Cost-environment efficiency analysis of construction industry in China: A materials balance approach

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Abstract: This study utilizes the data envelopment analysis technique with materials balance condition to evaluate the inherent trade-offs between environmental and cost outcomes among different types of energy consumptions in China's construction industry. Environmental and cost efficiency that is decomposed into technical efficiency and allocative efficiency are estimated, and the possible environmental impact and economic cost of reallocating energy inputs for improving efficiency are obtained. The estimation results show that: i) China's construction industry has the ability to produce its current level of industrial added value with fewer CO_2 emissions and fewer energy input cost through removing technical inefficiency and adjusting energy consumption structure. ii) There are 31.9% and 6.1% reduction potentials on CO_2 emissions if this industry attained the most environmentally efficient and the most costly efficient situation, respectively. iii) The average shadow cost of CO_2 emissions reduction in this industry is very low, suggesting that it should control CO_2 emissions through optimizing energy consumption structure and improving energy efficiency, instead of relying on end-of-pipe emission abatement technologies or emission trading systems.

Key words: CO_2 emissions; cost efficiency; Data Envelopment Analysis; environmental efficiency; materials balance condition; trade-offs

1 Introduction

Carbon dioxide (CO_2) emissions derived from energy consumption make a major contribution to China's environmental problems associated with greenhouse gas emissions (Chen, Shen, Song, Shi and Li, 2017). As one of the most carbon-intensive industries in China, the proportion of coal, oil, nature gas and electricity to the energy consumption in construction industry during 2011-2015 are 11.3%, 73.1%, 0.4% and 14.8%, respectively. The annual growth rate of energy consumption in China's construction industry during 2011-2015, which accounts for 34.8%, is higher than the annual growth rate of China's total energy consumption (28.3%) and

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industrial energy consumption (23.5%). Moreover, the proportion of energy consumption in the construction industry to the total energy consumption of the society also rises with almost 5% annual growth rate. Since 2010, China's new building construction has accounted for nearly half of the world's new construction growth, but the per capita building area in China is still far lower than other major developed countries (Zhou, Khanna, Feng, Ke and Levine, 2018). The Report on Building Energy Consumption states that carbon emission reduction in the construction industry is significant for meeting the peaking target of carbon emissions which would appear no longer than 2030 (CABEE, 2017). Since CO_2 emissions are the inevitable by-product of economic activities with the environmental side effects, theoretically reasonable measurements of environmental and economic (cost) efficiency of CO_2 emissions are imperative for providing useful information on policy making for carbon emission reduction and relative efficiency improvement (Wang and Wei, 2014; Halkos, Tzeremes and Kourtzidis, 2016; Guo Zhang and Zhang, 2018; Zhang, Jin and Shen, 2018; Xian, Wang, Shi, Zhang, Wei and Huang, 2018). It would lead to better trade-offs on environmental and economic outcomes of China's construction industry and the whole ecosystem.

A number of attempts have already been made to measure the economic and/or environmental efficiency for construction industry. For instance, Tatari and Kucukvar (2011) proposed an analytical tool to measure the eco-efficiency of construction materials by using Data Envelopment Analysis (DEA) and a linear programming-based mathematical approach. Xue, Wu, Zhang, Dai and Su. (2015) pointed out that DEA-based Malmquist productivity index is a proper way to evaluate the energy consumption efficiency, and measured the change on energy consumption productivity for China's construction industry from 2004 to 2009 among 26 provinces. Chancellor and Lu (2016) estimated construction productivity and efficiency in China from 1995 to 2012, and pointed out that construction productivity has experienced a significant growth since 1995. Zhang, Li, Xia and Skitmore (2018) used a modified DEA method to analyze the carbon efficiency which was decomposed into several carbon efficiencies of different building materials such as cement, steel, and aluminum. The results showed that in most China's provinces, the carbon efficiencies are quite low, particularly for aluminum related carbon emissions.

The studies mentioned above are limited in improving technical or environmental efficiency on the trade-offs of economic outcomes and environmental emissions, and ignored to consider the allocative efficiency through adjusting inputs. Hence, they might obtain limited economic meanings and policy implications for China's construction industry. Indeed, there are some efficiency evaluation had been decomposed into technical efficiency and allocative efficiency (Shi and Grafton, 2010; Shi, 2010; Wang, Wei and Huang, 2018; Wang, Yang, Wei and Zhang, 2018). However, they only distinguish the allocation between pollution related inputs (e.g., energy) and non-pollution related inputs, but not focus on the allocation among different pollution-related inputs (e.g., fossil fuels and renewables).

The pollution-generating technologies in efficiency evaluation can be generally formalized in five ways: i) treating pollution as free disposable inputs (Reinhard, Knox Lovell and Thijssen, 2000; Mahlnerg and Sahoo, 2011). ii) considering pollutions as outputs under the weak disposability assumption (Färe, Grosskopf and

Tyteca, 1996; Fahlen and Ahlgren, 2012; Kwon, Cho and Sohn, 2017; Zhang, Sun and Huang, 2018). iii) using the sum of the additive/multiplicative inverse of pollution values as outputs values (Seiford and Zhu, 2002; Wang et al., 2012). iv) treating pollutions as costly disposable outputs in the by-production model (Førsund, 2009; Murty, Russel and Levkoff, 2012; Xian, Wang, Wei and Huang, 2019). However, these ways all have a disadvantage of violating the first law of thermodynamics, and thus, might obtain the biased estimation results of efficiency evaluation, especially when concerning the physical productivity and needing to quantify energy flows through industrial systems. (Hampf and Rødseth, 2015; Wang, Mi and Wei, 2018). The influence of construction activities (e.g., demolition of buildings) on the environmental system, the utilization of natural resources (e.g., coal and oil), and the problems of cutting down emissions (e.g., CO_2 emissions) all should be considered into efficiency evaluation of the construction industry when including the emissions from energy consumption. Hence, it is vital of important to quantify the energy or materials flows through construction activities.

Based on the law of thermodynamics and materials balance principle (MBP) condition, this study assumes the inevitability of generating residuals. We propose four data envelopment analysis based (DEA-based) models with MBP to estimate technical efficiency (*TE*), environmental efficiency (*EE*), cost efficiency (*CE*), and total cost efficiency (*TCE*) in China's construction industry, respectively. In addition, the environmental and cost trade-offs could also be identified in this industry.

This study's primary contribution is that it provides a method that can help policy makers and managers to balance the economic costs and ecological benefits of carbon abatement in the construction industry. In addition, because of the predominate role of fossil-fuel in carbon discharges for China's construction industry, this method also provides an assessment on the allocation efficiency of energy inputs, and the costs and benefits of substituting one fuel with another.

This paper is organized as follows: Section 2 introduces the materials balance principle, and Section 3 presents the DEA-based models for environmental and cost efficiency measurement with MBP. In section 4, we describe the datasets and their resources. Section 5 presents the estimation results and discussions. Section 6 draws the conclusions.

2 Materials balance principle

Materials balance principle (MBP) is the balance of the materials between inputs, desirable outputs and undesirable outputs in the production progress. Ayres and Kneese (1969) first introduced the materials balance principle from the theoretical perspective, and then Lauwers, Van Huylenbroeck and Rogiers (1999) introduced it in the use of efficiency and productivity measurement. Furthermore, Colli, Lauwers and Van Huylenbroeck (2005) and Colli Lauwers and Van Huylenbroeck (2007) presented the aspects of the MBP in the DEA technique, and concluded that the DEA-based MBP method is more tightly linked to the economic analysis when measuring the efficiency and productivity than other DEA-based methods. The MBP method, which can all concern the physical efficiency, economic prices and pollution cost, closely ties the production efficiency and productivity with environmental and economic context. It bridges the gap between conventionally environmental efficiency and economic efficiency, and thus, makes the environmental and economic outcomes equally explicit.

MBP declares that the total amount of emission contents (i.e., carbon) in the inputs must equal the emission contents in desirable output plus the emission contents in the residuals that may cause CO_2 emissions. In specific, the balance equation can be written as:

$$\alpha \boldsymbol{x} - \beta \boldsymbol{y} = \boldsymbol{u} + \boldsymbol{a} \qquad (1)$$

where $\boldsymbol{x}$, $\boldsymbol{y}$, $\boldsymbol{u}$ denotes the inputs, desirable outputs and undesirable outputs, respectively. $\boldsymbol{a}$ denotes the abatement amount of pollutants. $\boldsymbol{a}=\mathbf{0}$ represents the situation in which there is no carbon abatement activities, and $\boldsymbol{a}>\mathbf{0}$ represents the situation in which the carbon abatement activities are implemented. In addition, α and β are the vectors of emission factors in inputs and the vectors of recuperation factors in desirable outputs, respectively. $\alpha = 0$ if $\boldsymbol{x}$ is non-polluting input, whereas $\alpha \neq 0$ if $\boldsymbol{x}$ is polluting input. Similarly, $\beta = 0$ if desirable output $\boldsymbol{y}$ does not contain polluting mass (i.e., carbon), whereas $\beta \neq 0$ if desirable output $\boldsymbol{y}$ contains polluting mass.

