



# Measuring environmental-adjusted dynamic energy efficiency of China's transportation sector: a four-stage NDDF-DEA approach

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**Abstract** The energy consumption and CO<sub>2</sub> emissions of the transportation sector in China have increased greatly in recent years, accompanied by the growing regional disparities. Considering undesirable output and environmental impact factors, a four-stage DEA (data envelope analysis) combined with NDDF model (non-radical directional distance function) is adopted in this paper to calculate the energy efficiency and eliminate the environmental impacts of Chinese transportation sector. In this paper, five environmental factors are considered, including GDP per capita, consumption level, urbanization level, economic openness level, and transport infrastructure. The empirical results on the panel data for 30 provinces of China from 2005 to 2016 show that the energy efficiency of the transportation sector in China decreases from Eastern to Western region. After the adjustment of environmental factors, energy efficiency still shows a decreasing trend from Eastern to Western region, while energy efficiency increases more in Eastern region and less in Central region and Western region. The potential of energy efficiency improvement for some Central and Western provinces is relatively high. Some policy suggestions are proposed to

improve the energy efficiency of Chinese transportation sector.

**Keywords** TFEEE · Environmental adjust · Four-stage DEA · NDDF model

## Introduction

Since reform and opening up in 1978, China has experienced rapid economic development with GDP growing at an average annual rate of 9.6% during 1978–2016, and the mobility of labor and capital from the growing transportation sector has contributed significantly to this success. During this period, China's transportation sector has continuously cracked various technical barriers, which makes the scale of transportation gradually meet the needs of social modernization. At the same time, transportation has become one of the fastest growing industries in China. Despite the rapid development of China's transportation sector, there is still a lack of transportation capacity (Cui & Li, 2014) and China's transportation sector needs further development to meet the demand of society (Zhou et al., 2014). However, the further development of China's transportation industry faces resource and environmental constraints, as the transport sector is an important contributor to energy consumption and environmental pollution.

Convenient transportation is the basic requirement of a country's economic development, and the rapid economic development of China in recent years is inseparable from the growth of

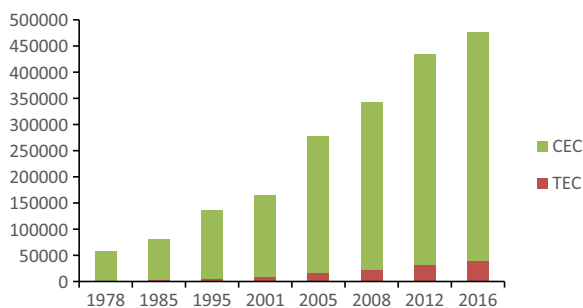
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transportation demand and the construction of transportation facilities. However, the transportation sector belongs to the resource occupation and energy consumption industry, and its development depends on the consumption of petroleum fuel and the emission of greenhouse gas. According to *China Statistical Yearbook* (2018), the average annual growth rate of energy consumption in China is 6.84%, while the annual growth rate of energy consumption in the transportation industry is 8.72% from 2005 to 2016. In addition, the proportion of energy consumption of the transportation industry in the total national energy consumption rises from 7.47% in 2005 to 8.91% in 2016 (National Statistical Bureau of China, 2018). Figure 1 shows the comparison of energy consumption in China and energy consumption in China's transportation industry during the past 30 years. It is obvious from Fig. 1 that the proportion of TEC (energy consumption in China's transportation sector) to CEC (the total energy consumption in China) is increasing. Due to the large consumption of various kinds of energy, the annual increase of greenhouse gas emissions will also generate great harm to the environment. In a sense, the rapid development of transportation industry in recent years is at the cost of high investment and pollution emissions. In order to achieve sustainable development of China's transportation industry, improving the energy efficiency of this industry has become the most effective way.

In order to measure the provincial sustainable development of China's transportation sector, this paper combines the NDDF model and four-stage DEA model to calculate and adjust the environmental energy efficiency in China's transportation sector and further eliminate the influence of external environmental factors. The paper is



**Fig. 1** Proportion of energy consumption in China's transportation industry

organized as followed. In sect. "Literature review," we review some of the most relevant literature. Section "Methodology" is introduces the methodology. In sect. "Data description," we make the data description. Section "Empirical results" describes the empirical results and further discussion. Finally, we conclude the paper and give some policy implications in sect. "Conclusion and policy implication."

## Literature review

The Data Envelopment Analysis (DEA) model was originally developed to measure operating efficiency and technique efficiency in industry. Over the years, DEA model had been deeply modified and widely applied to many sectors such as agricultural sectors (Vlontzos et al., 2014), health services (Tsai & Molinero, 2002), construction sectors (Zhang et al. 2018), service sectors (Lin & Zhang, 2017), and commercial banks (Wang et al., 2014). This model also makes efficiency an indicator to reflect whether energy and other inputs have been used efficiently in a department (Clinch et al., 2001). Then, the freight energy efficiency combined with commodity-based analysis was used to evaluate production efficiency in transportation sector of US (Vanek & Morlok, 2000). Some relative efficiency was used to measure the depth of governmental support for private sector (Hsu & Hsueh, 2009). With the deeply research of DEA model by many scholars, it had been constantly improved. The four-stage DEA model was originally proposed to measure the energy efficiency without the impacts of environmental factors, and the final result was clearly different from the initial result (Fried et al., 1999).

From these quantitative methods, it will be found that DEA models have also been widely applied to transportation efficiency evaluation. Without considering undesirable outputs, DEA was applied to provide an efficiency measurement of four Australian and twelve other international container ports (Tongzon, 2001). In addition, the consumption of energy in China's transportation is so large, and the energy utilization is not very high; so, the energy consumption caused by transportation sector cannot be ignored (Ji & Chen, 2006). A multi-stage framework combined with DEA model and Malmquist index was used to evaluate the efficiency and productivity of the Chinese railway sector (Li & Hu,

2011). They used the new four-stage DEA model and some new index to measure the environmental adjusted energy efficiency of Taiwan's service sectors during 2001–2008, which had been divided into four parts (Fang et al., 2013). A super-SBM model with unexpected output was proposed in 2013 to calculate the environmental energy efficiency in China during 1991–2001 (Li et al., 2013). For more accurate measurement, Cui and Li (2014) used the three-stage DEA model and took passenger turnover volume and freight turnover volume as outputs to calculate the adjusted energy efficiency of Chinese transportation sector during 2003–2012. A non-radial DEA model under management generality was used to measure environmental efficiency of China's transportation industry during 2006–2011 (Song et al., 2016b). Then, a new energy efficiency model integrating energy conservation and output growth was proposed to measure energy efficiency of China's transportation sector and analyses possible influencing factors (Liu & Lin, 2018). Some researchers also used a global meta-frontier approach to analyze energy efficiency and savings potential in China's transportation sector (Feng & Wang, 2018).

