(p)*.

In model (8), the regional collaboration coalition can be viewed as treating all participators as having the same observation set *D(p)*. Participators of different coalitions are evaluated in different frontiers in DEA allocation model (8). Models (7) and (8) could be regarded as meta-frontier DEA models. We assume that all members of the coalition share the same best practice through the available inputs and outputs. This constraint helps avoid the impacts of geographic disparities of economic fundamentals and technological levels in national allocation. Furthermore, this allocation process may be labelled as a resource-pooling-only game of lower level collaboration, that is, one modification of the Linear Transformation of Products (LTP) games, proposed by Timmer, Borm, Suijs, (2000) and extended by Lozano (2013) in a DEA form. In this case, regions jointly plan and allocation of pooled available resources (CO_2 abatement tasks) in their own coalition.

$$
\begin{aligned}
&\operatorname{Min} T_2^{'} = \sum_{i=1}^{n} p_{ic} * \Delta c_i \\
\text{s.t.}\quad &\sum_{i=1}^{n} \hat{y}_i = 1,\ i = 1,2,...,n, \\
&\sum_{j\in D(p)} \eta_{ij} E_j \le tE_i,\ i = 1,2,...,n,\ p = 1,2,...,P, \forall i \in D(p) \\
&\sum_{j\in D(p)} \eta_{ij} K_j \le tK_i,\ i = 1,2,...,n,\ p = 1,2,...,P, \forall i \in D(p) \\
&\sum_{j\in D(p)} \eta_{ij} L_j \le tL_i,\ i = 1,2,...,n,\ p = 1,2,...,P, \forall i \in D(p) \\
&\sum_{j\in D(p)} \eta_{ij} Y_j \ge \hat{y}_i,\ i = 1,2,...,n,\ p = 1,2,...,P, \forall i \in D(p) \\
&\sum_{j\in D(p)} \eta_{ij} C_j = tC_i - \Delta c_i,\ i = 1,2,...,n,\ p = 1,2,...,P, \forall i \in D(p) \\
&\sum_{j\in D(p)} \Delta c_j = tB_p,\ p = 1,2,...,P, \forall j \in D(p), \\
&0 \le \Delta c_i \le tC_i^u, \\
&\hat{y}_i, \eta_j \ge 0,\ j = 1,2,...,n.
\end{aligned} \tag{8}
$$

Property 1. The optimal value of model (8) is convex with respect to the carbon abatement amount Δc_i. The target function $f(\Delta c_i) = \min T_2^{'}$ is convex with respect to Δc_i.

Proof. For any carbon allocation task Δc_i which satisfies the constraint $0 \le \Delta c_i \le tC_i^u$, we can obtain the optimal values of $\hat{y}_i^*$, Δc_i^*, η_j^* and t^* by solving model (8). Here we assume that, ($\hat{y}_{i1}, \eta_{j1}, t_1$) and ($\hat{y}_{i2}$, η_{j2}, t_2) are the corresponding optimal solutions for the optimal Δc_{i1} and Δc_{i2} (Δc_{i1}, Δc_{i2} $\in \left[0, tC_i^u\right]$). As in Feng, Chu, Ding, Bi, & Liang (2015), a feasible solution by a linear combination is constructed, that is, $\omega \hat{y}_{i1} + (1-\omega)\hat{y}_{i2}$, $\omega\Delta c_{i1} + (1-\omega)\Delta c_{i2}$, $\omega\eta_{j1} + (1-\omega)\eta_{j2}$ and $\omega t_1 + (1-\omega)t_2$, $0 \le \omega\Delta c_{i1} + (1-\omega)\Delta c_{i2} \le tC_i^u$, $0 \le \omega \le 1$, $j = 1,2,...,n$. Model (8) can be solved with the constructed linear combination solution. The optimal result of the objective target should be less than or equal to $\omega T_{21}^{'} + (1-\omega)T_{22}^{'}$, that is, $f(\omega\Delta c_{i1} + (1-\omega)\Delta c_{i2}) \le \omega T_{21}^{'} + (1-\omega)T_{22}^{'}$. Thus, the target function $f(\Delta c_i) = \min T_2^{'}$ is convex with respect to Δc_i.

Property 1 indicates that there exists an optimal carbon abatement task in the national abatement allocation process. The convexity means that the optimal allocated carbon abatement task is a balanced result, which is more economical than other allocated carbon allocation tasks. To achieve the most economical carbon abatement process, the central government would have the motivation to adjust the carbon abatement allocation continuously. We believe that the optimal carbon abatement task is then accurately obtained by the proposed DEA approach in this paper.

The implementation procedures of estimating allocated carbon abatement considering regional collaborations are summarized as follows.

Step 1: Estimating the marginal abatement costs (called MACs for short) for each region by equation (3) based on models (1) and (2).

Step 2: Evaluating the allocated carbon abatement amount ($\Delta C_j, j = 1, 2, ...n$) of each region by model (6) based on the obtained MAC_j from step 1.

Step 3: Re-evaluate the carbon abatement allocation considering possible regional collaborations by using model (8).

Step 4: Calculate the maximized industrial GDP ($\hat{Y}_j$) and economical levels considering regional collaborations by model (8). Compare the allocated results from different regional collaborations.

4. Empirical Analysis

4.1. Data

Our data contains 30 provinces, autonomous regions and municipalities in mainland of China. As with most empirical studies of China a lack of data availability for Tibet leads to its exclusion from the modelling process. These regions can be grouped into three major areas, that is, the eastern, central and western areas (Hu and Wang, 2006). Regional groupings can be seen in Table 2. The eastern area has the best level of economic development in China, its GDP output contributed 55.34% of Chinese total GDP in 2014 (National Bureau of statistics of China, 2015). The central area is regarded as the agricultural base for the country, whilst the western area has the lowest population density and the lowest level of economic development in China. It is thus highly reasonable to presume heterogeneity in regions. The three areas regarded as main regional classification and used to provide policy implications of carbon abatement are also observed in several studies, for example, Wang, Lv, Bian, & Cheng (2017) and Wang, Wei, & Zhang (2013).