The MBP satisfies the weak G-disposability assumption (i.e., the laws of thermodynamics) that is a summing-up formulation (Welch and Barnum, 2009). This assumption states that the increase in pollution (i.e., $\Delta \boldsymbol{u}$) should equals the sum of three components: the increase in emission bound in input (i.e., $\alpha \Delta \boldsymbol{x}$), the reduction in emission bound in desirable output (i.e., $\beta \Delta \boldsymbol{y}$), and the reduction in abatement of pollution (i.e.,$\Delta \boldsymbol{a}$). Moreover, the weak G-disposability formulation can be written as:

$$\Delta \boldsymbol{u} = \alpha \Delta \boldsymbol{x} + \beta \Delta \boldsymbol{y} + \Delta \boldsymbol{a} \qquad (2)$$

3 Efficiency measurement

In this sub-section, following Wang, Mi and Wei (2018), we propose four DEA-based MBP models to estimate technical efficiency (*TE*), environmental efficiency (*EE*), cost efficiency (*CE*) and total cost efficiency (*TCE*) for adjusting polluting inputs and associated pollutions, respectively.

This study considers a sample with *n* observations, and each observation *j* has polluting (i.e., energy) inputs, non-polluting (non-energy) inputs, desirable outputs and undesirable outputs (i.e., pollutions or emissions) denoted by $(x_{ij}^{E}, x_{mj}^{NE}, y_{rj}, u_{ij})$, where i=1,…,l, m=1,…,f, r=1,…,s, and j=1,…,n.

First, for technical efficiency, in the situation that the observed inputs are not located on the efficient boundary of the technology set, it can be projected onto the efficient boundary of the technology set by proportionally shrinking the observed inputs. That is, by solving the following DEA-based minimizing programming with MBP for the under estimated observation j_0:

$$
\begin{aligned}
&\min \theta^T \\
&s.t.\ \theta^T x_{ij_0}^E = \sum_{j=1}^{n} \lambda_j x_{ij}^E + d_{ij}^{Tx^E},\ i=1,\ldots,l \\
&\quad x_{mj_0}^{NE} = \sum_{j=1}^{n} \lambda_j x_{mj}^{NE} + d_{mj}^{Tx^{NE}},\ m=1,\ldots,f \\
&\quad y_{rj_0} = \sum_{j=1}^{n} \lambda_j y_{rj} - d_{rj}^{Ty},\ r=1,\ldots,s \\
&\quad \theta^T u_{ij_0} = \sum_{j=1}^{n} \lambda_j u_{ij} + d_{ij}^{Tu},\ i=1,\ldots,l \\
&\quad \alpha_{ij} d_{ij}^{Tx^E} = d_{ij}^{Tu},\ i=1,\ldots,l;\ j=1,\ldots,n
\end{aligned}
\tag{3}
$$

where $d_{ij}^{Tx^E}$, $d_{mj}^{Tx^{NE}}$,d_{rj}^{Ty} and d_{ij}^{Tu} respectively represents the slack variables of polluting input, non-polluting input, desirable output and pollution implementing the weak G-disposability of MBP; λ_j represents the intensity variables indicating the convex combination of all observations; and α_{ij} is the emission factor denoting the unit emission bound in polluting input. In addition, objective function θ^T , which represents the *TE*, would proportionally shrink all observed polluting inputs until they are projected onto the efficient boundary of the technology set. The last equation associated with the first and four equations is the MBP condition.

Second, for environmental efficiency, since the amount of desirable output y_r (r=1,…,s) is fixed, the emission content $\alpha \boldsymbol{x} - \beta \boldsymbol{y}$ will be minimized when the emission content in inputs (i.e., $\alpha \boldsymbol{x}$) is minimized. Thus, the objective of *EE* is to achieve the minimal amount of emission content in all polluting inputs. Given the desirable output y_r (r=1,…,s), the associated DEA-based minimizing programming with MBP for the under estimated observation j_0 can be written as follows:

$$
\begin{aligned}
&\min \sum_{i=1}^{l} \alpha_{ij_0} \theta_i^E x_{ij_0}^E \\
&s.t.\ \theta_i^E x_{ij_0}^E = \sum_{j=1}^{n} \lambda_j x_{ij}^E + d_{ij}^{Ex^E},\ i=1,\ldots,l \\
&\quad x_{mj_0}^{NE} = \sum_{j=1}^{n} \lambda_j x_{mj}^{NE} + d_{mj}^{Ex^{NE}},\ m=1,\ldots,f \\
&\quad y_{rj_0} = \sum_{j=1}^{n} \lambda_j y_{rj} - d_{rj}^{Ey},\ r=1,\ldots,s \\
&\quad \theta_i^E u_{ij_0} = \sum_{j=1}^{n} \lambda_j u_{ij} + d_{ij}^{Eu},\ i=1,\ldots,l \\
&\quad \alpha_{ij} d_{ij}^{Ex^E} = d_{ij}^{Eu},\ i=1,\ldots,l;\ j=1,\ldots,n
\end{aligned}
\tag{4}
$$

Similarly, in model (4), $d_{ij}^{Ex^E}$, $d_{mj}^{Ex^{NE}}$,d_{rj}^{Ey} and d_{ij}^{Eu} respectively represents the slack variables of polluting input, non-polluting input, desirable output and pollution implementing the weak G-disposability of MBP; λ_j

represents the intensity variables; α_{ij} is the emission factor; and the last equation associated with the first and four equations indicates the MBP condition. Moreover, θ_i^E represents the variable for adjusting each polluting input and its associated undesirable output, and the adjustment can be different among different polluting inputs and undesirable outputs. It measures the resource allocation efficiency of each polluting input and the trade-offs among different types of these inputs.

After solving model (4), the *EE*, which is the ratio of minimal emission content over observed emission content, can be estimated by:

$$EE = \frac{\sum_{i=1}^{l} \alpha_{ij} \left(\theta_i^E x_{ij}^E - d_{ij}^{Ex^E} \right)}{\sum_{i=1}^{l} \alpha_{ij} x_{ij}^E}, \quad j = 1, \ldots, n. \tag{5}$$

The value of *EE* takes between zero and one, and *EE*=1 indicates that there is no possible to generate the observed amount of desirable output with a smaller emission using the currently available technology. Furthermore, *EE* can be decomposed into environmentally allocative efficiency (*EAE*) and environmentally technical efficiency (*ETE*) as follows:

$$\begin{aligned} EE &= \frac{\sum_{i=1}^{l} \alpha_{ij} \left(\theta_i^E x_{ij}^E - d_{ij}^{Ex^E} \right)}{\sum_{i=1}^{l} \alpha_{ij} x_{ij}^E} \\ &= \frac{\sum_{i=1}^{l} \alpha_{ij} \left(\theta_i^E x_{ij}^E - d_{ij}^{Ex^E} \right)}{\sum_{i=1}^{l} \alpha_{ij} \left(\theta^T x_{ij}^E - d_{ij}^{Tx^E} \right)} \times \frac{\sum_{i=1}^{l} \alpha_{ij} \left(\theta^T x_{ij}^E - d_{ij}^{Tx^E} \right)}{\sum_{i=1}^{l} \alpha_{ij} x_{ij}^E} \\ &= EAE \times ETE, \quad j = 1, \ldots, n. \end{aligned} \tag{6}$$

where *EAE* relates to the correct polluting input mix, and *ETE* relates to the operation on the efficient production frontier. The value of *EAE* and *ETE* both take between zero and one, and the one value indicates full efficiency.

Third, for cost efficiency, if the prices of polluting inputs are all available, the objective of *CE* is to obtain the minimal amount of cost on all polluting inputs. Hence, the associated DEA-based minimizing programming with MBP for the under estimated observation j_0 can be written as follows:

$$
\begin{aligned}
& min \sum_{i=1}^{l} p_{ij_0} \theta_i^C x_{ij_0}^E \\
& s.t.\ \ \theta_i^C x_{ij_0}^E = \sum_{j=1}^{n} \lambda_j x_{ij}^E + d_{ij}^{Cx^E},\ i = 1,\ldots,l \\
& \quad x_{mj_0}^{NE} = \sum_{j=1}^{n} \lambda_j x_{mj}^{NE} + d_{mj}^{Cx^{NE}},\ m = 1,\ldots,f \\
& \quad y_{rj_0} = \sum_{j=1}^{n} \lambda_j y_{rj} - d_{rj}^{Cy},\ r = 1,\ldots,s \\
& \quad \theta_i^C u_{ij_0} = \sum_{j=1}^{n} \lambda_j u_{ij} + d_{ij}^{Cu},\ i = 1,\ldots,l \\
& \quad \alpha_{ij} d_{ij}^{Cx^E} = d_{ij}^{Cu},\ i = 1,\ldots,l;\ j = 1,\ldots,n
\end{aligned}
\tag{7}
$$

where $d_{ij}^{Cx^E}$, $d_{mj}^{Cx^{NE}}$, d_{rj}^{Cy} and d_{ij}^{Cu} respectively represents the slack variables of polluting input, non-polluting input, desirable output and pollution implementing the weak G-disposability of MBP; p_{ij_0} is the price of polluting input; and the last equation indicates the MBP condition. Similar with model (4), θ_i^C is the variable for adjusting each polluting input and its associated undesirable output to achieve the minimal cost. It measures the cost allocation efficiency of each polluting input, and measures the trade-offs among different types of these inputs.