For calculating energy efficiency including energy consumption and pollutant emission in the same time, they proposed a global, directional distance function model to measure economic efficiency, CO<sub>2</sub> emission efficiency, and marginal abatement costs in transportation sector then used the empirical results to point out the weak link between economic development and environmental pollution (Wang & He, 2017). Zhang and Wei (2015) proposed a dynamic index by combining the meta-frontier approach with the non-radial Luenberger productivity indicator to calculate the total factor carbon emission efficiency in China's transportation sector from 2000–2012. Tone (2002) came up with a new undesirable-DEA model called slack-based measure (SBM), which took the undesirable output into consideration and calculate more accurate environmental energy efficiency. After the regional and temporal compare and analysis with the SBM model, this conclusion that railway performs better than highway in efficiency had been found (Liu et al., 2017). Then, the super-efficiency SBM model, including undesirable outputs, combined with the window data envelopment analysis model was used to calculate environmental efficiency of China's highway

transportation, the level of sustainable development, and energy consumption redundancy. They also used empirical results to point out that the Chinese government needs to take measures to reduce energy consumption and air pollution (Song et al., 2016a, b).

Besides the traditional DEA model, directional distance function (DDF) is also a very common method for the treatment of environmental pollution indicators, especially the non-radial DDF method, which could allow undesirable output to vary at different rates from desirable output (Zhou et al., 2012). This approach will make a more realistic interpretation of the treatment of undesirable outputs in the efficiency measurement process. Therefore, this paper employs NDDF-DEA model for the measurement of total factor energy-environmental efficiency (TFEEE) of Chinese transportation sector. However, in existing studies on energy efficiency in the transportation industry, few of them have included undesired outputs and external environmental disturbances in the same framework. Lipsy and Schipper (2013) revealed the relationship between energy utilization efficiency and carbon dioxide emissions by comparing the energy intensity of Japan's passenger transport sector with the USA and other developed countries, and also taking into account political context and carbon dioxide emissions. Song et al. (2015) calculated the environmental energy efficiency of China's transportation sector in each province from 2003 to 2012 by considering unexpected output carbon dioxide emissions with undesirable-SBM approach and divided all provinces into east, central, and west regions for comparison. In view of current literatures, this paper combines the NDDF model for the treatment of undesirable outputs, and four-stage DEA approach for the elimination of external environmental impacts, to measure the environment-adjusted energy efficiency in China's provincial transportation sector.

## Methodology

Non-radical DDF method has a distinct advantage in dealing with undesirable outputs, for it allows undesirable outputs to vary at different rates from desirable

outputs. In this paper, a four-stage NDDF-DEA model was employed to evaluate TFEED of China’s transportation sector. The details of this model will be described as follows.

The NDDF-DEA model

According to Zhou et al. (2012), the production technology under constant return of scale (CRS) for all decision-making units is:

$$T = \left\{ \begin{array}{l} (K, L, E, Y, H, Y^g, Y^c) : \\ \sum_{n=1}^N Z_n K_n \leq K, \sum_{n=1}^N Z_n L_n \leq L, \sum_{n=1}^N Z_n E_n \leq E, \sum_{n=1}^N Z_n Y_n^g \geq Y^g, \\ \sum_{n=1}^N Z_n Y_n^c = Y^c, Z_n \geq 0, (n = 1, 2, 3, \dots, N) \end{array} \right\} \tag{1}$$

where  $K, L,$  and  $E$  indicate capital input, labor input, and energy input, respectively;  $Y^g$  indicates desirable output, and  $Y^c$  indicates undesirable output.

Then, we consume the weight vector of the relative importance of each inputs and outputs:

$$W^T = (\omega_K, \omega_L, \omega_E, \omega_Y, \omega_Y) \tag{2}$$

The direction vector which indicates the direction of increase or decrease for each inputs and outputs when production technology is determined is consumed as:

$$G = (-g_K, -g_L, -g_E, g_Y, -g_Y) \tag{3}$$

The direction vector  $G$  indicates that, in an ideal setting, all decision units want to maximize the desirable output in the direction  $g_Y$  while minimize inputs and undesirable output along the direction  $-g_K, -g_L, -g_E, -g_Y$ .

Based on the assumptions above, the non-radical directional distance function (NDDF) of DMU  $i$  in period  $t$  is as below:

$$\begin{aligned} & D(K_{it}, L_{it}, E_{it}, Y_{it}^g, Y_{it}^c : G) \\ & = \text{Max} \left( \beta_{K,it}^* K_{it} + \bar{K}_{it} + \beta_{L,it}^* L_{it} + \bar{L}_{it} + \beta_{E,it}^* E_{it} + \bar{E}_{it} + \beta_{Y^g,it}^* Y_{it}^g + \bar{Y}_{it}^g + \beta_{Y^c,it}^* Y_{it}^c + \bar{Y}_{it}^c \right) \\ & \text{s.t.} \left\{ \begin{array}{l} \sum_{i=1}^N z_{it} K_{it} \leq L_{it} - \beta_{K,it}^* K_{it} - \bar{K}_{it} \\ \sum_{i=1}^N z_{it} L_{it} \leq L_{it} - \beta_{L,it}^* L_{it} - \bar{L}_{it} \\ \sum_{i=1}^N z_{it} E_{it} \leq E_{it} - \beta_{E,it}^* E_{it} - \bar{E}_{it} \\ \sum_{i=1}^N z_{it} Y_{it}^g \geq Y_{it}^g + \beta_{Y^g,it}^* Y_{it}^g + \bar{Y}_{it}^g \\ \sum_{i=1}^N z_{it} Y_{it}^c = Y_{it}^c - \beta_{Y^c,it}^* Y_{it}^c - \bar{Y}_{it}^c \\ z_{it} > 0, \beta_{K,it}^*, \beta_{L,it}^*, \beta_{E,it}^*, \beta_{Y^g,it}^*, \beta_{Y^c,it}^*, \bar{K}_{it}, \bar{L}_{it}, \bar{E}_{it}, \bar{Y}_{it}^g, \bar{Y}_{it}^c \geq 0 \end{array} \right. \tag{4} \end{aligned}$$