We focus on China's regional carbon allocations during the period 2012-2014. Labour, capital stock and energy consumption are the three inputs, industrial added value is the desirable output, and CO_2 denotes the undesirable output. Capital stock and industrial GDP are all expressed at 2012 prices for consistency. In the industrial production process, SO_2 emission, soot emission, dust emission and NO_x emission can also be regarded as undesirable outputs. While SO_2, NO_x and other emissions may have their own abatement processes, that is, reduced by technical investments by government such as installing scrubbers and dust collection (Wang, Wei, & Huang, 2016). Compared with other emissions, the CO_2 emissions abatement is more directly affected by fossil energies consumption and therefore the generated CO_2 levels may be directly related to industrial production. Thus, this study only uses the CO_2 emission as the undesirable output.

DEA models require the number of evaluated DMUs to be more than three times the total number of inputs and outputs to maintain validity (Friedman and Sinuany-Stern, 1998). When permitting collaborations this may not be true of our modelling and hence we use multiple years of data to maintain sufficient quantity for robust inference. As three years is a short period, it is reasonable to assume that no significant technical changes occur in the period (Charnes, Cooper, Lewin, & Seifor, 1994; Halkos and Tzeremes, 2009). The three-year data sample for our DEA ensures the collaborating region has the least sample amount of DMUs (27), which is greater than three times of total number of inputs and outputs (total five inputs and outputs are used in the model).

Data on labour and capital of industrial production systems are derived from the Industrial Statistical Yearbook of China issued in each of 2013, 2014 and 2015. The industrial added value is collected from the Statistical Yearbook of China over the same time frame. Data on energy consumption is obtained from Energy Statistical Yearbook of China during the same period. Regional CO_2 emissions are not available in existing data sources but following Li, Mu, Zhang, & Gui (2012), they can be estimated by multiplying the amounts of combined energy consumptions with their corresponding carbon emission coefficients. The carbon emission coefficients are obtained from the Intergovernmental Panel on Climate Change (2007). Table 1 shows the descriptive statistics for the data of all the variables in China during 2012-2014.

Table 1

Descriptive statistics (2012-2014).

Indicators		**Unit**	**Max**	**Min**	**Average**	**Std. Dev**
Input	Energy	10^4 tons[a]	19392.8	839.0	6864.8	4469.0
	Labour	10^4 people	1470.5	11.7	324.7	337.9
	Capital stock	10^9 CNY	4087.3	71.9	1102.1	852.8
Desirable output	Industrial GDP	10^9 CNY	2859.6	45.9	845.6	703.9
Undesirable output	CO_2 emission	10^4 tons	72313.2	1833.9	22767.6	16413.4

[a] Note: the unit refers to standard coal equivalent.

4.2. Efficiency and carbon abatement costs

Based on the data for 2012 to 2014, we estimate the annual average environmental efficiencies and corresponding annual average shadow prices following models (1) and (2) respectively. The arithmetic average results for three years are shown in Table 2. There are five regions with efficiencies which are higher than 0.85: Beijing, Tianjin, Guangdong, Inner Mongolia and Chongqing. These regions have better performance in energy consumption and carbon emission than other regions in China. There also exist efficiencies in 14 regions which are less than the average efficiency (0.55).

This indicates that these regions have not performed well in energy consumption and carbon emission abatement. Interestingly, it is observed that there exist no efficient regions in Table 2. This phenomenon arises because efficiencies for some regions for one specific year might be efficient (i.e., efficiency is equal to 1), but not for other years. For example, Beijing and Tianjin are efficient in 2014, but not efficient during 2012-2013. Employing annual average DEA efficiencies with three-year data reduces the gap of regional efficiencies, and helps avoid the time disturbance on efficiencies in a short period.

Table 2 presents remarkable spatial disparities. The eastern area has the highest average efficiency result among the three areas, 0.64. The central area sits just below this at 0.60 and is higher than the western area, 0.37. Amongst the regions Ningxia province has the lowest, just 0.11. A strong correlation between economic development and energy efficiency is suggested. Higher GDP regions might have more possibilities to invest in eliminating heavy pollutant industries and to adopt advanced production technologies; both may increase regional environmental efficiencies.

Similarly, remarkable geographic disparities are also seen in regional carbon's MACs in Table 2. The MACs denote the opportunity costs for carbon abatement tasks converted into CNY values of GDP, and are measured in CNY per ton. The average MAC is 1861.56 CNY per ton, which tells us that 1861.56 CNY must be spent to reduce carbon emission by one ton. Average MAC values for the east, central and west areas are 1957.3, 1679.97, and 1946.31CNY. Interestingly, Pearson's correlation coefficient of efficiencies and MACs is -0.9520 for only the central regions, and is significant at the 1% level. This indicates that regions with higher efficiencies would have lower MACs only for central cases. For example, Inner Mongolia has the highest efficiency of 0.9479, but the lowest MAC of 81.25 CNY per ton.

By contrast Beijing and Guangdong, both economically developed regions, have much higher MACs than average, 3565.50 and 2100.61, respectively. This phenomenon might be partially explained by the gap between CO_2 emissions and industrial GDP in the provinces. The industrial carbon intensities (i.e., the ratio of CO_2 emission and industrial GDP) for Beijing and Guangdong are 1.3223 and 1.2779, respectively, which are less than those of other regions. It is not economical for regions with the lowest industrial carbon intensities to reduce their corresponding MACs by technological improvements or industrial structure transformations.

Comparing MACs in this paper with ones in existing relative studies, we discover that our average MAC is larger than the ones in Wang and Wei (2014), whose average industrial MAC is 45.81USD per ton for China's major cities during 2006-2010. However, our result is as similar to the average MAC estimated in Zhou, Fan, & Zhou (2015). Differences in MACs might be caused by different technical efficiencies, including differential impacts from primitive technology, operational scale, industrial structure and the variation of the data on efficiency evaluation (Wang, Bian, & Xu, 2015; Ha, Kant, & Maclaren, 2008).

Table 2

Efficiency results and corresponding carbon abatement costs.