Replacing the emission factors in equation (5) and (6), *CE* and its two components of costly allocative efficiency (*CAE*) and costly technical efficiency (*CTE*) can be computed as:

$$
\begin{aligned}
CE &= \frac{\sum_{i=1}^{l} p_{ij} \ \ \theta_i^C x_{ij}^E - d_{ij}^{Cx^E}}{\sum_{i=1}^{l} p_{ij} x_{ij}^E} \\
&= \frac{\sum_{i=1}^{l} p_{ij} \ \ \theta_i^C x_{ij}^E - d_{ij}^{Cx^E}}{\sum_{i=1}^{l} p_{ij} \ \ \theta^T x_{ij}^E - d_{ij}^{Tx^E}} \times \frac{\sum_{i=1}^{l} p_{ij} \ \ \theta^T x_{ij}^E - d_{ij}^{Tx^E}}{\sum_{i=1}^{l} p_{ij} x_{ij}^E} \\
&= CAE \times CTE, \quad j = 1,\ldots,n.
\end{aligned}
\tag{8}
$$

For each j (j=1,…,n) observation, except for the values associated with minimal emission $\sum_{i=1}^{l} \alpha_{ij} \ \ \theta_i^{E*} x_{ij}^E - d_{ij}^{Ex^E*}$ and minimal cost $\sum_{i=1}^{l} p_{ij} \ \ \theta_i^{C*} x_{ij}^E - d_{ij}^{Cx^E*}$, two additional values can be identified: (i) the cost relating to the emission minimizing point, $\sum_{i=1}^{l} p_{ij} \ \ \theta_i^{E*} x_{ij}^E - d_{ij}^{Ex^E*}$; and (ii) the emission relating to the cost minimizing point, $\sum_{i=1}^{l} \alpha_{ij} \ \ \theta_i^{C*} x_{ij}^E - d_{ij}^{Cx^E*}$. θ_i^{E*}, $d_{ij}^{Ex^E*}$, θ_i^{C*}, $d_{ij}^{Cx^E*}$ are the optimal solutions of model (4) and (7). Hence, the cost of moving from the cost minimizing point to the emission minimizing point can be identified as $\sum_{i=1}^{l} p_{ij} \;\; \theta_i^{E*} x_{ij}^{E} - d_{ij}^{Ex^{E}*} \;\; - \sum_{i=1}^{l} p_{ij} \;\; \theta_i^{C*} x_{ij}^{E} - d_{ij}^{Cx^{E}*}$. This cost could be named as the shadow cost (SC) of emission reduction. In addition, the emission surplus consequences of shift from the emission minimizing point to the cost minimizing point can be similarly identified as $\sum_{i=1}^{l} \alpha_{ij} \;\; \theta_i^{C*} x_{ij}^{E} - d_{ij}^{Cx^{E}*} \;\; - \sum_{i=1}^{l} \alpha_{ij} \;\; \theta_i^{E*} x_{ij}^{E} - d_{ij}^{Ex^{E}*}$. This difference could be named as shadow emission (SE) of cost reduction.

Finally, for total cost efficiency, the cost of polluting inputs and the cost of pollutions are both taken into consideration. Then, a new minimal cost would be identified. The sum of the economic cost of polluting input and the social cost of pollutions is interrupted as total cost. In this case, the associated DEA-based minimizing programming with MBP for the under estimated observation j_0 can be written as follows:

$$
\begin{aligned}
& min \sum_{i=1}^{l} \;\; p_{ij_0} + \alpha_{ij} w_{ij_0} \;\; \theta_i^{TC} x_{ij_0}^{E} \\
& s.t. \;\; \theta_i^{TC} x_{ij_0}^{E} = \sum_{j=1}^{n} \lambda_j x_{ij}^{E} + d_{ij}^{TCx^{E}}, \; i = 1, \ldots, l \\
& \qquad x_{mj_0}^{NE} = \sum_{j=1}^{n} \lambda_j x_{mj}^{NE} + d_{mj}^{TCx^{NE}}, \; m = 1, \ldots, f \\
& \qquad y_{rj_0} = \sum_{j=1}^{n} \lambda_j y_{rj} - d_{rj}^{TCy}, \; r = 1, \ldots, s \\
& \qquad \theta_i^{TC} u_{ij_0} = \sum_{j=1}^{n} \lambda_j u_{ij} + d_{ij}^{TCu}, \; i = 1, \ldots, l \\
& \qquad \alpha_{ij} d_{ij}^{TCx^{E}} = d_{ij}^{TCu}, \; i = 1, \ldots, l; \; j = 1, \ldots, n
\end{aligned}
\qquad (9)
$$

In model (9), w_{ij_0} is the price of polluting input; $d_{ij}^{TCx^{E}}$, $d_{mj}^{TCx^{NE}}$, d_{rj}^{TCy} and d_{ij}^{TCu} respectively represents the slack variables of polluting input, non-polluting input, desirable output and pollution; and the last equation indicates the MBP condition. θ_i^{TC} is the variable for adjusting each polluting input and its associated undesirable output to achieve the totally minimal cost.

Then, *TCE* and its two components of total cost allocative efficiency (*TCAE*) and total cost technical efficiency (*TCTE*) can be formulated as:

$$
\begin{aligned}
TCE &= \frac{\sum_{i=1}^{l} \quad p_{ij_0} + \alpha_{ij} w_{ij_0} \quad \theta_i^{TC} x_{ij}^{E} - d_{ij}^{TCx^E}}{\sum_{i=1}^{l} \quad p_{ij_0} + \alpha_{ij} w_{ij_0} \quad x_{ij}^{E}} \\
&= \frac{\sum_{i=1}^{l} \quad p_{ij_0} + \alpha_{ij} w_{ij_0} \quad \theta_i^{TC} x_{ij}^{E} - d_{ij}^{TCx^E}}{\sum_{i=1}^{l} \quad p_{ij_0} + \alpha_{ij} w_{ij_0} \quad \theta^{T} x_{ij}^{E} - d_{ij}^{Tx^E}} \times \frac{\sum_{i=1}^{l} \quad p_{ij_0} + \alpha_{ij} w_{ij_0} \quad \theta^{T} x_{ij}^{E} - d_{ij}^{Tx^E}}{\sum_{i=1}^{l} \quad p_{ij_0} + \alpha_{ij} w_{ij_0} \quad x_{ij}^{E}} \qquad (10) \\
&= TCAE \times TCTE, \quad j = 1, \ldots, n.
\end{aligned}
$$

The estimation of *TCE* could help to assess the impact of carbon price (e.g., allowance price and carbon taxes) on the environmental efficiency and the amount of CO_2 emissions.

4 Dataset and descriptive statistics

This research contains the data of China's 27 provincial construction industry sectors during the period of 2011-2015. Heilongjiang, Guangxi, and Hainan are not included because they do not have coal consumption data in their construction industries.

Our study focuses on the inherent trade-offs between environmental and cost outcomes among different types of energy consumptions in China's construction industry. The CO_2 emissions is considered as the environmental outcome, and the added value of construction industry is considered as the economic outcome. We use different kinds of CO_2 emissions from the consumption of coal, oil, and electricity in either the construction phase of buildings or the construction activities. Moreover, the other inputs data for the construction industry are also be taken into consideration. We use seven non-energy inputs: the net value of fixed asset, labor, and construction materials including cement, steel, glass, wood, and aluminum; three energy inputs: coal, oil, and electricity. Additionally, the provincial CO_2 emission factors and the prices of coal, oil, and electricity are considered in our calculation.

The data of energy consumptions (i.e., coal consumption, oil consumption, and electricity consumption) are obtained from the energy balance table (the subsector of "construction" within the "total final consumption" sector) in the *China Energy Statistical Yearbook*, whereas the construction materials data are collected from the *China Statistical Yearbook on Construction*. The data of added value of construction industry, the net value of fixed asset, and labor are collected from the *China Statistical Yearbook*. For CO_2 emissions, we first calculate the CO_2 emissions from the combustion of coal and oil through referring the CO_2 emission factors (IPCC, 2006) and the calorific values (NRDC, 2008). As for the CO_2 emissions of electricity, we first obtain the CO_2 emissions of the national electricity generation according to the associated primary energy consumption in electricity generation, and then we use the ratio of the amount of electricity consumption for the construction industry by the national electricity consumption to calculate the CO_2 emissions from electricity in the construction industry. Furthermore, the CO_2 emission factors of each energy input for each province, which is named as provincial CO_2 emission factors of each energy input, are the ratio of the amount of CO_2 emissions of an energy to the amount of the associated energy consumption. Because of the different energy consumption structure among provinces, the provincial CO_2 emission factors are also various among provinces. The information on prices of all energy are derived from Wind Data and the database of China National Coal Association. The price of CO_2 emissions is the seven pilot carbon markets' average price of CO_2 emission allowance during 2013-2016 (i.e., 33.39 Yuan/tonne) which is obtained from the China's carbon trading website. We first obtain the average price of CO_2 emissions in each pilot carbon market during 2013-2016, and then we use the arithmetic average price of CO_2 emissions for these seven pilots as the national price of CO_2 emissions. Tables 1 to 4 presented in the Appendix describe the summary statistics of the input and output data, provincial CO_2 emission factors, and prices of energy inputs.