$D(K_{it}, L_{it}, E_{it}, Y_{it}^g, Y_{it}^c : G) = 0$  indicates the DMU on the production frontier, and this DMU is under optimal production conditions;  $\beta_{K,it}^* K_{it}, \beta_{L,it}^* L_{it}, \beta_{E,it}^* E_{it}, \beta_{Y^g,it}^* Y_{it}^g,$  and  $\beta_{Y^c,it}^* Y_{it}^c$  denote the changes of each inputs and outputs, and  $\bar{K}_{it}, \bar{L}_{it}, \bar{E}_{it}, \bar{Y}_{it}^g,$  and  $\bar{Y}_{it}^c$  denote the non-radical slacks of each inputs and outputs.

Then, the changes and slacks of each inputs and outputs of DMU  $i$  in period  $t$

$\beta_{it}^* (\beta_{K,it}^*, \beta_{L,it}^*, \beta_{E,it}^*, \beta_{Y^g,it}^*, \beta_{Y^c,it}^*)$  and  $(\bar{K}_{it}, \bar{L}_{it}, \bar{E}_{it}, \bar{Y}_{it}^g, \bar{Y}_{it}^c)$  can be obtained from linear planning Eq. (4).

On the basis of NDDF, the total factor energy-environmental efficiency is:

$$TFEEEE_{it} = \frac{1}{4} \left[ \frac{\frac{Y_{it}^g}{K_{it}}}{\frac{Y_{it}^g + \beta_{Y^g, it}^* Y_{it}^g + \bar{Y}_{it}^g}{K_{it} - \beta_{K, it}^* K_{it} - \bar{K}_{it}}} + \frac{\frac{Y_{it}^g}{L_{it}}}{\frac{Y_{it}^g + \beta_{Y^g, it}^* Y_{it}^g + \bar{Y}_{it}^g}{L_{it} - \beta_{L, it}^* L_{it} - \bar{L}_{it}}} + \frac{\frac{Y_{it}^g}{E_{it}}}{\frac{Y_{it}^g + \beta_{Y^g, it}^* Y_{it}^g + \bar{Y}_{it}^g}{E_{it} - \beta_{E, it}^* E_{it} - \bar{E}_{it}}} + \frac{\frac{Y_{it}^g}{Y_{it}^c}}{\frac{Y_{it}^g + \beta_{Y^g, it}^* Y_{it}^g + \bar{Y}_{it}^g}{Y_{it}^c - \beta_{Y^c, it}^* Y_{it}^c - \bar{Y}_{it}^c}} \right] \tag{5}$$

Four-stage DEA model

Fried et al. (1999) originally presented the four-stage DEA to obtain a calculation of managerial efficiency that generated by exogenous characters of external operating environment. With the four-stage DEA model, environmental factors will be separated, and accurate efficiency can be measured. But the four-stage model proposed by Fried et al. (1999) uses the traditional DEA model in the first stage, in which radial vector would produce a little error. In this paper, the NDDF approach is combined with the four-stage DEA to get more accurate value. The first stage calculates the TFEEE using the observable inputs and outputs according to the NDDF-DEA model.

In this paper, the negative output of carbon dioxide emission is shown as environmental cost. The non-radial slacks of each inputs and outputs in NDDF model are the target that can be reduced. With respect to input and undesirable output, slacks are called input-saving target, emission-reducing target, and output-increasing target.

It follows that each DMU will score higher TFEEE by saving input, reducing CO2 emission and increasing desirable output. Due to the large differences in the external environment of different provinces, this has different effects on the index of TFEEE. In addition, since the slack is the difference between the actual input or output and the input or output in the full efficiency state, the slack can be regarded as the non-efficiency quantification, and the slack can be quantitatively analyzed to study the influence of the external environmental difference. We use a cross-sectional tobit regression model to adjust these environmental impacts in the second stage. This model is proposed to deal with data in which the value of dependent variable is truncated or discrete. Unlike the traditional two-stage DEA model,

the four-stage model takes the slack of inputs and outputs as the explanatory variables, rather than the efficiency values which are between 0 and 1, thus could effectively avoiding possible measurement errors. Due to the value of slack and environmental variable is partly discontinuous, this model is suitable for our research. Tobit regression model is defined as follows:

$$s^*_{ik} = f^i(Z_k, \beta^i) + U_{ik} \dots (i = 1, L, m; k = 1, L, n) \tag{6}$$

In this model,  $s$  includes  $S^-, S_r^g$  and  $S_r^b$ , and  $k$  is denoted by DMU, from 1 to  $n$ ;  $I$  represents units of input and undesired output, from 1 to  $m$ .  $\beta$  is a coefficient used to make an estimate of non-radial slack, and  $u$  represents the random disturbance term.

The third stage uses the estimated coefficients from the above equations to calculate the slack in estimate, and adjust input and undesirable output,

$$adj\_X_{ik} = X_{ik} + \{ \max[f^i(Z_k, \beta^i)] - f^i(Z_k, \beta^i) \} \dots \tag{7}$$

(  $i = 1, L, m; k = 1, L, n$  )

where  $adj\_X_{ik}$  is the input or undesirable output after environmental adjustment in the  $i$ th sector and  $k$ th year, and  $X_{ik}$  refers to actual input or undesirable output in the  $i$ th sector and  $k$ th year.

Fried et al. (1999) originally proposed this method which using tobit model to adjust external environment factors. In this stage, firstly use the tobit regression in the second step to calculate input and undesirable output slack in the estimate, and then with the maximum estimate of input and undesirable output slack minus the estimate value of each decision-making unit under the same input or undesirable output conditions as a punishment (Fang et al., 2013). The final adjusted input and the undesired output will be obtained by adding the above difference to the actual input or undesirable output of each decision-making unit. We adjust the undesirable output in this stage because this variable is

viewed as an input of environment. The decision-making unit with better external environment will get larger punishment; it can make all the decision-making units in the same level of the external environment. Then, these new variables can be used to calculate energy efficiency without the influence of external environment.