	Region	Efficiency	MAC
Eastern area	Beijing	0.8635	3565.50
	Tianjin	0.8772	867.68
	Hebei	0.2648	1240.08
	Liaoning	0.3746	1489.38
	Shanghai	0.6968	2651.56
	Jiangsu	0.5897	2726.34
	Zhejiang	0.7267	1988.96
	Fujian	0.7487	1483.71
	Shandong	0.5159	2063.21
	Guangdong	0.9371	2100.61
	Hainan	0.4284	1353.22
Central area	Shanxi	0.1997	4444.68
	Inner Mongolia	0.9479	81.25
	Jilin	0.5594	1359.78
	Heilongjiang	0.6917	1360.91
	Anhui	0.4527	2222.34
	Jiangxi	0.5467	1558.63
	Henan	0.5746	2285.12
	Hubei	0.4809	2312.28
	Hunan	0.8378	566.41
	Guangxi	0.7504	608.30
Western area	Chongqing	0.8542	815.03
	Sichuan	0.4633	1670.93
	Guizhou	0.2210	4030.62
	Yunnan	0.3758	1373.27
	Shaanxi	0.6108	1363.01
	Gansu	0.2191	1279.99
	Qinghai	0.2377	1238.95
	Ningxia	0.1126	4378.38
	Xinjiang	0.1980	1366.59

Note: Region in this paper is used to define the provinces and hence we refer to the three groupings of provinces as “areas”.

Figure 1 further illustrates the dynamic changing trend of the MACs. During 2012-2014, China’s average MACs decreased from 2418.17 to 1572.73 CNY per ton. Only a slight decrease is shown during 2013-2014. Moreover, our three areas MACs also show decreasing trends from 2012 to 2013. During 2013-2014 MACs fall in the east, but rise in the less developed central and western areas. Over the three years the eastern area has decreased its MAC by 57.69%, while central and western areas have reduced their MACs by 26.87% and 3.89%, respectively. By 2014 the west had the highest MAC, having been the lowest in 2012. The rationality behind these changes is that national level emission abatement policies and regulations have been widely advocated by the regions, especially eastern China. These policies provide incentives for regions to reduce their carbon abatement costs. The eastern area significantly reduced its MAC to enable it to perform more carbon abatement tasks effectively. China's eastern region has the strongest economic and technological foundations among the three areas and therefore has the ability to do the most. However, for central and western areas there still exists scope to improve their MACs in the future, but the present focus is on wealth generation.

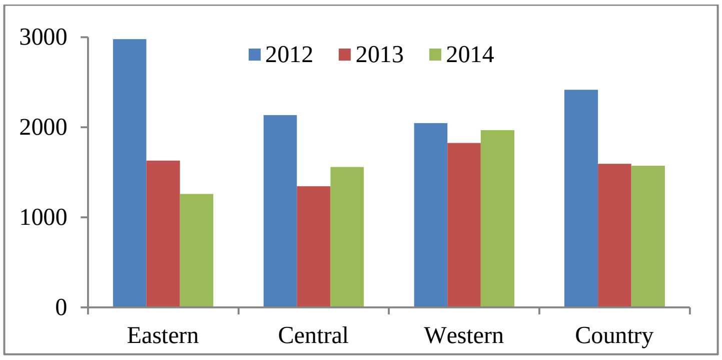

Fig.1 Average MACs of three areas and the country during 2012–2014.

4.3. Allocating CO_2 emissions abatement

To effectively reduce China's large carbon emissions, the total carbon abatement task should be reasonably allocated to each region, paying attention to their environmental performance. This paper uses the proposed approach of model (6) to allocate carbon abatement tasks among China's regions. Regions may prefer to work collectively to allocate within their areas. In calibrating model (6), we draw upon policy announcements relevant to the period.

The "13th - five - year working scheme of controlling greenhouse gases" sets the carbon intensity reduction target as 22% for China's industrial sector. Assuming that China's GDP growth rate keeps constant in next period for the allocation, we set the annual total CO_2 abatement ratio at 4.4%. This value is taken from "China's low carbon energy saving and emission abatement plan during 2014-2015 issued by the State Council". Although this may be a simplification in times of slowing economic growth in China, it is still reasonable given policy efforts to restore the growth path; it can avoid becoming distracted by non-carbon-abatement issues. The next three-year abatement task is obtained as 26.40% (i.e., the sum of 4.40%, 8.80%, and 13.20% of carbon abatement tasks) of the CO_2 abatement amount in 2014. Then we set the three-year national total CO_2 abatement amount B as 186601 10^4 tons. To set the target CO_2 abatement task B_p for each collaboration area, we divided the national total CO_2 abatement amount B according the proportion of the total CO_2 emission amount coming from that collaboration. To avoid the total carbon abatement task being allocated to a small group of regions, we assume that each region could not reduce more than 30% of its current carbon emissions due to the limitations of current production scale and technology ($C_i^u = 0.3C_i$). The 30%

abatement upper limit follows Wu, Zhu, & Liang (2016) and is explored in the appendix of this paper. B_p and C_i^u can be easily adjusted to represent different scenarios.

We propose three regions for collaboration, which is the treatment afforded by most Chinese policy. The eastern, central and western areas discussed above thus form our regions for the purpose of the analysis that follows. By solving models (6) and (8), detailed allocation results affected by national collaboration and intra-area collaborations (i.e., collaborations within eastern, central or western areas, respectively) during 2012 - 2014 are outlined. We illustrate these in Figure 2 and 3. For carbon abatement tasks, the comparison of the national allocation and intra-area allocations for each region is shown in Fig. 2 (unit: 10^4 tons), and the comparison of maximized industrial GDP output (i.e., $\hat{Y}_i$ in model (6)) of each region is shown in Fig. 3 (Unit: 10^9 CNY).

Figure 2 shows that in the national allocation, 17 regions should decrease their carbon emissions, and 13 regions may keep their carbon emissions constant (i.e., each carbon abatement is equal to zero). The rationality of regions keeping their carbon emission constant can be attributed to two aspects: (1) the relative carbon abatement costs are too high to reduce their carbon emissions, for example, MACs of Beijing, Shanghai, Shanxi, Anhui, Henan, Hubei, Guizhou, and Ningxia are all higher than 2000 CNY per ton, much higher than the average MAC for the country. (2) They have lower environmental efficiency performances. The average efficiency of regions without any more allocated CO_2 abatement (0.47) is lower than the total average efficiency of 0.55. To achieve the national target, it is more economical for these regions to increase economic outputs than to reduce carbon emissions. Carbon allocation tasks are affected by the mixed impacts of their carbon abatement costs and environmental efficiencies.