5 Results and discussions

5.1 Environmental and cost efficiency

The efficiency measurement results of *EE*, *CE* and *TCE* are presented in Table 1 and Fig. 1. It is worth noting that the mean value, maximum value and minimum value of *CE* and *TCE*, and their components, are very close. The reason is that the pollution price is quite small compared with the price of polluting inputs. It leads that the total cost is also quite close to the cost of polluting inputs. Therefore, the results of *CE* and *TCE* are similar, and we will focus on *TCE* and its corresponding results in the following discussions.

On the one hand, for environmental efficiency, the mean value of 0.678 implies that China's construction industry on average could be able to produce its currently industrial added value with 32.2% fewer CO_2 emissions associated with polluting inputs during 2011-2015. In addition, the mean values of *EAE* (0.707) and *ETE* (0.943) indicate that the average sector of construction industry has the ability to produce its currently industrial added value with 29.3% fewer carbon emissions from polluting input through energy consumption structure optimization and with 5.7% fewer carbon emissions from polluting input through technical efficiency improvement of energy consumption. On the other hand, for total cost efficiency, its mean value (0.663) suggests that the construction industry could be able to reduce 33.7% total cost on average maintaining its current amount of industrial added value. In specific, the average sector of construction industry could reduce 8.6% total cost through removing technical inefficiency and reduce 29.5% total cost through adjusting energy consumption structure during 2011-2015.

Table 1 Efficiency measurement results

	EE	*EAE*	*ETE*	*CE*	*CAE*	*CTE*	*TCE*	*TCAE*	*TCTE*
Mean	0.678	0.707	0.943	0.662	0.705	0.913	0.663	0.705	0.914
St. Dev.	0.348	0.342	0.084	0.359	0.344	0.125	0.359	0.344	0.123
Maximum	1	1	1	1	1	1	1	1	1
Minimum	0.072	0.076	0.652	0.056	0.061	0.426	0.056	0.062	0.433

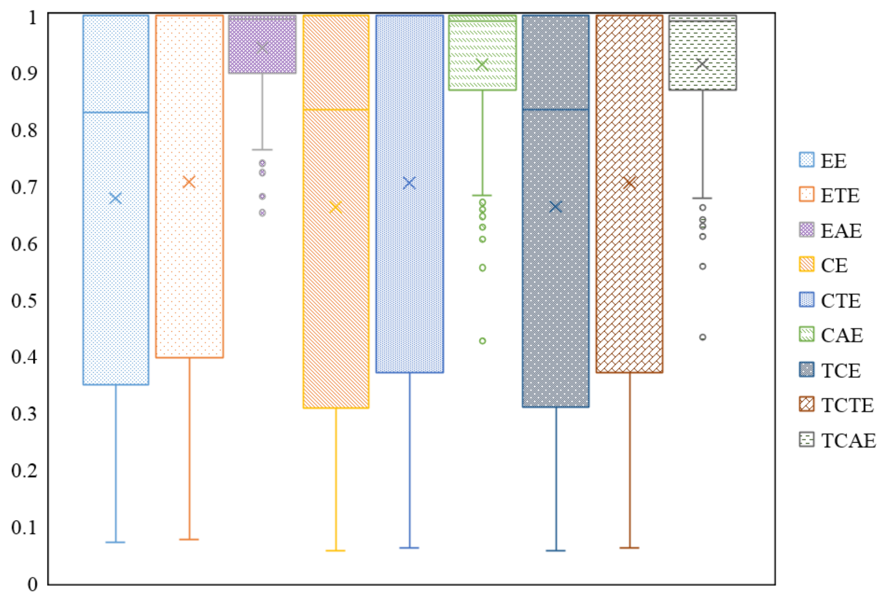

Figure 1 Box plot of different efficiency and their decomposition

Associated with the efficiency changes, total values on energy savings and CO_2 emission reductions of the 27 provincial construction industry sectors are identified and reported in Table 2. The changes on polluting inputs and total CO_2 emissions are all annual average values. Firstly, Table 2 shows that China's construction industry would annually reduce 3.2 million tonnes of coal consumption (36.4%), 4.1 million tonnes of oil consumption (28.8%) and 15.6 billion kWh of electricity consumption (24.0%) to produce the same industrial added value if the technical inefficiency was eliminated in this industry. Then, the total CO_2 emissions would reduce by 28.7% (30.0 million tonnes).

Table 2 Changes on polluting inputs and CO_2 emissions associated with efficiency changes

	Polluting inputs and CO_2	Unit	Change	
			Absolute value	Percentage (%)
Observation to *TE*	Coal	Million tonne	-3.2	-36.4
	Oil	Million tonne	-4.1	-28.8
	Electricity	Billion kWh	-15.6	-24.0
	Total CO_2 emissions	Million tonne	-30.0	-28.7
Observation to *EE*	Coal	Million tonne	-3.4	-38.6
	Oil	Million tonne	-5.0	-34.6
	Electricity	Billion kWh	-15.8	-24.4
	Total CO_2 emissions	Million tonne	-33.3	-31.9
Observation to *TCE*	Coal	Million tonne	-3.2	-36.4
	Oil	Million tonne	-5.1	-35.8
	Electricity	Billion kWh	-15.2	-23.4
	Total CO_2 emissions	Million tonne	-6.3	-6.1
TCE to *EE*	Coal	Thousand tonne	-196.6	-3.5
	Oil	Thousand tonne	163.0	1.8
	Electricity	Million kWh	-655.6	-1.3

Total CO_2 emissions	Thousand tonne	-389.3	-0.5

Secondly, if the construction industry was environmentally efficient, it would annual decrease 3.4 million tonnes of coal consumption, 5.0 million tonnes of oil consumption and 15.8 billion kWh of electricity consumption keeping its current industrial added value unchanged. Correspondingly, the construction industry would annually decrease its total CO_2 emissions by 31.9% (33.3 million tonnes). Specifically, to realize this reduction of CO_2 emissions, this industry needs to reduce its coal consumption by 38.6%, oil consumption by 34.6%, and electricity consumption 24.4%.

Thirdly, it can be notable that there is 36.4% (3.02 million tonnes), 35.8% (5.1 million tonnes) and 23.4% (15.2 billion kWh) reduction potentials on coal consumption, oil consumption and electricity consumption if China's construction industry is costly efficient. Moreover, the total CO_2 emissions would reduce by 6.3 million tonnes (6.1%). This indicates that the achievement of cost minimizing for energy input mix would be helpful to save all types of energy consumption and to control their corresponding CO_2 emissions in China's construction industry.

Finally, it can be seen that there is 196.6 thousand tonnes and 655.6 million kWh reduction potentials on coal and electricity consumption, associated with an increase of 163 thousand tonnes of oil consumption, if the average industry removing from the cost minimizing point to emission minimizing point. Correspondingly, the construction industry would have annually average 389.3 thousand tonnes (0.5%) reduction potentials on total CO_2 emissions through adjusting energy consumption structure, that is, reducing coal consumption and electricity consumption by 3.5% and 1.3%, and increasing oil consumption by 1.8% as a compensation. This is a powerful implication that the optimization of energy consumption structure is an efficient way to control carbon emissions in China's construction industry with reasonable amount of cost increase.

5.2 Environmental and cost trade-offs

The estimation results of environmental and cost trade-offs in emission are illustrated in Tables 3 and 4. At the national average level, the construction industry would decrease CO_2 emissions of per unit industrial added value of construction sector by 29.3% if it was on the technically efficient frontier, and by 32.2% if it was environmentally efficient. Simultaneously, this industry would averagely decrease total cost of per unit industrial added value by 29.5% if it was technically efficient, and by 33.7% if it was on the costly efficient frontier. These 29.3% and 29.5% decreases imply that if the construction industry could remove the technical inefficiency, its generation cost and CO_2 emissions would both reduce by more than one quarter. Therefore, in the short term, there is no need to purchase expensive technologies on carbon control in China's construction industry, such as carbon capture and storage technology, for CO_2 emission reduction.