In the final stage, the adjusted data of inputs and undesirable outputs and original expected outputs are used to conduct the NDDF model in the first step. Then, the environmental-adjusted energy efficiency in China's transportation sector will be calculated.

## Data description

### Data sources and descriptive statistics

The data used in this paper is derived from *China Statistical Yearbook* (2006–2017), *China Energy Statistical Yearbook* (2006–2017), and the statistical yearbook of various China provinces and autonomous regions (2006–2017). Taiwan, Hong Kong, Macao special administrative regions, and the Tibet autonomous region are not included in this paper due to the lack of relevant data. Table 1 is the descriptive statistics of the data, including input and output variables.

Min, max, mean, and SD represent the minimum value, maximum value, mean value, and standard deviation, respectively, of 360 variables of 30 provinces during 2005–2016

### Input variables

The input mainly includes the use amount of human, financial, and material resources (Hu & Kao, 2007). For transportation sector, manpower includes the amount of all current employees in the transportation industry; financial resources consist of employee salaries and total

investment in transportation equipment and facilities; and material resources include the use of various raw materials and various types of energy. Therefore, we select three input variables in this article, including labor, capital, and energy consumption. The labor variable is represented by the number of people engaged in the transportation industry in each province in that year, and this indicator can be obtained directly from *China Statistical Yearbook* (2006–2017). Capital represents the total fixed capital investment in the transportation industry by the provinces in that year, which can also be directly obtained from the relevant statistical yearbook. Energy consumption refers to the total amount of energy consumed by the transportation industry of each province in that year, and the consumption needs to be converted into standard coal. For this variable, we first find the energy balance tables of various provinces and then calculate this variable according to the conversion coefficient of that various energy to standard coal.

### Output variables

A single indicator real GDP is chosen as output variable to calculate the energy efficiency of service sector in Taiwan (Fang et al., 2013). Freight turnover volume and passenger turnover volume are chosen as output variables to measure transportation energy efficiency (Cui & Li, 2014). We consider the price of passenger or freight fluctuates with the season or festival, and this phenomenon is most obvious in air transport. Therefore, we choose the GDP (gross domestic product) as expected output and the CO<sub>2</sub> (carbon dioxide) emissions as undesirable output in this paper. The GDP indicator can be directly obtained from *China Statistical Yearbook* (2006–2017). To calculate the CO<sub>2</sub> emissions, we use the conversion ratio provided by United States Department of Energy 1999, which will be shown in Table 2. Then, with this ratio, we can calculate CO<sub>2</sub> emissions more accurately in the same unit.

**Table 1** Descriptive statistics of input and output variables

Variable	Type	Unit	OBS	Min	Max	Mean	SD
Labor	Input	10 thousand capita	360	2.72	85.40	23.12	14.34
Capital	Input	100 million Yuan	360	32.48	3738.00	851.56	664.39
Energy	Input	10 thousand tons standard coal	360	30.50	2932.54	859.83	582.37
GDP	Desirable output	100 million Yuan	360	31.88	3209.72	772.94	625.75
Emission	Undesirable output	10 thousand tons	360	15.75	993.29	303.32	199.49

**Table 2** The conversion ratio

Types of energy	Unit( Kg-c/Kgce)
Fire coal	0.702
Fuel oil	0.478
Natural gas	0.389

## Environmental factors

These variables are used in stage III to eliminate environmental impact, so that we can measure the real transportation energy efficiency. In this paper, five indicators have been selected. The indicator GDP per capita represents the ratio of annual GDP to total population of each province. When a province has a higher GDP per capita, the transportation sector may get higher investment, and this is conducive to the renewal of transportation facilities and tools. The index level of consumption represents the annual consumption of person in each province. If the consumption level of a province is high, people of this province can choose a more comfortable and more expensive transport. This condition will bring greater economic benefits to the province. Therefore, different consumption levels will affect the output of the transportation industry. This index degree of urbanization is the ratio of urban population to total population. A province with low urbanization will face lower compensation for demolition when constructing traffic, and the charge on opposite province will be higher. The variable level of economic openness called foreign trade dependence is denoted by the ratio of total import and export to GDP, and it is often used as a measure of economic openness. As some provinces are in the coastal areas and have more ports, they are in a relatively high level of economic openness compared with other provinces. Therefore, different degrees of economic openness will also affect the external environment of the transportation sector. In addition, transportation infrastructure is also an important factor that affects the efficiency of the transportation sector; so, this paper employed integrated traffic density to measure the level of transportation infrastructure, which is calculated by the total mileage of

railways and highways divided by the area of each province.

## Empirical results

### Environmental energy efficiency before adjustment

In the stage I, NDDF model was employed to calculate TFEEE with original input variables and output variables; the results of were affected by the external environment and were shown in Table 3. The average TFEEE of three regions in the Eastern provinces, Central provinces, and Western provinces according to the geographical division of China is shown in Table 4.

From Table 3, the average TFEEE score of Chinese transportation sector is 0.73, and 17 provinces are higher than the average score. The TFEEE of transportation sector in these provinces shows different trends. For example, Guangdong and Fujian provinces have the similar average TFEEE score, but Guangdong remains at a relatively low level and more fluctuates around the average from 2005 to 2016. In addition, some provinces have low average TFEEE scores, but in the TFEEE score, these provinces are still at the high level in several years. For example, the energy efficiency of Sichuan province from 2005 to 2007 is much higher than average score of the province. However, most of the provinces with overall low TFEEE score remain at the low level and with no obvious fluctuations between 2005 and 2016.