Four regions, Hebei, Inner Mongolia, Gansu and Qinghai should, due to their low MACs undertake the upper-level carbon abatement task (i.e., reduce 30% of C_i). Interestingly Inner Mongolia also has the highest efficiency and the largest carbon abatement proportion. Even though Inner Mongolia has the highest efficiency of carbon emission abatement, its MAC is still the lowest (81.25 CNY per ton). Thus output in Inner Mongolia might be sacrificed to reduce more carbon emissions to achieve the highest economical level for the country.

Total carbon abatements for eastern, central and western areas are 92963, 58750 and 34888 10^4 tons, respectively. Ratios of carbon abatement tasks to carbon emissions (called carbon abatement ratio for short) for eastern, central and western areas are 10.6453%, 8.1265% and 6.6568%, respectively. Here, the eastern area has the highest abatement ratio and the western area has the lowest. As such, it is reasonable to allocate a greater proportion of the abatement to the east.

The explanation behind the areal diversity is that, the eastern area has the strongest economic foundation and highest technology level in China. It is easier for more economically developed regions to adjust their industrial structure or energy structure or adopt advanced technologies to reduce their carbon emissions. While underdeveloped areas, such as the western area, face greater policy pressure to enact economic growth. Thus the carbon emission task would be reduced to enable the pursuit of economic growth. A similar rank among areas is also achieved by Wu, Zhu, & Liang (2016). Our approach has stronger motivation provided by our consideration of MACs.

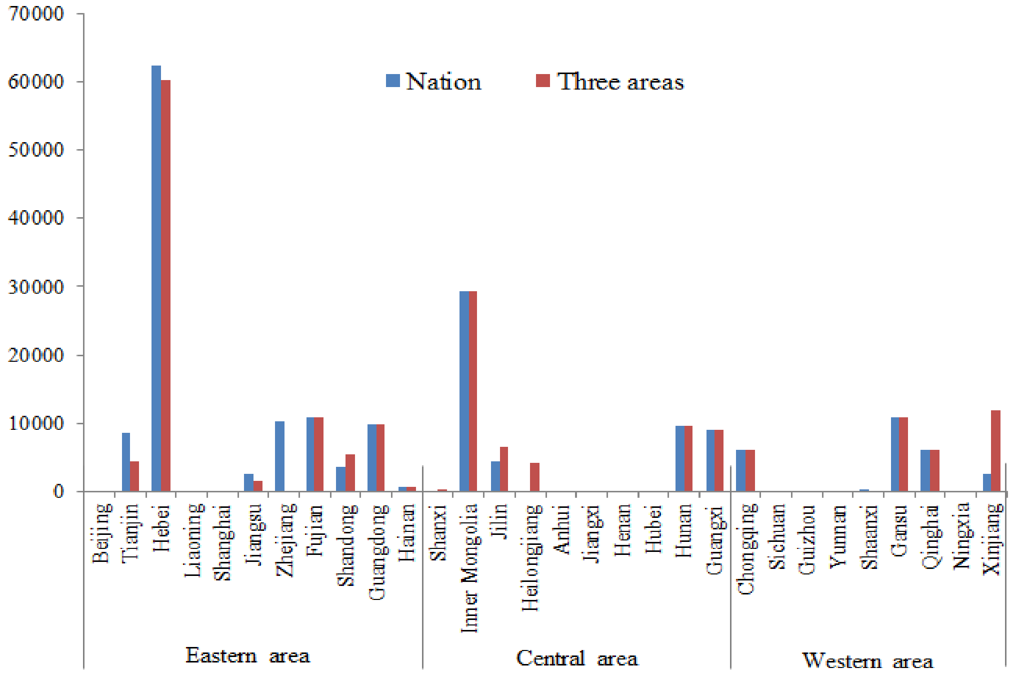

Fig. 2 Result comparison of allocated carbon abatement tasks.

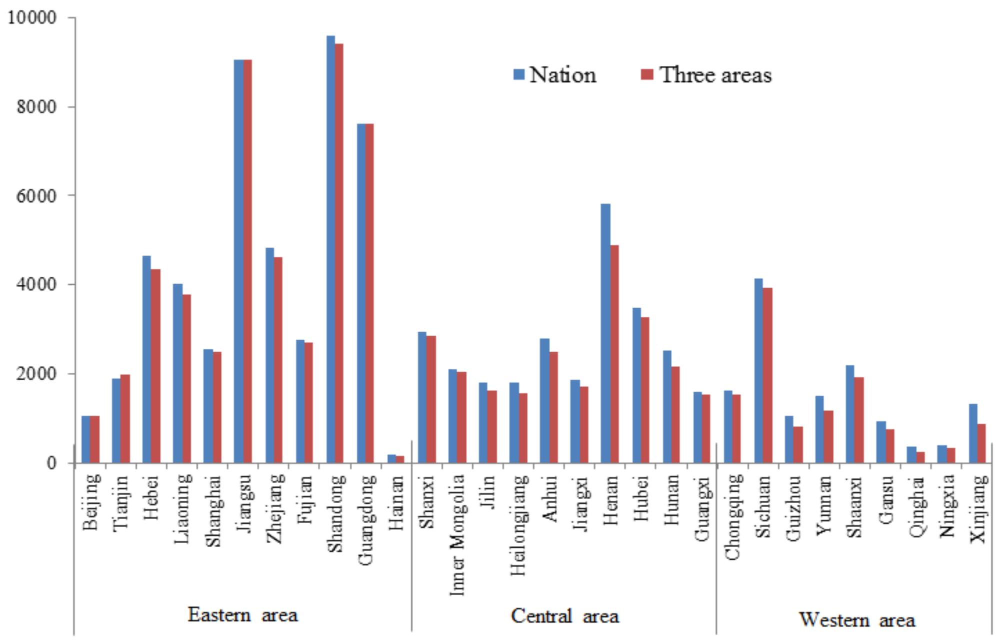

Fig. 3 Result comparison of allocated maximized industrial GDP.