In addition, Table 3 shows that the construction industry would have 31.7% reduction potentials on CO_2 emissions of per unit industrial added value if it was costly efficient, and would have 4.9% more reduction potentials on CO_2 emissions of per unit industrial added value if it continued shifting to the totally cost minimizing point along the technical efficiency frontier. These reduction percentages suggest that the construction industry would reduce CO_2 emissions by achieving the costly efficient point, i.e., cost efficiency promotion would not lead to extra CO_2 emissions on cost reduction. Table 4 presents that the average industry would decrease 33.2% total cost of per unit industrial added value if having attained cost efficiency, and would decrease 7.7% more total cost of per unit industrial added value if it continued reaching the emission minimizing point along the technical efficiency frontier. These results indicate that approaching the environmentally efficient point would reduce economic and social cost in China's construction industry, i.e., environmental efficiency increase would not lead to extra cost on emission abatement. Hence, it can be concluded that the activities and policies on carbon control or CO_2 emission reduction would have positive synergistic impacts on energy conservation and energy cost savings in China's construction industry.

Table 3 Environmental and cost trade-offs regarding CO_2 emission change

Region	CO_2 emissions per unit added value of construction industry (g/Yuan)	Percentage change in CO_2 emissions per unit added value of construction industry (%)						
		Observation to TE	Observation to EE	Observation to TCE	TE to EE	TE to TCE	TCE to EE	EE to TCE
Beijing	0.0269	-2.5	-2.8	-2.8	-0.3	-0.3	0.0	0.0
Tianjin	0.0913	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Hebei	0.0136	-76.5	-76.9	-76.9	-2.5	-2.3	-0.1	0.1
Shanxi	0.0636	-31.0	-31.9	-31.8	-1.8	-1.7	-0.1	0.1
Inner Mongolia	0.1460	0.0	-5.1	-5.1	-5.1	-5.1	0.0	0.0
Liaoning	0.0286	-14.3	-16.3	-16.3	-3.0	-3.0	0.0	0.0
Jilin	0.0539	-16.5	-28.4	-23.2	-12.9	-6.9	-5.4	6.2
Shanghai	0.0507	-8.6	-15.0	-15.0	-6.5	-6.5	0.0	0.0
Jiangsu	0.0100	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Zhejiang	0.0140	-28.2	-32.8	-32.7	-8.3	-8.2	-0.2	0.2
Anhui	0.0197	-45.3	-50.8	-49.9	-13.0	-11.3	-1.8	1.9
Fujian	0.0149	-24.2	-25.8	-25.7	-3.9	-3.7	-0.2	0.2
Jiangxi	0.0207	-11.4	-11.7	-11.7	-0.8	-0.8	0.0	0.0
Shandong	0.0168	-47.5	-51.9	-50.4	-8.8	-6.1	-2.8	2.9
Henan	0.0241	-12.1	-13.9	-13.3	-3.5	-2.9	-0.6	0.6
Hubei	0.0500	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Hunan	0.0130	-72.3	-77.1	-77.0	-17.4	-17.1	-0.4	0.4
Guangdong	0.0185	-32.3	-40.1	-40.0	-11.2	-11.1	-0.2	0.2
Chongqing	0.0154	-38.7	-42.1	-42.0	-8.5	-8.3	-0.2	0.2
Sichuan	0.0196	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Guizhou	0.0106	-86.9	-88.2	-88.2	-10.2	-10.1	-0.1	0.1
Yunnan	0.0387	-32.5	-32.7	-32.7	-1.2	-1.2	0.0	0.0
Shaanxi	0.0155	-64.5	-69.6	-69.4	-15.1	-14.4	-0.8	0.8
Gansu	0.0089	-86.0	-86.9	-86.8	-6.1	-5.4	-0.8	0.8
Qinghai	0.0737	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Ningxia	0.0708	-44.9	-45.8	-45.1	-3.9	-1.3	-2.3	2.6

Xinjiang	0.0425	-15.9	-24.3	-21.2	-9.4	-3.7	-5.3	6.0
Mean	**0.0360**	**-29.3**	**-32.2**	**-31.7**	**-5.7**	**-4.9**	**-0.8**	**0.9**

At the provincial level, firstly, Tables 3 and 4 shows that there are five provinces are all technically efficient, environmentally efficient and costly efficient (i.e., Tianjin, Jiangsu, Hubei, Sichuan and Qinghai). In the meantime, although Inner Mongolia is also technically efficient, it is neither environmentally efficient or costly efficient. On the one hand, if it attained full environmental efficiency, it would decrease 5.1% CO_2 emissions per unit industrial added value, and reduce 4.2% total cost per unit industrial added value. On the other hand, Inner Mongolia would reduce 4.2% total cost per unit industrial added value if it attained full cost efficiency, and would increase 5.1% CO_2 emissions per unit industrial added value. Therefore, when it reaching environmental efficiency point, there is a positive synergy effect on improving cost efficiency in Inner Mongolia; whereas there is no positive synergy effect on improving environmental efficiency. Therefore, environmental efficiency improvement is encouraged in the construction industry of Inner Mongolia.

Secondly, the difference of percentage change presented in the last two columns implies that different regions show various types of environmental and cost trade-offs. It is quite interesting and informative that there are 10 provinces (i.e., Beijing, Tianjin, Inner Mongolia, Liaoning, Shanghai, Jiangsu, Jiangxi, Hubei, Sichuan and Qinghai) have overlapped environmental efficiency point and cost efficiency point. This leads to a strong implication that it is possible for these regions to attain full cost efficiency and environmental efficiency simultaneously in their construction industry sectors.

Finally, it is noted that, Gansu presents the smallest CO_2 emissions per unit industrial added value of 0.0089 (g/Yuan), and the lowest total cost per unit industrial added value of 0.0091 (Yuan/Yuan). Moreover, it is neither environmentally efficient nor costly efficient. To attain the environmental efficiency, it would reduce 86.9% emission of per unit industrial added value and would reduce 88% cost of per unit industrial added value. To reach the cost efficiency point, it would reduce 86.8% emission of per unit industrial added value and would reduce 88% cost of per unit industrial added value.

Table 4 Environmental and cost trade-offs regarding total cost change

Region	Total cost per unit added value of construction industry (Yuan/Yuan)	Percentage change in total cost per unit added value of construction industry (%)						
		Observation to TE	Observation to EE	Observation to TCE	TE to EE	TE to TCE	TCE to EE	EE to TCE
Beijing	0.0347	-2.2	-3.3	-3.3	-1.3	-1.3	0.0	0.0
Tianjin	0.1467	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Hebei	0.0134	-75.9	-76.5	-76.5	-3.8	-3.8	0.0	0.0
Shanxi	0.0562	-29.9	-31.2	-31.3	-2.5	-2.6	0.1	-0.1
Inner Mongolia	0.1109	0.0	-4.2	-4.2	-4.2	-4.2	0.0	0.0

Liaoning	0.0286	-14.3	-21.7	-21.7	-10.2	-10.2	0.0	0.0
Jilin	0.0546	-18.5	-39.8	-46.6	-25.3	-34.0	15.0	-11.5
Shanghai	0.0605	-10.2	-19.1	-19.1	-9.0	-9.0	0.0	0.0
Jiangsu	0.0102	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Zhejiang	0.0193	-32.6	-39.6	-39.7	-15.0	-15.1	0.1	-0.1
Anhui	0.0225	-47.7	-56.3	-56.7	-21.8	-22.4	0.8	-0.8
Fujian	0.0219	-25.1	-27.8	-27.8	-6.8	-6.9	0.0	0.0
Jiangxi	0.0235	-11.4	-12.0	-12.0	-1.4	-1.4	0.0	0.0
Shandong	0.0177	-47.7	-55.2	-56.9	-15.2	-18.2	3.6	-3.4
Henan	0.0241	-13.5	-11.8	-14.8	0.1	-3.0	3.1	-2.7
Hubei	0.0747	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Hunan	0.0188	-64.8	-69.5	-69.6	-15.4	-15.6	0.2	-0.2
Guangdong	0.0231	-33.4	-41.9	-41.9	-13.3	-13.4	0.0	0.0
Chongqing	0.0197	-37.8	-42.1	-42.1	-10.6	-10.7	0.1	-0.1
Sichuan	0.0389	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Guizhou	0.0132	-86.6	-87.8	-87.9	-10.4	-11.1	0.7	-0.7
Yunnan	0.0656	-32.9	-33.1	-33.1	-1.4	-1.4	0.0	0.0
Shaanxi	0.0179	-64.3	-73.1	-73.4	-25.0	-26.0	1.4	-1.3
Gansu	0.0091	-87.1	-88.0	-88.0	-7.2	-7.4	0.3	-0.3
Qinghai	0.1248	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Ningxia	0.0806	-45.2	-47.0	-47.6	-8.8	-11.1	2.9	-2.7
Xinjiang	0.0406	-14.5	-15.0	-16.1	0.2	-2.2	2.5	-2.3
Mean	**0.0434**	**-29.5**	**-33.2**	**-33.7**	**-7.7**	**-8.6**	**1.1**	**-1.0**

5.3 Shadow cost and shadow emission

We estimate the annual average shadow cost (SC) and shadow emission (SE) for each province, which are shown in Table 5. The second column presents the SE for removing from the emission minimizing point to cost minimizing point, and the third and fourth columns present the SE per unit industrial added value of construction industry sector and its proportion in CO_2 emissions of unit industrial added value. The fifth to seventh column present the SC, SC per unit industrial added value and its proportion in cost of unit industrial added value, respectively. Jilin shows the highest proportion SE per unit added value of construction industry in CO_2 per unit added value of construction industry (6.21%), and the highest proportion SC per unit added value of construction industry in cost per unit added value of construction industry (14.93%). It means that the polluting minimizing point and the cost minimizing point of Jilin are far away, and hence, it needs to pay a lot of extra economic cost (or environmental cost) for controlling pollution (or reducing generation cost). Moreover, the last column presents the unit SC per tonne of CO_2 emissions reduction for each region and the average industry. Jilin shows the highest unit SC for CO_2 emissions reduction (100.766 Yuan/tonne), while the average SC of CO_2 emissions reduction in China's construction industry is 7.014 Yuan/tonne during 2011-2015. Note that, this cost is much lower than the current price of CO_2 emission allowance in China's pilot carbon market, which is approximately 33.4 Yuan/tonne on average. This implies that China's construction industry is suggested to implement independent carbon emission reduction activities through optimizing the energy consumption structure and improving energy efficiency. Furthermore, the cost related to optimizing the energy consumption structure and improving energy efficiency could additionally be partially offset through the pollution tax savings of SO_2, NO_x, and dust and soot emissions; since these pollutions could be significantly reduced associate with energy consumption structure adjustment and energy efficiency promotion for CO_2 emission control.