In terms of the geographical distribution of China, we can also find that most of the Eastern provinces have relatively high energy efficiency, and only Hebei province has an efficiency of 1. When observing the raw data, we find that Eastern region invests much more capital, labor, and energy in transportation than those in the other two regions, and certainly, the transport sector in Eastern region contributes far more to GDP than the other two regions. In Eastern region, Shanghai, Shandong, and Guangdong are the top three provinces in terms of energy input in the past 12 years, and their TFEEE scores are higher, among which Shandong province is close to 1. In contrast, Western region spends much less on transportation, but two provinces, Ningxia and Qinghai, both have a high energy efficiency score of 1. We compare the original input and output data of these two provinces with other provinces and find that

**Table 3** TFEEE before adjustment

Region	Province	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
East region	Beijing	0.94	0.62	0.52	0.41	0.55	0.70	0.93	0.67	0.85	0.84	1.00	1.00
	Tianjin	0.82	0.85	0.72	0.69	0.72	0.85	0.80	0.70	0.99	0.83	0.92	1.00
	Shanghai	0.68	0.66	0.58	0.50	0.45	0.86	0.97	1.00	1.00	1.00	1.00	0.79
	Liaoning	0.75	0.52	0.54	0.43	0.65	0.58	0.73	0.70	0.64	0.67	1.00	1.00
	Hebei	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Shandong	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.87	0.80	0.90
	Jiangsu	1.00	0.81	0.85	0.79	0.92	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Zhejiang	0.84	0.86	0.82	0.76	0.65	0.73	0.66	0.60	0.69	0.73	0.64	0.69
	Fujian	1.00	1.00	1.00	0.95	0.83	0.78	0.68	0.68	0.65	0.70	0.80	1.00
	Guangdong	1.00	0.73	0.70	0.57	0.64	0.67	0.72	0.82	0.74	1.00	1.00	1.00
	Hainan	1.00	1.00	1.00	0.83	0.72	0.74	1.00	0.79	0.74	0.72	0.71	0.79
	Guangxi	0.63	0.66	0.58	0.50	0.44	0.46	0.48	0.44	0.55	0.50	0.54	0.58
	East average		0.89	0.81	0.78	0.70	0.71	0.78	0.83	0.78	0.82	0.82	0.87
Central region	Hunan	0.85	0.82	0.74	0.55	0.58	0.60	0.54	0.61	0.74	0.74	0.68	0.70
	Hubei	0.60	0.52	0.51	0.51	0.55	0.55	0.50	0.48	0.51	0.53	0.49	0.46
	Henan	1.00	0.91	0.97	1.00	0.93	0.77	0.69	0.72	0.72	0.90	0.80	0.85
	Shanxi	0.93	1.00	1.00	0.73	0.49	0.57	0.54	0.55	0.67	0.74	0.84	0.88
	Anhui	1.00	1.00	0.86	0.89	0.71	0.83	0.76	0.65	0.60	0.59	0.55	0.52
	Jiangxi	0.79	0.69	0.81	0.89	0.74	0.74	0.71	0.83	0.94	0.84	0.82	0.81
	Jilin	0.70	0.74	0.65	0.59	0.56	0.49	0.50	0.50	0.58	0.59	0.54	0.54
	Heilongjiang	0.92	0.70	0.68	0.61	0.54	0.54	0.55	0.65	0.72	0.69	0.60	0.59
	Inner Mongolia	0.72	0.76	0.71	0.72	0.85	0.80	0.79	0.81	0.85	0.84	0.78	0.76
	Central Average		0.84	0.79	0.77	0.72	0.66	0.65	0.62	0.65	0.70	0.72	0.68
West region	Shaanxi	0.58	0.53	0.53	0.47	0.48	0.46	0.42	0.47	0.56	0.58	0.49	0.57
	Gansu	0.67	0.83	1.00	1.00	0.95	0.83	0.68	0.63	0.57	0.39	0.40	0.41
	Qinghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Ningxia	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Xinjiang	0.54	0.57	0.61	0.51	0.45	0.42	0.40	0.48	0.53	0.56	0.52	0.68
	Sichuan	0.75	0.69	0.65	0.51	0.41	0.38	0.37	0.37	0.52	0.45	0.57	0.54
	Chongqing	0.64	0.66	0.58	0.55	0.53	0.50	0.48	0.43	0.46	0.52	0.51	0.55
	Yunnan	0.50	0.46	0.44	0.42	0.29	0.26	0.27	0.30	0.29	0.29	0.29	0.29
	Guizhou	0.62	0.62	0.61	0.57	0.84	0.80	0.82	0.94	0.90	1.00	1.00	1.00
	West average		0.70	0.71	0.71	0.67	0.66	0.63	0.60	0.63	0.65	0.64	0.64

their input is far lower than other provinces, especially Qinghai. Except for these two Western provinces, the TFEEE score of other Western provinces is low and

especially in Yunnan. Other Central and Western provinces, such as Shaanxi, Gansu, Hunan, and Anhui, have similar energy efficiency scores closed to 0.7.



**Table 4** Average energy efficiency of three regions

Region	Provinces	Average energy efficiency
Eastern region	Beijing, Tianjin, Shanghai, Liaoning Hebei, Shandong, Jiangsu, Zhejiang Fujian, Guangdong, Hainan, Guangxi	0.808
Central region	Hunan, Hubei, Henan, Shanxi, Anhui, Jiangxi, Jilin, Heilongjiang Inner Mongolia	0.707
Western region	Shaanxi, Gansu, Qinghai, Ningxia Xinjiang, Sichuan, Chongqing, Yunnan, Guizhou	0.659

Table 4 shows the geographical distribution of China and which provinces are included in Eastern, Central, and Western regions. We can find that the TFEE score of Chinese transportation sector shows a decreasing trend from Eastern region to Western region (Wu et al., 2015; Yang et al., 2018). But the Eastern region has significantly higher TFEE than the other two regions while the Central and Western regions have very similar TFEE scores.

#### The results of tobit regression model

In stage II and stage III, we establish the tobit regression model with the slack of input and undesired output as the dependent variables which were obtained through software MaxDEA. The results were shown in Table 5. We also select five environmental factors, GDP per capita, consumption level, urbanization level, economic openness level, and integrated traffic density, as independent variables which have been defined before. Therefore, the five environment variables selected in this paper have obvious effects on slacks and can be used for external environment adjustment.

Combining the current situation of the transportation industry and relevant literature, if the coefficient of one

environmental factor is negative, its increase will result in less input slacks and undesirable output slacks. On the contrary, the increase on one environmental factor with positive coefficient will lead to more input slacks and undesirable output slacks.