Comparing allocated results affected by national collaboration with those affected by intra-area collaborations, the carbon allocation tasks of 10 regions have been adjusted. In the eastern intra-area collaboration, Tianjin, Hebei, Jiangsu and Zhejiang should be allocated a lower carbon abatement task, while Shandong should increase its efforts. In the central intra-area collaboration, Shanxi, Jilin and Heilongjiang should increase their carbon abatement tasks. In the western intra-area collaboration, Shaanxi could slightly reduce its corresponding carbon abatement task, and Xinjiang should increase its contribution. Based on the comparison of allocation results, we conclude that regional collaborations would result in increased carbon abatement tasks for central regions, but mixed effects would exist in eastern and western regions. In both collaborations, the eastern area has the greatest total GDP output, followed by the central area and then the western area. This matches the ranking currently observed.

To confirm the effectiveness of the proposed allocation model, we further calculate the allocation results estimated by the conventional DEA allocation model. The conventional DEA allocation model for carbon allocation treats the maximized national total GDP as the target function, but other settings are identical to those in model (7). Necessarily, only the comparison of national allocation results between the conventional and proposed models are illustrated in Fig.4.

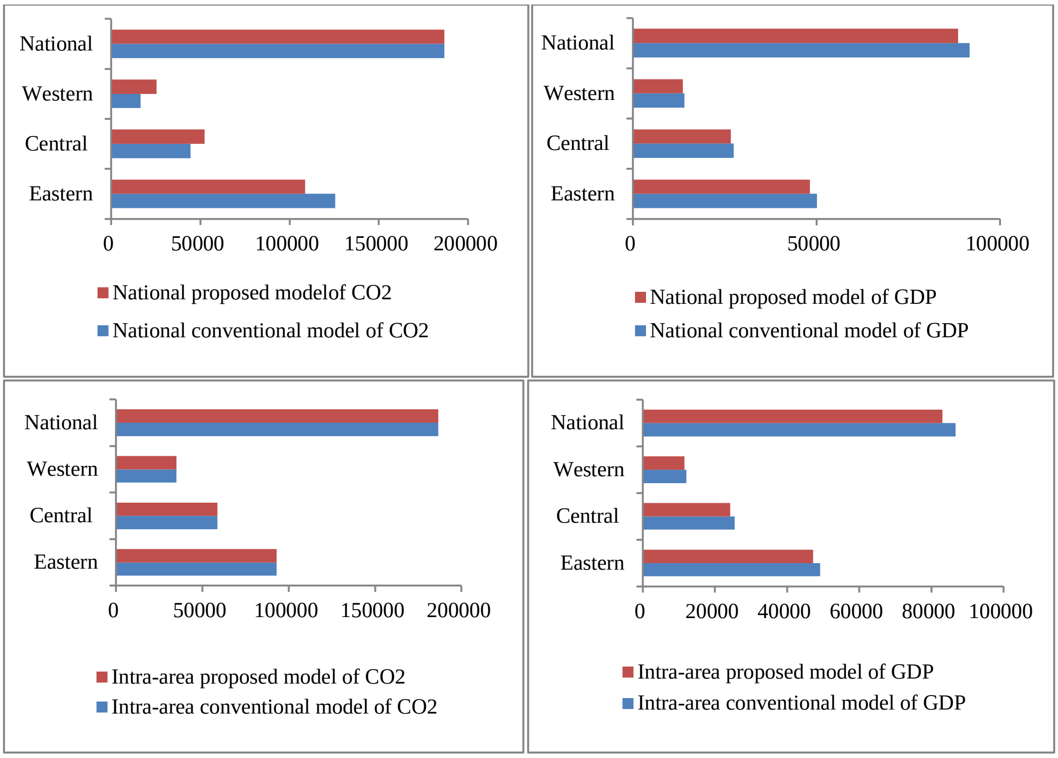

Fig. 4 Comparisons of allocation results between the conventional model and proposed model.

The results indicate that: (1) with the consideration of MACs, the eastern area could reduce its carbon abatement task (i.e., 16915 10^4 tons) and central and western areas would have more carbon abatement tasks (i.e., 7879 and 9036 tons, respectively). (2) Considering the existence of MACs, the potential maximized GDPs for all the areas of China would be significantly decreased, for example, the GDP reduction is 3149 10^9 CNY for the whole country. The above results indicate that the proposed DEA allocation could effectively estimate the carbon allocations affected by corresponding MACs. The ignorance of MACs would result in overestimation of maximized GDP and changes of allocation results.

4.4. Regional collaboration and carbon allocations

To further illustrate the effects of regional collaborations, we present the carbon abatement task allocations for the three areas under a series of different groupings in Table 3. We compare the grand coalition of the three separate areas, and the three combinations that see two areas paired together. E, C and W denote eastern, central and western areas specifically, respectively, and braces, {}, denote collaboration. From Table 3, according to the proportions of carbon emission to national carbon emissions of the three areas during the period 2012-2014, the allocated carbon dioxide abatement tasks of eastern, central and western areas are 92963, 56888, and 36750 10^4 tonnes, respectively. Considering the eastern area, we can see it receives its highest allocation of tasks when in the grand coalition (108761 10^4 tons) and its lowest when it acts alone (92963 10^4 tons). By contrast the other two regions receive their smallest allocation when they are acting in collaboration with the eastern area. Comparing with the Shapley (1953) allocations confirms that these are equal to the values for each region when acting alone. This certifies the robustness of the DEA method.

Table 3

Results of allocated carbon abatement amounts affected by regional collaborations.

Area	Allocated carbon abatement tasks					
	{E,C,W}	**{E},{C},{W}**	**{E,C},{W}**	**{E,W},{C}**	**{E },{C,W}**	**Shapley V**
E	108671	92963	99379	104839	92963	92963
C	52427	58750	52334	58750	56888	58750
W	25503	34888	34888	23012	36750	34888
China	186601	186601	186601	186601	186601	186601

Table 4

Results of maximized industrial GDP affected by regional collaborations.

Area	Maximized industrial GDP				
	{E,C,W}	**{E},{C},{W}**	**{E,C},{W}**	**{E,W},{C}**	**{E},{C,W}**
E	48241	47213	48090	47663	47213
C	26714	24204	26500	24204	25036
W	13631	11600	11600	12546	13059
China	88586	83017	86190	84413	85308

We also consider the impact of coalitions on GDP in Table 4. A national coalition maximizes GDP for each region whilst acting alone delivers the lowest. Finally, Table 5 considers the economical level for each regional collaboration combination. For the whole nation and central area, the full national coalition is the most economical. Meanwhile, the eastern area would do well to act alone, and the western area achieves its highest economical level when collaborating with the east. From these results, we conclude that the national level coalition achieves the nationally most economical results and maximized GDP output. This is consistent with Proposition 1. In collaborations, developing regions have a more economical carbon abatement process than the already developed east; the task may thus be transferred across to the more economically developed east. The western area would lobby for this, as it performs best in collaboration with the east.