Table 5 Shadow cost and shadow emission

Region	SE (thousand tonne)	SE per unit added value of construction industry (g/thousand Yuan)	SE per unit added value of construction industry / CO_2 per unit added value of construction industry (%)	SC (million Yuan)	SC per unit added value of construction industry (Yuan/thousand Yuan)	SC per unit added value of construction industry / cost per unit added value of construction industry (%)	SC per unit CO_2 (Yuan/ tonne)
Beijing	0.000	0.0000	0.00	0.000	0.0000	0.00	0.0000
Tianjin	0.000	0.0000	0.00	0.000	0.0000	0.00	0.0000
Hebei	2.168	0.0324	0.11	0.281	0.0042	0.01	0.0657
Shanxi	1.136	0.0248	0.06	1.243	0.0270	0.10	0.3909
Inner Mongolia	0.000	0.0000	0.00	0.000	0.0000	0.00	0.0000
Liaoning	0.000	0.0000	0.00	0.000	0.0000	0.00	0.0000
Jilin	124.415	3.7045	6.21	299.025	8.0565	14.93	100.7663
Shanghai	0.000	0.0000	0.00	0.000	0.0000	0.00	0.0000
Jiangsu	0.000	0.0000	0.00	0.000	0.0000	0.00	0.0000
Zhejiang	8.892	0.0226	0.21	5.155	0.0144	0.11	0.6095
Anhui	33.724	0.3746	1.93	16.160	0.1801	0.83	4.2564
Fujian	2.947	0.0237	0.25	0.746	0.0064	0.06	0.2211
Jiangxi	0.000	0.0000	0.00	0.000	0.0000	0.00	0.0000
Shandong	92.264	0.4603	2.86	127.632	0.6541	3.69	20.8448
Henan	17.123	0.1533	0.57	102.414	0.9169	3.00	34.2158
Hubei	0.000	0.0000	0.00	0.000	0.0000	0.00	0.0000
Hunan	8.259	0.0647	0.44	7.684	0.0603	0.30	1.0697
Guangdong	8.135	0.0440	0.23	2.053	0.0109	0.04	0.3467
Chongqing	1.931	0.0270	0.24	1.022	0.0143	0.11	0.3657
Sichuan	0.000	0.0000	0.00	0.000	0.0000	0.00	0.0000
Guizhou	0.513	0.0187	0.14	3.597	0.1308	0.78	1.5575
Yunnan	0.000	0.0000	0.00	0.000	0.0000	0.00	0.0000
Shaanxi	7.897	0.1252	0.80	18.345	0.2856	1.38	4.9314
Gansu	1.506	0.0636	0.78	0.561	0.0245	0.31	0.2747
Qinghai	0.000	0.0000	0.00	0.000	0.0000	0.00	0.0000
Ningxia	8.569	0.8099	2.56	9.880	0.9882	2.96	7.4549
Xinjiang	69.838	1.9279	6.00	23.038	0.7774	2.68	12.0067
Mean	**14.419**	**0.292**	**0.866**	**22.920**	**0.450**	**1.159**	**7.014**

6 Conclusions

This study applied the MBP combined DEA-based model to jointly evaluate the environmental and cost efficiency of China's construction industry. Several informative findings are identified. First, China's construction industry would be able to produce its currently industrial added value on average with fewer CO_2 emissions and fewer cost associated with polluting inputs through removing technical inefficiency and adjusting energy consumption structure during 2011-2015.

Second, the total CO_2 emissions of China's construction industry would reduce by 28.7% (30 million tonnes), 31.9% (33.3 million tonnes), and 6.1% (6.3 million tonnes) to produce the current industrial added value if the technical inefficiency, environmental inefficiency, and cost inefficiency were eliminated in this industry, respectively.

Third, additionally 0.5% reduction potentials on total CO_2 emissions would be identified through reducing coal consumption and electricity consumption by 3.5% and 1.3%, and increasing oil consumption by 1.8% as a compensation in this industry.

Fourth, there is positive synergy effect with respect to energy cost savings and emission reduction in this industry. In specific, China's construction industry would reduce its unit CO_2 emissions by 31.7% if attaining the optimal cost efficiency, and reduce its unit total cost by 33.2% if attaining the optimal environmental efficiency.

Fifth, the average shadow cost of CO_2 emissions reduction in China's construction industry, which is 7.014 Yuan/tonne during 2011-2015, is much lower than the current price of CO_2 emissions in Chinese carbon markets. The implementation of independent carbon emission reduction activities through optimizing the energy consumption structure and improving energy efficiency is encouraged in China's construction industry in the short term instead of adopting the much expensive CO_2 emission control techniques (e.g., end-of-pipe treatment), or relying on carbon emission trading systems.

The above findings deliver several policy implications. First, if there would be additionally energy cost in realizing the emission abatement potential for some certain regions, the optimization of energy consumption structure should be encouraged to control carbon emissions in construction industry with reasonable amount of cost increase. In other words, the carbon reduction targets should be achieved step by step for these regions to avoid excessive short-term cost increasing. Second, if there would be simultaneously energy cost reduction and emission decrease for some regions, the acceleration of energy structure adjustment should be to encouraged to achieve carbon reduction in construction industry. Third, the implementation of pollution tax for pollutions would promote the synergistic effect between pollution reduction and carbon emission reduction. In specific, it would increase the consumption cost of high-carbon energy, thereby optimizing the energy consumption structure and reducing both pollution and carbon emissions.

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References

Ayres, R. U. and A. V. Kneese. 1969. Production, consumption, and externalities. Am. Econ. Rev. 59(3), 282–297.

CABEE., 2017. China Association of Building Energy Efficiency: The Report on Building Energy Consumption. http://www.sohu.com/a/208615242_99960447. [in Chinese]

Chancellor, W. and Lu, W. 2016. A Regional and Provincial Productivity Analysis of the Chinese Construction Industry: 1995 to 2012. J. Constr. Eng. M. 142(11), 05016013.

Chen, J., Shen, L., Song, X., Shi, Q., Li, S. 2017. An empirical study on the CO2 emissions in the Chinese construction industry. J. Clean. Prod. 168, 645-654.

Coelli, T.J., Lauwers, L., and Van Huylenbroeck, G., 2005. Formation of technical, economic and environmental efficiency measures that are consistent with the materials balance condition. Centre for Efficiency and Productivity Analysis Working Paper 06-2005, http://www.uq.edu.au/economics/cepa/docs/wp/wp062005.pdf.

Coelli, T.J., Lauwers, L., Van Huylenbroeck, G., 2007. Environmental efficiency measurement and the materials balance condition. J. Prod. Anal. 28, 3–12.

Fahlen, E., Ahlgren, E. 2012. Accounting for external environmental costs in a study of a Swedish district-heating system – an assessment of simplified approaches. J. Clean. Prod. 165-176.

Färe, R., Grosskopf, S., Tyteca, D., 1996. An activity analysis model of the environmental performance of firms—application to fossil-fuel-fired electric utilities. Ecol. Econ. 18(2), 161–175.

Førsund, F. R. 2009, Good Modelling of Bad Outputs: Pollution and Multiple-Output Production. Int. Rev. Environ. Resour. Econ. 3 (1), 1-38.

Guo, J., Zhang, Y., Zhang, K. 2018. The key sectors for energy conservation and carbon emissions reduction in China: Evidence from the input-output method. J. Clean. Prod. 180-190.

Hailu, A. and Veeman, T. S. 2001. Non-parametric productivity analysis with undesirable outputs: an application to the Canadian pulp and paper industry. Am. J. Agr. Eco.83, 605–616.

Hampf, B. and Rødseth, K. L. 2015. Carbon dioxide emission standards for US power plants: An efficiency analysis perspective. Energy Econ. 50, 140-153.