Economic level has a significant negative effect on the slack of labor and carbon emissions, but a significant positive effect on the slack of capital and energy; therefore, the impact of economic development on TFEE in China's transportation sector is uncertain. The coefficients of consumption level on slack of labor, capital, and the slack of CO<sub>2</sub> emissions are significantly positive, which indicates that the increase of consumption level will lead to a decrease in capital and labor input, as well as carbon emissions in China's transportation sector, which may contribute to an increase in TFEE. Urbanization has a significant negative effect on the slack of capital and energy, and a significant positive effect on the slack of labor; therefore, the impact of economic development on TFEE in China's transportation sector is also uncertain. The coefficients of economic openness level are positive on three inputs and negative on undesirable output, and all significant on the 5% level, which indicates that openness may reduce capital, labor, and energy inputs to the transportation

**Table 5** The result of tobit regression model

Independent variables	Dependent variables			
	Slack of labor	Slack of capital	Slack of energy	Slack of CO <sub>2</sub>
constant	-13.3595***	129.9021***	-213.8611**	-47.8175***
GDP per capita	-2.0224*	2.2149***	67.6869*	-20.0441**
Consumption level	2.1293*	75.8780*	-10.8563	31.2383***
Urbanization level	0.2493***	-8.4501**	-1.5975***	5.0046
Economic openness level	2.5590***	122.6959**	45.6270*	-73.2237**
Integrated traffic density	1.6249**	-61.5325	-170.1965***	-20.3652*

\*\*\*, \*\*, and \* represent 1%, 5%, and 10% significance, respectively

sector but increases carbon emissions, and the overall impact on TFEEE remains uncertain. Integrated traffic density has a significant negative effect on carbon emissions, but a significant positive effect on the slack of labor, and the overall impact on TFEEE remains uncertain.

#### The results after environmental adjustment

After the environmental factors were adjusted, we rerun the NDDF model with adjusted inputs and undesirable output and original desirable output. The adjusted TFEEE score was represented in Table 6. Then, we also measure the TFEEE of three regions in Eastern provinces, Central provinces, and Western provinces according to the geographical division of China and show it in Table 7. The result of the fourth step has a significant difference from the original TFEEE.

After the adjustment of external environmental factors, it can be obviously observed from Table 6 that the number of provinces with a TFEEE score of 1 was still Hebei, Ningxia, and Qinghai. The average TFEEE score of Chinese transportation sector was 0.82, rising 0.09 compared with the result before the external environmental adjustment. Relative to the original results, TFEEE score increases in 26 provinces, and in 6 provinces, it increases by more than 0.15, only a subtle reduction in Henan.

In terms of Chinese geographical distribution, compared with the original results, the TFEEE of the transportation industry in some eastern provinces has been greatly improved. Most of Eastern provinces have improved their energy efficiency scores, and almost all are above 0.8 except Liaoning and Guangxi. Comparing with the initial efficiency score before adjustment, we find that most of the Eastern provinces such have significantly reduced the amount of investment after the adjustment, especially the two provinces (Shanghai and Beijing) have an obvious decrease on the amount of energy, capital, and labor input. Therefore, we compare the urbanization rate of different provinces and find that the urbanization rate of Eastern provinces is higher than that of Central and Western provinces. We search for information on urbanization level to find out the relationship between this indicator and the transportation sector, and after that, we find that more urbanized provinces face higher costs when building transportation infrastructure and equipment. For example, provinces with high urbanization may face high demolition costs

and many extra costs when building roads or railways because the compensation standard of country and city still has large difference.

Although the TFEEE of Central provinces has not been greatly improved, in general, they have made some small improvements. Moreover, none of Central provinces has risen TFEEE of the transportation sector up to 1 after environmental adjustment, but many Central provinces have significantly improved their TFEEE scores such as Jilin and Hubei. In Western region, Gansu, Xinjiang, and Yunnan provinces get obvious increase, but the score of the latter one is still at a low level. Different from the overall efficiency improvement in Central region, there have been great fluctuations in some Western provinces such as Gansu.

#### Regional environmental efficiency comparison

We plot the average TFEEE of China's three regions from 2005 to 2012 before and after the environmental adjustment, as shown in Figs. 2 and 3. In Fig. 2, the TFEEE of three regions in China has a significant low period from 2006 to 2011. These results are consistent with the policy guidance in the 11th five-year plan (2006–2010) period that a series of new policies in the transport sector are implemented to reverse the trend of energy intensity increase (Zhou et al., 2014). Compared Fig. 2 with Fig. 3, it is obvious that the TFEEE of the three regions after adjustment has been significantly improved compared with the original results, and the plotline in Fig. 3 is flatter. The phenomenon that the gaps between Eastern, Central, and Western have become larger is worthy noticed. This reflects that, compared with the Central and Western regions, the environmental adjustment makes the TFEEE of Eastern regions improved more. In addition, the rise in Central and Western regions is similar in the two groups, indicating that the external environment of Central and Western regions is closer.

Then, we compare the energy efficiency of different regions in Table 7 with original environmental energy efficiency. Easy to see that the TFEEE of transportation sector has been improved in all regions and still declines from East to West. The transportation TFEEE rises from 0.808 to 0.886 in Eastern regions, 0.707 to 0.765 in Central regions, and 0.659 to 0.799 in Western regions. The dramatic increase in TFEEE in the Western region's transportation sector indicates that the external environment is significantly limiting the region's transportation