Table 5

Economical levels affected by regional collaborations.

Area	Allocated economical levels				
	{E,C,W}	**{E},{C},{W}**	**{E,C},{W}**	**{E,W},{C}**	**{E },{C,W}**
E	30.67	35.97	33.90	31.15	35.97
C	136.99	86.21	136.99	86.21	98.04
W	45.66	27.25	27.25	47.62	28.90
China	42.92	40.98	42.37	40.65	42.19

4.5. Further discussion

Based on the aforementioned analysis, some conclusions and implications are derived for the benefit of carbon abatement policy and the practical implementation thereof. Our conclusions demonstrate the key tension between regional objectives and the nationally efficient allocation. For example the east may seek to limit is allocation of carbon abatement tasks by avoiding collaboration, but this would be to the detriment of the other areas and the whole country; as these areas would prefer the national collaboration. A practical explanation is that, as mentioned above, intuitively, the economically developed area has more potential to reduce carbon emissions. Thus, the eastern area should accept more of the carbon allocation burden in the national allocation vision. However, such compliance from the east is against its economic increment target; a collaboration struggle appears in east China.

That the eastern economically developed regions have limited carbon emission quotas compared with other areas is also indirectly proved by Zhang, Wang, & Da (2014) with a collaboration estimation by the Shapley value method. Different from the existing literature, one merit of our collaborative DEA allocation is to provide exact allocated results with all possible regional collaborations. Consequently, a novel vision of carbon allocation, considering the collaborative relationship between allocated objects in the DEA method, may be achieved.

Policy should encourage collaboration at the national level (e.g., joint carbon abatement or the integrated carbon trading market among regions) to allow the central and western areas to concentrate on upping their industrial output whilst the east shoulders the burden of abatement. Such a move could facilitate the transfer of technology and energy-intensive industries westward and hence create a greater future economical carbon abatement process in central and western provinces. Considering the struggle against collaboration implied for the eastern area, the appropriate compensation for carbon reduction (e.g., low-carbon subsidies for industrial sectors or firms) should be enacted by the central government to facilitate the potential regional collaborations on carbon reduction. Given the better economic development recognised in the eastern area, energy-saving and carbon-free technological updating could be advocated to reduce the extra carbon abatement task (Jia, Li, & Shao, 2018).

Necessarily, the DEA approach is linked to historic data, but it is an effective means for identifying the carbon abatement task allocations based on corresponding costs. Our results have permitted the consideration of regional collaborations in China, highlighting tensions and delivering the case for collaboration. For China, the national-level solution is optimal.

5. Conclusions

By modifying the DEA allocation approach, this paper has presented an analysis of the division of carbon abatement tasks considering corresponding regional level carbon abatement costs. Introducing a modified DEA allocation approach permitted the study of the dual optimisation of carbon reduction and output maximization. A meta-frontier DEA allocation model for any DMUs is further proposed, which can reflect the potential collaboration of decision making units.

For industrialised and industrialising nations alike, the challenge of controlling carbon emissions is a pressing one, and the lessons from China should resonate. Our work is, like existing studies, a closed system which focuses entirely on the industrial sector. We have demonstrated there exist remarkable geographic disparities in environmental efficiencies and carbon abatement costs which previous DEA works have struggled to internalise. Regional collaborations can help influence members' abatement tasks, and our framework gives, for the first time, clear insight into how.

Our most important findings, however, concern the roles regional collaborations might play at the national level. A clear case is made for greater allocations for eastern China, where high economic development and lower abatement costs mean that greater efforts can be accommodated. Allocating more to a block like this gives the two less developed areas, especially western China, the chance to develop economically such that they two might take on greater tasks in the future. Consequently greater discrepancies between regions emerge on abatement task allocated, but wealth differentials narrow in the long run; both processes embed regional identity and facilitate the continuance of such coalitions.

Some policy suggestions are that, the consideration of regional collaborations against the grand coalition of all provinces demonstrates that the latter delivers the most efficient outcome, but it is inherently unstable due to the optimality of other contributions for individual regions. Chinas most developed eastern area has the most to gain from allocating independently, whilst the less developed central and western areas wish to join with the east. Lessons in promoting collaboration are clear and policy should seek to ensure that this is done. Policy-makers should consider our findings carefully and ensure that the conflicts of carbon abatement task allocation are resolved.

However, some limitations in discussion also exist. We limited our collaborations to the most common Chinese relationships. There is, however, no reason why longer term coalitions between geographically disparate provinces should not engage. For example, the third highest MAC region, Shanghai may work with the third lowest, Guangxi. Whilst the economic motivations for such a relationship are clear, the lack of geographical connectivity is likely to raise questions about the costs of working together. Here we argue that maintaining a sector focus is pertinent to the current economic make-up of the constituent provinces and positing coalitions with existing infrastructure remains most realistic now and into the future.

For China, the national allocation should be adopted, a result that extends globally from the theoretical work. China's need to achieve over the three study years is very clear for its international position and domestic environment, but other nations face similar dilemmas and the DEA modelling process constructed above should resonate in their decision making. We have simplifications informed by policy but these may be readily adjusted to other settings and signposts for wider adoption.

Furthermore, considering that the areal collaboration in China is still currently difficult to realize, the collaborative DEA model could be more meaningful if adopted in a small-scale regional analysis, for example, the collaboration among provinces or cities. The novel vision of this study could also help the central government to reasonably decompose the national carbon abatement target for local governments and facilitate regional collaboration in the future. The proposed method can also be adopted in other applications with related collaborations, such as, the resource allocation for companies or institutions. Notably, carbon abatement costs in this study are estimated based on the carbon reduction and energy saving target, which can be modified with the consideration of other factors in future applications.

DEA has an important role to play in addressing pressing environmental issues in an efficient and transparent way and the modifications we make in this paper will aid that process. For all concerned, the options, and consequences, of costly improvement allocations are clear and must be heeded by all collaboration efforts.