Halkos, G. E., Tzeremes, N. G., Kourtzidis, S. A. 2016. Measuring Sustainability Efficiency Using a Two‐Stage Data Envelopment Analysis Approach. J. Ind. Ecol. 20(5), 1159-1175.

IPCC. 2006. Intergovernmental Panel on Climate Change: 2006 IPCC Guidelines for National Greenhouse Gas Inventories.

Kwon, D. S., Cho, J. H., Sohn, S. Y. 2017. Comparison of technology efficiency for CO2 emissions reduction among European countries based on DEA with decomposed factors. J. Clean. Prod. 109-120.

Lauwers, L., Van Huylenbroeck, G., Rogiers, G. 1999. Technical, economic and environmental efficiency analysis of pig fattening farms. Ninth European Congress of Agricultural Economists. 24 August 1999.

Mahlberg, B., Sahoo, B.K. (2011). Radial and non-radial decompositions of Luenberger productivity indicator with an illustrative application. Int. J. Prod. Econ. 131,721–726.

Murty, S., Russel, R. R., Levkoff, S. B. (2012). On modeling pollution-generating technologies. J. Environ. Econ. Manag. 64, 117-135.

NDRC. 2008. National Development and Reform Commission: Comprehensive Energy Consumption Calculation General. China Standard Press, Beijing.

Reinhard, S., Knox Lovell, C. A., Thijssen, G. J. 2000. Environmental efficiency with multiple environmentally detrimental variables; estimated with Sfa and Dea, Eur. J. Oper. Res. 121. 287–303.

Seiford, L. M. and Zhu, J. 2002. Modeling undesirable factors in efficiency evaluation. Eur. J. Oper. Res. 142(1), 16–20.

Shi, X. 2010. Restructuring in China's State‐owned Enterprises: Evidence from the Coal Industry. China & World Econ. 18(3), 90-105.

Shi, X. and Grafton, R. Q. 2010. Efficiency impacts of the Chinese industrial transition: a quantitative evaluation of reforms in the coal industry. Econ. Change & Restructuring. 43(1), 1-19.

Sueyoshi, T. and Goto, M. 2012. Data envelopment analysis for environmental assessment: comparison between public and private ownership in petroleum industry. Eur. J. Oper. Res. 216(3), 668-678.

Tatari, O. and Kucukvar, M. 2011. Eco-efficiency of construction materials: data envelopment analysis. J. constr. Eng. M. 138(6), 733-741.

Wang, K., Mi, Z., Wei, Y. M. 2018. Will pollution taxes improve joint ecological and economic efficiency of thermal power industry in China? A DEA-based materials balance approach. J. Ind. Ecol. doi.org/10.1111/jiec.12740.

Wang, K., Yang, K., Wei, Y. M., Zhang, C. 2018. Shadow prices of direct and overall carbon emissions in China’s construction industry: a parametric directional distance function-based sensitive estimation. Struct. Change. Econ. Dynam. 47, 180-193.

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? Energy Policy. 46, 574-584.

Wang, K. and Wei, Y. M. 2014. China's regional industrial energy efficiency and carbon emissions abatement costs. Appl. Energ. 130, 617-631.

Wang, K., Wei, Y. M., Huang, Z. 2018. Environmental efficiency and abatement efficiency measurements of China's thermal power industry: A data envelopment analysis based materials balance approach. Eur. J. Oper. Res. 269(1), 35-50.

Welch, E., Barnum, D. 2009. Joint environmental and cost efficiency analysis of electricity generation. Ecol. Econ. 68 (8), 2336–2343.

Xue, X., Wu, H., Zhang, X., Dai, J., Su, C. 2015. Measuring energy consumption efficiency of the construction industry: the case of China. J. Clean. Prod. 107, 509-515.

Xian, Y., Wang, K., Wei, Y. M., Huang, Z. 2019. Would China's power industry benefit from nationwide carbon emission permit trading? An optimization model-based ex post analysis on abatement cost savings. Appl. Energ. 235, 978-986.

Xian, Y., Wang, K., Shi, X., Zhang, C., Wei, Y. M., Huang, Z. 2018. Carbon emissions intensity reduction target for China's power industry: An efficiency and productivity perspective. J. Clean. Prod. 197, 1022-1034.

Zhang, J., Li, H., Xia, B., Skitmore, M. 2018. Impact of environment regulation on the efficiency of regional construction industry: A 3-stage Data Envelopment Analysis (DEA). J. Clean. Prod. 200, 770-780.

Zhang, Y., Bian, X., Tan, W. 2018. The linkages of sectoral carbon dioxide emission caused by household consumption in China: evidence from the hypothetical extraction method. Empir. Econ. 54(4), 1743-1775.

Zhang, Y., Jin, Y-L., Shen, B. 2018. Measuring the energy saving and CO2 emissions reduction potential under China's Belt and Road Initiative. Comput. Econ. In press. doi.org/10.1007/s10614-018-9839-0

Zhang, Y., Sun, Y., Huang, J. 2018. Energy efficiency, carbon emission performance, and technology gaps: Evidence from CDM project investment. Energy Policy. 119-130.

Zhou, N., Khanna, N., Feng, W., Ke, J., Levine, M. 2018. Scenarios of energy efficiency and CO2 emissions reduction potential in the buildings sector in China to year 2050. Nat. Energy. 3(11), 978.

Appendix

Table A.1 Summary statics of inputs

Year	Variable	The net value of fixed asset	Labor	Cement	Steel	Glass	Wood	Aluminum	Coal	Oil	Electricity
	Unit	Million yuan	Thousand person	Thousand tonne	Thousand tonne	Thousand m^2	Thousand m^3	Thousand tonne	Thousand tonne	Thousand tonne	Million kWh
2011	Mean	31712	1383	103578	23907	36135	8339	1346	339	498	2117
	St.Dev.	22214	1468	174943	28506	37064	9740	1959	417	330	1230
	Maximum	91361	6195	754309	141118	144352	46073	7466	1616	1540	5128
	Minimum	4010	88	3071	683	2688	228	29	26	86	502
2012	Mean	34251	1534	136300	33331	56797	14151	2094	332	495	2249
	St.Dev.	24034	1718	239401	39356	65141	19604	3399	387	336	1229
	Maximum	104073	7393	1149636	153388	278429	87671	17163	1646	1550	5297
	Minimum	3993	90	3133	898	2300	175	53	20	99	577
2013	Mean	36744	1616	86882	26744	35373	10431	1816	340	546	2437
	St.Dev.	24897	1788	86356	22766	41937	9955	2650	493	355	1310
	Maximum	108081	7635	350470	98226	185594	37014	13475	1857	1730	5284
	Minimum	4070	119	3329	911	1789	214	79	10	102	655
2014	Mean	38177	1634	94702	34095	55004	13211	2172	294	545	2679
	St.Dev.	25546	1878	95451	29768	53857	14520	3166	429	367	1373
	Maximum	110042	7872	358283	111703	187074	61995	16012	1940	1753	5959
	Minimum	4106	110	3619	989	1111	256	77	16	105	670
2015	Mean	39047	1830	72447	27893	45303	12561	1980	328	563	2553
	St.Dev.	26292	1905	77626	26313	48721	12126	1738	491	383	1380
	Maximum	115373	7832	357324	104910	188344	46364	5688	2122	1814	6031
	Minimum	4250	109	3375	849	2309	330	107	18	137	615

Table A.2 Summary statics of outputs

Year	Variable	Added value of construction industry	CO_2 from coal	CO_2 from oil	CO_2 from electricity	Total CO_2
	Unit	Million Yuan	Thousand tonne	Thousand tonne	Thousand tonne	Thousand tonne
2011	Mean	79372	670	1556	1518	3743
	St.Dev.	76097	823	1034	886	1892
	Maximum	342143	3197	4821	3524	7976
	Minimum	5871	52	268	123	485
2012	Mean	95761	656	1547	1522	3725
	St.Dev.	97804	764	1053	911	1815
	Maximum	433653	3256	4849	3484	7948
	Minimum	7136	36	308	126	495
2013	Mean	119462	663	1703	1617	3983
	St.Dev.	118492	946	1113	970	1907
	Maximum	537216	3443	5412	3879	8874
	Minimum	8053	20	318	155	540
2014	Mean	127419	591	1702	1698	3991
	St.Dev.	130361	860	1151	1034	1945
	Maximum	590754	3812	5489	3864	9084
	Minimum	8236	32	327	152	567
2015	Mean	130391	640	1754	1506	3901
	St.Dev.	133567	951	1200	972	1984
	Maximum	599652	4170	5680	3515	8955
	Minimum	7954	36	427	130	642