**Table 6** TFEEE after adjustment

Region	Province	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
East region	Beijing	1.00	0.72	0.63	0.53	0.57	0.70	0.90	0.73	0.90	0.90	1.00	1.00
	Tianjin	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.95	1.00	1.00
	Shanghai	1.00	1.00	0.95	0.87	0.62	0.79	0.91	1.00	1.00	1.00	1.00	0.85
	Liaoning	0.69	0.60	0.62	0.59	0.66	0.67	0.73	0.72	0.69	0.70	1.00	1.00
	Hebei	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Shandong	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.87	0.82	0.94
	Jiangsu	0.97	0.92	0.90	0.88	0.92	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Zhejiang	0.93	0.94	0.92	0.88	0.82	0.83	0.76	0.70	0.77	0.77	0.75	0.80
	Fujian	1.00	1.00	1.00	0.99	0.92	0.93	0.87	0.86	0.78	0.81	0.89	0.97
	Guangdong	1.00	0.82	0.78	0.68	0.70	0.72	0.77	0.86	0.77	1.00	1.00	1.00
	Hainan	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.91	0.88
	Guangxi	0.83	0.81	0.73	0.70	0.65	0.65	0.66	0.67	0.67	0.67	0.70	0.72
	East average		0.95	0.90	0.88	0.84	0.82	0.86	0.88	0.88	0.88	0.89	0.92
Central region	Hunan	0.89	0.83	0.77	0.70	0.73	0.76	0.71	0.72	0.80	0.78	0.79	0.80
	Hubei	0.66	0.61	0.59	0.58	0.59	0.67	0.66	0.68	0.60	0.61	0.62	0.61
	Henan	0.99	0.83	0.91	0.95	0.87	0.77	0.74	0.78	0.76	0.90	0.81	0.85
	Shanxi	0.86	0.86	0.85	0.73	0.67	0.71	0.68	0.69	0.76	0.77	0.83	0.87
	Anhui	0.98	0.87	0.89	0.91	0.82	0.83	0.82	0.78	0.72	0.70	0.69	0.68
	Jiangxi	0.86	0.77	0.82	0.85	0.79	0.79	0.79	0.88	0.95	0.85	0.85	0.84
	Jilin	0.78	0.73	0.74	0.72	0.72	0.71	0.70	0.66	0.71	0.66	0.65	0.66
	Heilongjiang	0.81	0.71	0.73	0.78	0.72	0.71	0.62	0.72	0.77	0.74	0.67	0.67
	Inner Mongolia	0.72	0.77	0.77	0.79	0.85	0.82	0.80	0.80	0.84	0.85	0.80	0.86
	Central Average		0.84	0.78	0.78	0.78	0.75	0.75	0.72	0.74	0.77	0.76	0.75
West region	Shaanxi	0.73	0.69	0.67	0.65	0.64	0.63	0.63	0.67	0.64	0.65	0.59	0.61
	Gansu	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.92	0.79	0.66	0.65	0.65
	Qinghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Ningxia	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Xinjiang	0.77	0.84	0.84	0.79	0.73	0.70	0.68	0.72	0.73	0.69	0.64	0.77
	Sichuan	0.89	0.80	0.75	0.66	0.58	0.59	0.60	0.60	0.52	0.55	0.59	0.60
	Chongqing	0.78	0.77	0.78	0.80	0.81	0.79	0.78	0.79	0.60	0.61	0.62	0.64
	Yunnan	0.64	0.62	0.64	0.64	0.58	0.60	0.61	0.64	0.59	0.58	0.58	0.58
	Guizhou	1.00	0.88	0.84	0.77	0.90	0.88	0.91	0.97	0.94	0.98	1.00	1.00
	West average		0.87	0.84	0.84	0.81	0.81	0.80	0.80	0.81	0.76	0.75	0.74

sector. After elimination of environmental factors, the transportation industry in the Central region has the least increase in TFEEE, indicating that the internal operation

and development level of the transportation industry in this region differs significantly from that of other regions, which is an important constraint for TFEEE

**Table 7** Adjusted average TFEEE of three regions

Region	Provinces	Average energy efficiency
Eastern region	Beijing, Tianjin, Shanghai, Liaoning Hebei, Shandong, Jiangsu, Zhejiang Fujian, Guangdong, Hainan, Guangxi	0.886
Central region	Hunan, Hubei, Henan, Shanxi, Anhui, Jiangxi, Jilin, Heilongjiang Inner Mongolia	0.765
Western region	Shaanxi, Gansu, Qinghai, Ningxia Xinjiang, Sichuan, Chongqing, Yunnan, Guizhou	0.799

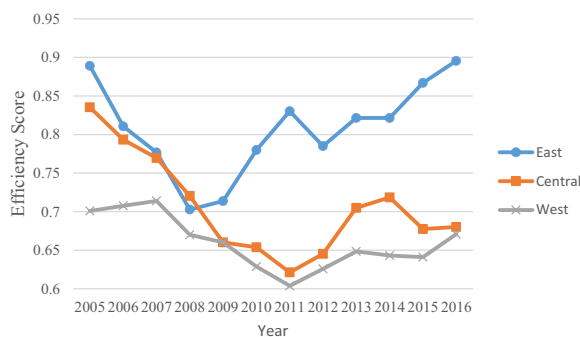
increase. The external environment in the Eastern regions is favorable, but factor costs are an important constraint to TFEEE in the transportation industry, and TFEEE can be greatly improved by removing environmental impacts. The above analysis shows that the Western region has the greatest potential for TFEEE improvement.

**Conclusion and policy implication**

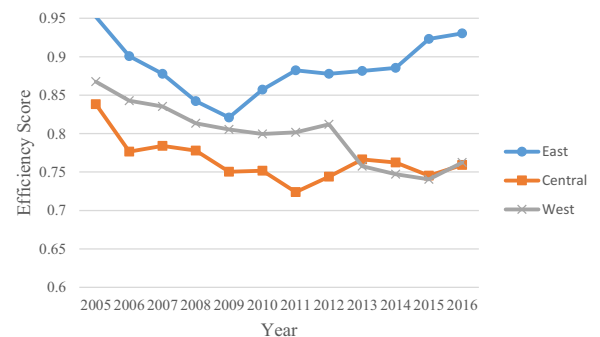
This paper combines NDDF model and four-stage DEA model, evaluating the TFEEE of 30 provinces in China from 2005 to 2016. Based on the non-radial method, this paper adjusts the inputs and unexpected output using tobit regression analysis of inputs and output slack by external environmental factor. Making deeper analysis of these external environmental factors and empirical results, the following conclusions are drawn: (1) the overall ranking of transportation energy efficiency remains unchanged before and after the adjustment of external environmental factors, with Eastern region being the highest, followed by Central region and Western region being the lowest. However, the energy efficiency of transportation sector in Western region increases more than that in Eastern and Central

regions after the adjustment of external environmental factors, which is a significant limit for TFEEE improvement in Western region’s transportation sector. (2) The external environment has a certain impact on TFEEE, and when the external environment becomes relatively equitable, TFEEE will increase in all regions. Hence, the adjustment of the external environment enables all provinces to show their potential for efficiency improvement. (3) Some environmental factors, such as the level of urbanization, have inverse impacts on the TFEEE of the transportation sector. Since these seemingly good economic conditions may bring high compensation for demolition and large labor costs.

According to the above conclusion, two policy implications are provided for Chinese transport development: (1) reducing regional imbalances in TFEEE of the transportation sector. Besides promoting energy consumption and greenhouse gas emission reduction in all regions, the government should also take measures to promote technological innovation in Central and Western regions, so that the efficiency of these two regions will be improved. (2) Second is relatively improving the external environment of transportation sector in Eastern region. Some economic and environmental factors have led to higher transportation costs in Eastern region.