Appendix

Table A.1
Sensitivity analysis.

	30%	**40%**	**50%**	**60%**	**70%**
Beijing	0.0000	0.0000	0.0000	0.0000	0.0000
Tianjin	0.2000	0.1413	0.1667	0.2000	0.2333
Hebei	0.3000	0.3491	0.2340	0.1125	0.0048
Liaoning	0.0000	0.0000	0.0000	0.0000	0.0000
Shanghai	0.0000	0.0000	0.0000	0.0000	0.0000
Jiangsu	0.0156	0.0000	0.0000	0.0000	0.0000
Zhejiang	0.1213	0.0000	0.0000	0.0000	0.0000
Fujian	0.2000	0.2667	0.3333	0.4000	0.4667
Shandong	0.0170	0.0000	0.0000	0.0000	0.0000
Guangdong	0.1000	0.1333	0.1667	0.2000	0.2333
Hainan	0.1000	0.1333	0.1667	0.2000	0.2333
Shanxi	0.0000	0.0000	0.0000	0.0000	0.0000
Inner Mongolia	0.3000	0.4000	0.5000	0.6000	0.7000
Jilin	0.0902	0.0000	0.0000	0.0000	0.0000
Heilongjiang	0.0000	0.0000	0.0000	0.0000	0.0000
Anhui	0.0000	0.0000	0.0000	0.0000	0.0000
Jiangxi	0.0000	0.0000	0.0000	0.0000	0.0000
Henan	0.0000	0.0000	0.0000	0.0000	0.0000
Hubei	0.0000	0.0000	0.0000	0.0000	0.0000
Hunan	0.2000	0.2667	0.3333	0.4000	0.4667
Guangxi	0.2000	0.2667	0.3333	0.4000	0.4667
Chongqing	0.2000	0.2667	0.3333	0.4000	0.4667
Sichuan	0.0000	0.0000	0.0000	0.0000	0.0000
Guizhou	0.0000	0.0000	0.0000	0.0000	0.0000
Yunnan	0.0000	0.0000	0.0000	0.0000	0.0000
Shaanxi	0.0001	0.0000	0.0000	0.0000	0.0000
Gansu	0.3000	0.0000	0.0000	0.0000	0.0000
Qinghai	0.3000	0.3145	0.1654	0.1535	0.0000
Ningxia	0.0000	0.0000	0.0000	0.0000	0.0000
Xinjiang	0.0394	0.0037	0.0000	0.0000	0.0000
Std.	0.1122	0.1320	0.1451	0.1705	0.2007
Repeat	17	20	21	21	22

Table A.1 illustrates the sensitivity analysis by setting different upper level of carbon abatement (i.e., C_i^u). The first row shows various settings of C_i^u. From row 2 to row 31, there are ratios of allocated carbon abatement tasks to corresponding regional carbon emission amounts by different settings of C_i^u. In row 32, there are standard deviations for all the regions subjected to the specific C_i^u. In row 33, there are numbers of the repeated ratio attaining the corresponding C_i^u or 0. We believe that, the result of a specific C_i^u has the least standard deviation and repeated number could have the best explanation for carbon allocations. This indicates that the carbon abatement ratios have the least disparities among regions and least regions are constricted by the corresponding C_i^u. Comparing all the C_i^u, we discovered that the model incorporating C_i^u of 30% has a better result than others. Thus, 30% is set as the upper level of C_i^u in this study.

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Reference

[1] Beasley, J.E., 2003. Allocating fixed costs and resources via data envelopment analysis. Eur. J. Oper. Res. 147(1), 198-216.

[2] Bian, Y., Yang, F., 2010. Resource and environment efficiency analysis of provinces in China: A DEA approach based on Shannon's entropy. Energ. Policy 38, 1909-1917.

[3] Burnett, J.W., Bergstrom, J.C., Dorfman, J.H., 2013. A spatial panel data approach to estimating U.S. state-level energy emissions. Energ. Econ. 40, 396-404.

[4] Charnes, A., Cooper, W.W., Lewin, A.Y., Seifor, L.M., 1994. Data Envelopment Analysis: Theory, Methodology, and Application. Kluwer Academic Publishers, Norwell.

[5] China State Council, 2011. Work plan of controlling greenhouse emissions during 12th five-year plan period for China State Council. http://www.gov.cn/zwgk/2012-01/13/content_2043645.htm (last accessed 2018.03.13).

[6] Choi, Y., Zhang, N., Zhou, P., 2012. Efficiency and abatement costs of energy-related CO_2 emissions in China: A slacks-based efficiency measure. Appl. Energy 98, 198-208.

[7] Core Writing Team, Pachauri, R.K., Reisinger, A., 2007. Intergovernmental Panel on Climate Change (IPCC). IPCC Fourth Assessment Report: Mitigation of Climate Change 2007. http://www.ipcc.ch/publications_and_data/publications_ipcc_fourth_assessment_report_synthesis_report.htm (last accessed 14.03.17).

[8] Cui, L., Fan, Y., Zhu, L., Bi, Q., 2014. How will the emissions trading scheme save cost for achieving China's 2020 carbon intensity reduction target? Appl. Energy 136, 1043-1052.

[9] Du, J., Cook, W.D., Liang, L., Zhu, J., 2014. Fixed cost and resource allocation based on DEA cross-efficiency. Eur. J. Oper. Res. 235(1), 206-214.

[10] Fang, L., 2013. A generalized DEA model for centralized resource allocation. Eur. J. Oper. Res. 228(2), 405-412.

[11] Feng, C., Chu, F., Ding, J., Bi, G., Liang, L., 2015. Carbon Emissions Abatement (CEA) allocation and compensation schemes based on DEA. Omega 53, 78-89.

[12] Friedman, L., Sinuany-Stern, Z., 1998. Combining ranking scales and selecting variables in the DEA context: The case of industrial branches. Comput. Oper. Res. 25 (9), 781-791.

[13] Gomes, E.G., Lins, M.E., 2008. Modelling undesirable outputs with zero sum gains data envelopment analysis models. J. Oper. Res. Soc. 59(5), 616-23.

[14] Ha, N.V., Kant, S., Maclaren, V., 2008. Shadow prices of environmental outputs and production efficiency

of household-level paper recycling units in Vietnam. Ecol. Econ. 65(1), 98-110.