Table A.3 Provincial average CO_2 emission factors

	Emission factor of coal (tonne/tonne)					Emission factor of oil (tonne/tonne)					Emission factor of electricity (tonne/thousand kWh)				
Year	2011	2012	2013	2014	2015	2011	2012	2013	2014	2015	2011	2012	2013	2014	2015
Beijing	1.97	1.97	1.96	1.96	1.96	3.13	3.12	3.13	3.13	3.13	0.66	0.61	0.57	0.51	0.39
Tianjin	1.98	1.98	1.98	1.98	1.98	3.14	3.14	3.14	3.14	3.14	0.91	0.89	0.88	0.84	0.78
Hebei	1.97	1.97	1.98	1.98	1.98	3.13	3.13	3.13	3.13	3.11	0.91	0.82	0.76	0.75	0.71
Shanxi	1.97	1.97	1.98	1.98	1.98	3.11	3.10	3.11	3.10	3.10	0.89	0.86	0.90	0.85	0.81
Inner Mongolia	1.98	1.98	1.85	1.98	1.83	3.11	3.11	3.12	3.12	3.12	1.22	1.21	1.03	1.00	0.97
Liaoning	1.98	1.98	1.98	1.98	1.98	3.14	3.12	3.12	3.12	3.16	0.94	0.86	0.90	0.87	0.84
Jilin	1.98	1.98	1.95	1.93	1.93	3.11	3.11	3.12	3.12	3.12	1.05	1.02	0.94	0.99	0.99
Shanghai	1.98	1.98	1.98	1.98	1.98	3.12	3.11	3.10	3.10	3.10	0.74	0.73	0.77	0.75	0.72
Jiangsu	1.98	1.98	1.98	1.98	1.98	3.15	3.14	3.14	3.13	3.09	0.78	0.77	0.77	0.72	0.72
Zhejiang	1.98	1.98	1.98	1.98	1.98	3.13	3.13	3.13	3.13	3.13	0.68	0.64	0.62	0.60	0.55
Anhui	2.01	2.01	2.01	2.01	2.01	3.14	3.14	3.11	3.11	3.11	0.71	0.84	0.84	0.81	0.77
Fujian	1.98	1.98	1.98	1.98	1.98	3.13	3.11	3.10	3.10	3.10	0.69	0.59	0.58	0.57	0.49
Jiangxi	1.95	1.82	1.98	1.98	1.98	3.12	3.12	3.15	3.15	3.15	0.84	0.70	0.70	0.68	0.65
Shandong	1.98	1.96	1.98	1.98	1.98	3.13	3.14	3.14	3.14	3.14	0.88	0.83	0.78	0.76	0.78
Henan	1.98	1.98	1.98	2.34	1.98	3.12	3.12	3.09	3.06	3.11	0.92	0.85	0.85	0.85	0.80
Hubei	1.98	1.98	1.98	1.98	1.98	3.14	3.14	3.14	3.14	3.14	0.39	0.31	0.35	0.31	0.32
Hunan	1.95	1.95	1.96	1.96	1.97	3.12	3.12	3.13	3.13	3.13	0.63	0.50	0.53	0.47	0.41
Guangdong	1.98	1.98	1.98	1.98	1.98	3.08	3.08	3.09	3.09	3.06	0.69	0.66	0.65	0.62	0.56
Chongqing	1.98	1.98	1.98	1.98	1.98	3.13	3.13	3.13	3.13	3.13	0.69	0.52	0.62	0.54	0.56
Sichuan	1.98	1.98	1.98	1.98	1.98	3.02	3.03	3.03	3.03	3.03	0.27	0.24	0.22	0.16	0.11
Guizhou	1.98	1.98	1.98	1.98	1.98	3.11	3.12	3.11	3.10	3.11	0.66	0.53	0.56	0.49	0.38
Yunnan	1.96	1.96	1.96	1.96	1.96	3.11	3.11	3.11	3.11	3.11	0.46	0.36	0.26	0.18	0.12
Shaanxi	1.98	1.98	1.98	1.98	1.98	3.14	3.14	3.14	3.14	3.14	0.68	0.66	0.66	0.64	0.65
Gansu	1.98	1.98	1.98	1.98	1.98	3.10	3.10	3.10	3.10	3.10	0.66	0.62	0.57	0.53	0.51
Qinghai	1.98	1.98	1.98	1.98	1.98	3.12	3.12	3.12	3.12	3.12	0.25	0.22	0.24	0.23	0.21
Ningxia	1.98	1.98	1.98	1.98	1.98	3.14	3.15	3.14	3.14	3.14	1.00	0.91	0.90	0.86	0.82
Xinjiang	1.98	1.98	1.98	1.98	1.98	3.13	3.13	3.13	3.13	3.13	0.79	0.85	0.78	0.79	0.77

Table A.4 Provincial average prices of energy inputs

	Prices of coal (thousand Yuan/tonne)					Prices of oil (thousand Yuan/tonne)					Price of electricity (Yuan/ kWh)				
Year	2011	2012	2013	2014	2015	2011	2012	2013	2014	2015	2011	2012	2013	2014	2015
Beijing	1.22	1.01	0.75	0.64	0.50	7.14	7.36	6.90	6.36	4.50	0.38	0.41	0.40	0.39	0.35
Tianjin	1.22	1.01	0.75	0.64	0.50	7.14	7.36	6.90	6.36	4.50	0.39	0.42	0.41	0.40	0.35
Hebei	1.51	1.16	1.02	0.83	0.59	7.14	7.36	6.90	6.36	4.50	0.39	0.44	0.43	0.42	0.36
Shanxi	0.82	1.31	0.68	0.53	0.48	7.14	7.36	6.90	6.36	4.50	0.32	0.39	0.39	0.38	0.32
Inner Mongolia	1.33	0.56	0.56	0.55	0.42	7.14	7.36	6.90	6.36	4.50	0.33	0.31	0.34	0.31	0.29
Liaoning	1.36	1.01	1.01	0.65	0.58	7.14	7.36	6.75	6.49	4.71	0.40	0.41	0.42	0.40	0.37
Jilin	1.53	1.29	1.23	0.77	0.64	7.14	7.36	6.75	6.49	4.71	0.39	0.41	0.41	0.40	0.37
Shanghai	1.30	1.12	0.98	0.82	0.58	7.15	7.37	7.12	6.68	4.81	0.46	0.49	0.48	0.46	0.40
Jiangsu	1.16	1.10	0.97	0.74	0.54	7.15	7.37	7.12	6.68	4.81	0.44	0.46	0.46	0.43	0.38
Zhejiang	1.01	0.97	0.97	0.97	0.61	7.15	7.37	7.12	6.68	4.81	0.47	0.49	0.48	0.46	0.45
Anhui	1.41	1.25	1.05	0.84	0.58	7.15	7.37	7.12	6.68	4.81	0.40	0.44	0.44	0.43	0.37
Fujian	1.30	1.12	0.98	0.82	0.58	7.15	7.37	7.12	6.68	4.81	0.43	0.45	0.44	0.44	0.37
Jiangxi	1.54	1.19	1.02	0.83	0.67	7.15	7.37	7.12	6.68	4.81	0.44	0.49	0.49	0.46	0.40
Shandong	1.42	1.09	0.91	0.72	0.49	7.14	7.37	7.05	6.55	4.66	0.41	0.45	0.45	0.44	0.37
Henan	1.55	1.22	1.09	0.86	0.60	7.14	7.36	7.07	6.80	5.22	0.40	0.44	0.44	0.42	0.36
Hubei	1.43	1.07	0.92	0.77	0.62	7.14	7.36	7.07	6.80	5.22	0.44	0.48	0.48	0.46	0.40
Hunan	1.31	0.93	0.75	0.67	0.63	7.14	7.36	7.07	6.80	5.22	0.46	0.50	0.51	0.49	0.45
Guangdong	1.27	1.08	0.93	0.72	0.57	7.13	7.33	7.18	6.63	4.83	0.50	0.53	0.52	0.50	0.45
Chongqing	1.34	1.19	1.09	0.86	0.66	7.14	7.36	7.04	6.73	5.05	0.40	0.45	0.44	0.44	0.38
Sichuan	1.34	1.30	1.14	0.88	0.83	7.14	7.36	7.04	6.73	5.05	0.41	0.46	0.45	0.46	0.40
Guizhou	1.74	1.38	1.25	1.00	0.76	7.14	7.36	7.04	6.73	5.05	0.35	0.38	0.38	0.38	0.34
Yunnan	1.44	1.14	1.08	0.90	0.75	7.14	7.36	7.04	6.73	5.05	0.33	0.36	0.35	0.37	0.34
Shaanxi	1.24	1.24	0.53	0.45	0.40	7.14	7.36	6.79	6.33	4.85	0.35	0.40	0.38	0.39	0.33
Gansu	1.05	0.91	0.75	0.72	0.55	7.14	7.36	6.79	6.33	4.85	0.29	0.34	0.33	0.33	0.30
Qinghai	1.09	0.73	0.66	0.41	0.41	7.14	7.36	6.79	6.33	4.85	0.30	0.35	0.35	0.35	0.32
Ningxia	1.04	0.91	0.96	0.64	0.55	7.14	7.36	6.79	6.33	4.85	0.28	0.30	0.29	0.28	0.26
Xinjiang	0.46	0.54	0.50	0.30	0.24	7.14	7.36	6.79	6.33	4.85	0.25	0.25	0.25	0.25	0.25