**Fig. 2** The original transportation TFEEE of three areas in China



**Fig. 3** The transportation TFEEE after environmental adjustment of three areas in China

However, since these indicators are not easy to adjust, adjusting the compensation scheme for demolition is probably an easier way to achieve.

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#### Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

#### References

- Clinch, J. P., Healy, J. D., & King, C. (2001). Modelling improvements in domestic energy efficiency. *Environmental Modelling and Software*, *16*(1), 87–106.
- Cui, Q., & Li, Y. (2014). The evaluation of transportation energy efficiency: an application of three-stage virtual frontier DEA. *Transportation Research Part D: Transport and Environment*, *29*, 1–11.
- Fang, C. Y., Hu, J. L., & Lou, T. K. (2013). Environment-adjusted total-factor energy efficiency of Taiwan's service sectors. *Energy Policy*, *63*, 1160–1168.
- Feng, C., & Wang, M. (2018). Analysis of energy efficiency in China's transportation sector. *Renewable and Sustainable Energy Reviews*, *94*(6), 565–575.
- Fried, H. O., Schmidt, S. S., & Yaisawarng, S. (1999). Incorporating the operating environment into a nonparametric measure of technical efficiency. *Journal of Productivity Analysis*, *12*(3), 249–267.
- Hsu, F. M., & Hsueh, C. C. (2009). Measuring relative efficiency of government-sponsored R&D projects: a three-stage approach. *Evaluation and Program Planning*, *32*(2), 178–186.
- Hu, J. L., & Kao, C. H. (2007). Efficient energy-saving targets for APEC economies. *Energy Policy*, *35*(1), 373–382.
- Ji, X., & Chen, G. Q. (2006). Exergy analysis of energy utilization in the transportation sector in China. *Energy Policy*, *34*(14), 1709–1719.
- Li, L.-b., & Hu, J.-l. (2011). Efficiency and productivity of the Chinese railway system: application of a multi-stage framework. *African Journal of Business Management*, *22*(5), 8789–8803.
- Li, H., Fang, K., Yang, W., Wang, D., & Hong, X. (2013). Regional environmental efficiency evaluation in China: analysis based on the super-SBM model with undesirable outputs. *Mathematical and Computer Modelling*, *58*(5–6), 1018–1031.
- Lin, B., & Zhang, G. (2017). Energy efficiency of Chinese service sector and its regional differences. *Journal of Cleaner Production*, *168*, 614–625.
- Lipsy, P. Y., & Schipper, L. (2013). Energy efficiency in the Japanese transport sector. *Energy Policy*, *56*, 248–258.
- Liu, H., & Lin, B. (2017). Energy substitution, efficiency, and the effects of carbon taxation: evidence from China's building construction industry. *Journal of Cleaner Production*, *141*, 1134–1144.
- Liu, H., Yang, Z., Zhu, Q., & Chu, J. (2017). Environmental efficiency of land transportation in China: a parallel slack-based measure for regional and temporal analysis. *Journal of Cleaner Production*, *142*, 867–876.
- Song, X., Hao, Y., & Zhu, X. (2015). Analysis of the environmental efficiency of the Chinese transportation sector using an undesirable output slacks-based measure data envelopment analysis model. *Sustainability*, *7*, 9187–9206.
- Song, M., Zheng, W., & Wang, Z. (2016a). Environmental efficiency and energy consumption of highway transportation systems in China. *International Journal of Production Economics*, *181*, 441–449.
- Song, M., Zhang, G., Zeng, W., Liu, J., & Fang, K. (2016b). Railway transportation and environmental efficiency in China. *Transportation Research Part D: Transport and Environment*, *48*(12), 488–498.
- Tone, K. (2002). Continuous optimization a slacks-based measure of super-efficiency in data envelopment analysis. *European Journal of Operational Research*, *143*, 32–41.
- Tongzon, J. (2001). Efficiency measurement of selected Australian and other international ports using data envelopment analysis. *Transportation Research Part A: Policy and Practice*, *35*(2), 107–122.
- Tsai, P. F., & Molinero, C. M. (2002). A variable returns to scale data envelopment analysis model for the joint determination of efficiencies with an example of the UK health service. *European Journal of Operational Research*, *141*(1), 21–38.
- Vanek, F. M., & Morlok, E. K. (2000). Improving the energy efficiency of freight in the United States through commodity-based analysis: justification and implementation. *Transportation Research Part D: Transport and Environment*, *5*(1), 11–29.
- Vlontzos, G., Niavis, S., & Manos, B. (2014). A DEA approach for estimating the agricultural energy and environmental efficiency of EU countries. *Renewable and Sustainable Energy Reviews*, *40*, 91–96.
- Wang, Z., & He, W. (2017). CO2 emissions efficiency and marginal abatement costs of the regional transportation sectors in China. *Transportation Research Part D: Transport and Environment*, *50*, 83–97.
- Wang, K., Huang, W., Wu, J., & Liu, Y. N. (2014). Efficiency measures of the Chinese commercial banking system using an additive two-stage DEA. *Omega*, *44*, 5–20.
- Wu, J., Lin, L., Sun, J., & Ji, X. (2015). A comprehensive analysis of China's regional energy saving and emission reduction efficiency: from production and treatment perspectives. *Energy Policy*, *84*, 166–176.
- Yang, T., Chen, W., Zhou, K., & Ren, M. (2018). Regional energy efficiency evaluation in China: a super efficiency slack-based measure model with undesirable outputs. *Journal of Cleaner Production*, *198*, 859–866.
- Zhang, N., & Wei, X. (2015). Dynamic total factor carbon emissions performance changes in the Chinese transportation industry. *Applied Energy*, *146*, 409–420.

- Zhang, J., Hui, L. , Bo, X., & Martin. S. (2018). Impact of environment regulation on the efficiency of regional construction industry: A 3-stage Data Envelopment Analysis (DEA). *Journal of Cleaner Production*, 200, 770–780.
- Zhou, P., Ang, B. W., & Wang, H. (2012). Energy and CO<sub>2</sub> emission performance in electricity generation: a non-radial directional distance function approach. *European Journal of Operational Research*, 221, 625–635.
- Zhou, G., Chung, W., & Zhang, Y. (2014). Measuring energy efficiency performance of China's transport sector: a data envelopment analysis approach. *Expert Systems with Applications*, 41(2), 709–722.

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