[15] Halkos, G.E., Tzeremes, N.G., 2009. Exploring the existence of Kuznets curve in countries' environmental efficiency using DEA window analysis. Ecol. Econ. 68, 2168-2176.

[16] Hao, Y., Liu, Y., Weng, J., Gao, Y., 2016. Does the Environmental Kuznets Curve for coal consumption in China exist? New evidence from spatial econometric analysis. Energy 114, 1214-1223.

[17] Hilton, I., Kerr, O., 2017. The Paris agreement: China's 'New Normal' role in international climate negotiations. Clim. Policy 17(1), 48-58.

[18] Hu, J.L., Wang, S.C., 2006. Total-factor energy efficiency of regions in China. Energ. Policy 34, 3206-3217.

[19] Huda, M.S., McDonald, M., 2016. Regional cooperation on energy in South Asia: Unraveling the political challenges in implementing transnational pipelines and electricity grids. Energ. Policy 98, 73-83.

[20] Jiang, B., Sun, Z., Liu, M., 2010. China's energy development strategy under the low-carbon economy. Energy 35(11), 4257-4264.

[21] Jiang, M.X., Yang, D.X., Chen, Z.Y., Nie, P.Y., 2016. Market power in auction and efficiency in emission permits allocation. J. Environ. Manage. 183, 576-584.

[22] Jia, P., Li, K., Shao, S., 2018. Choice of technological change for China's low-carbon development: Evidence from three urban agglomerations. J. Environ. Manage. 206, 1308-1319.

[23] Li, H., Mu, H., Zhang, M., Gui, S., 2012. Analysis of regional difference on impact factors of China's energy-Related CO_2 emissions. Energy 39, 319-326.

[24] Lozano, S., Villa, G., 2004. Centralized resource allocation using data envelopment analysis. J. Prod. Anal. 22(1), 143-161.

[25] Lozano, S., Villa, G., Brännlund, R., 2009. Centralised reallocation of emission permits using DEA. Eur. J. Oper. Res. 193 (3), 752-760.

[26] Lozano, S., 2013. DEA production games. Eur. J. Oper. Res. 231, 405-413.

[27] Ramli, N.A., Munisamy, S., 2015. Eco-efficiency in greenhouse emissions among manufacturing industries: A range adjusted measure. Econ. Model 47, 219-227.

[28] Shapley, L.S., 1953. A value for N person games. Ann. Math. Stud. 28, 307-317.

[29] Srivastava, L., Misra, N., 2007. Promoting regional energy co-operation in South Asia. Energ. Policy 35, 360-3368.

[30] Sueyoshi, T., Goto, M., 2012. Weak and strong disposability vs. natural and managerial disposability in DEA environmental assessment: Comparison between Japanese electric power industry and manufacturing industries. Energ. Econ. 34, 686–699.

[31] Sun, J., Wu, J., Liang, L., Zhong, R.Y., Huang, G.Q., 2014. Allocation of emission permits using DEA: centralised and individual points of view. Int. J. Prod. Res. 52(2), 419-435.

[32] Timmer, J., Borm, P., Suijs, J., 2000. Linear transformation of products: games and economies. J. Optimiz. Theory App. 105 (3), 677-706.

[33] Uddin, N., Taplin, R., 2015. Regional cooperation in widening energy access and also mitigating climate change: Current programs and future potential. Global Environ. Chang. 35, 497-504.

[34] Wang, Y.S., Bian, Y.W., Xu, H., 2015. Water use efficiency and related pollutants' abatement costs of regional industrial systems in China: a slacks-based measure approach. J. Cleaner Prod. 101, 301-310.

[35] Wang, Z., He, W., 2017. CO_2 emissions efficiency and marginal abatement costs of the regional transportation sectors in China. Transport. Res. D. 50, 83-97.

[36] Wang, J., Lv, K., Bian, Y., Cheng, Y., 2017. Energy efficiency and marginal carbon dioxide emission abatement cost in urban China. Energ. Policy 105, 246–255.

[37] Wang, K., Wei, Y.M., Zhang, X., 2012. A comparative analysis of China’s regional energy and emission performance: Which is the better way to deal with undesirable outputs? Energ. Policy 46, 574-584.

[38] Wang, K., Wei, Y-M., Zhang, X., 2013. Energy and emissions efficiency patterns of Chinese regions: A multi-directional efficiency analysis. Appl. Energy 104, 105–116.

[39] Wang, K., Wei, Y., 2014. China’s regional industrial energy efficiency and carbon emissions abatement costs. Appl. Energy 130, 617-631.

[40] Wang, K., Wei, Y., Huang, Z., 2016. Potential gains from carbon emissions trading in China: A DEA based estimation on abatement cost savings. Omega 63, 48-59.

[41] Wu, J., Zhu, Q., Chu, J. An, Q., Liang, L., 2016. A DEA-based approach for allocation of emission reduction tasks. Int. J. Prod. Res. 54 (20), 5990-6007.

[42] Wu J, Zhu Q, Liang L., 2016. CO_2 emissions and energy intensity reduction allocation over provincial industrial sectors in China. Appl. Energy 166: 282-291.

[43] Zhang, Y.J., Wang, A.D., Da, Y.B., 2014. Regional allocation of carbon emission quotas in China: Evidence from the Shapley value method. Energ. Policy 74, 454–464.

[44] Zhou, P., Ang, B.W., 2008. Linear programming models for measuring economy-wide energy efficiency performance. Energ. Policy 36, 2911-2916.

[45] Zhou, P., Ang, B.W., Poh, K.L., 2008. Measuring environmental performance under different environmental DEA technologies. Energ. Econ. 30, 1-14.

[46] Zhou, P., Zhou, X., Fan, L.W., 2014. On estimating shadow prices of undesirable outputs with efficiency models: a literature review. Appl. Energy 130, 799-806.

[47] Zhou, P., Sun, Z.R., Zhou, D.Q., 2014. Optimal path for controlling CO_2 emissions in China: a perspective of efficiency analysis. Energ. Econ. 45, 99-110.

[48] Zhou, X., Fan, L.W., Zhou, P., 2015. Marginal CO2 abatement costs: Findings from alternative shadow price estimates for Shanghai industrial sectors. Energ. Policy 77, 109-117.