The Environmental-adjusted Energy Efficiency of China's Construction Industry: A Three-stage Undesirable SBM-DEA Model

Yufeng Chen (chenyufeng@gmail.com)
Zhejiang Gongshang University https://orcid.org/0000-0002-9027-0674

Lihua Ma
Zhejiang Gongshang University

Zhitao Zhu
Zhejiang Gongshang University

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Authors: Yufeng Chen[1, 2], Lihua Ma[1,3], Zhitao Zhu[1]

Affiliation:

[1]School of Economics, Center for Studies of Modern Business, Zhejiang Gongshang University, Hangzhou, 310018, China.

[2] College of Business Administration, Capital University of Economics and Business, Beijing, 100070, China.

[3]Hangzhou College of Commerce, Hangzhou, 311599, China

Corresponding author: Yufeng Chen

Corresponding address of Yufeng Chen:

No.18, Xuezheng Street, Jianggan District, Hangzhou, Zhejiang, China, 310018.

E-mail: chenyufeng@gmail.com

Tel: +86 13957109992

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Yufeng Chen[1, 2,*], Lihua Ma[1,3], Zhitao Zhu[1]

[1]School of Economics, Center for Studies of Modern Business, Zhejiang Gongshang University, Hangzhou, 310018, China.

[2] College of Business Administration, Capital University of Economics and Business, Beijing, 100070, China.

[3]Hangzhou College of Commerce, Hangzhou, 311599, China

Abstract: Construction industry is a pillar industry of China's national economy but its problems of high energy consumption, high pollution and low energy efficiency is increasingly prominent. The study on the energy efficiency of construction industry is of great significance for improving development quality and achieving the goal of energy saving and emission reduction. In this paper, a three-stage undesirable SBM-DEA model was employed to measure the energy efficiency in construction industry during 2005 -2016. The CO_2 directly emitted by the construction industry and indirectly emitted in the production of building materials were used as the undesirable output and the three-stage framework was employed to analyze and eliminate the influence of external environment. The empirical results showed that low efficiency of management in the construction industry is an important factor leading to the low level of energy efficiency in China's construction industry. For the energy efficiency value before and after adjustment, the "high-high" provinces has made full use of the superior external environment by their high management level, while the "high-low" provinces needs to fully realize the potential in promoting energy efficiency of its external environment by improving its own management of construction industry. On the contrary, the "low-high" provinces need to improve the external environment to ease its restrictions on the level of management in the construction industry. Environmental factors and management level should be considered simultaneously for different provinces to improve energy efficiency of construction industry.

Key words: Environmental-adjusted energy efficiency; Three-stage undesirable SBM-DEA; Management inefficiency; Construction industry

1. Introduction

The problems of resources, energy and environment have become increasingly prominent with the rapid development of economy and the acceleration of urbanization in China. As an important pillar industry of China's national economy, the problems of high energy consumption, high pollution and low energy efficiency in construction industry was particularly highlighted. The total output of China's construction industry reached 2,139.54 billion in 2017 while the added value accounting for 6.7% of China's GDP and its growth rate exceeded GDP growth by 3%①. At the same time, energy consumption in the construction industry reached 857 million tons of standard

* Corresponding author: Yufeng Chen
Corresponding address of Yufeng Chen:
No.18, Xuezheng Street, Jianggan District, Hangzhou, Zhejiang, China, 310018.
E-mail: chenyufeng@gmail.com
Tel: +86 13957109992

① The data come from *China Statistical Yearbook* (2018), National Bureau of Statistics of China.

coal, accounting for 20 percent of China's total energy consumption in 2015, and this number is still growing[②]. Figure 1 illustrates that the total construction carbon emission in China shows a trend of continuous growth, reaching 1.961 billion tons in 2016, which is about three times higher than 668 million tons in 2000, with an average annual growth of 6.96%, and construction industry account for 20.6% of China's energy consumption and 19.4% of its carbon emissions[③]. In addition, considering the energy consumption during heating, cooling, illumination and the production of building materials, construction industry will consume more than a third of China's total energy consumption[④]. The construction industry is an important emitter of carbon dioxide, haze and other pollutants (Lu et al., 2016; Feng et al., 2016), which will lead to a lot of grave consequences, such as lung diseases, traffic congestions in cities as well as economic loss (Zhang and Crooks, 2012).In view of the problems of high energy consumption, high pollution and low energy efficiency in construction, promoting the energy efficiency in the construction industry is crucial for improving development quality and achieving the goal of energy saving and emission reduction.

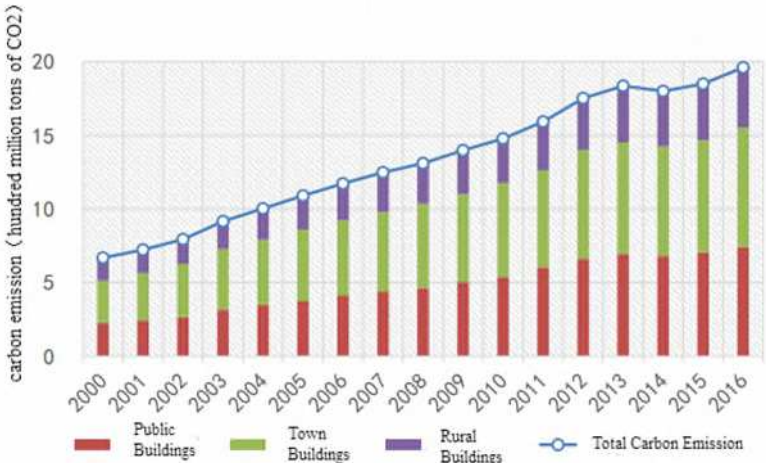

Figure 1: Carbon emission of construction industry during from 2000 to 2016

In this paper, the energy efficiency of China's construction industry was investigated by employing the three-stage undesirable SBM-DEA model, which was widely used in Energy and Environment modeling, for its superiority in dealing with the undesirable output, as well as in evaluating and eliminating the influence of external factors or random noises.. Based on the measurement of energy efficiency in China's construction industry, regional gaps, trends and influencing factors are the three main concerns in the discussion of this paper, followed by some policy implications for the sustainable development of China's construction industry. This paper contributes to current literature in two aspects. Firstly, the CO_2 directly emitted by the construction industry and indirectly emitted in the production of building materials were selected as an undesirable output to shed light on the full life cycle environmental performance of construction industry. Secondly, urbanization, economic level, environmental regulation, public investment, human capital and industrial structure of each province was selected as external factors to analyze the influencing factors of energy efficiency in China's construction industry within the three-stage framework.

② The data come from *China Statistical Yearbook* (2018), National Bureau of Statistics of China.

③ The data and figure come from *China building energy consumption report* (2018), China Association of Building Energy Efficiency.

④ The data come from *China building energy consumption report* (2018), China Association of Building Energy Efficiency.

This paper was organized as follows. Section 2 provided a brief literature review of the development of DEA model and some research about energy efficiency in construction industry. The methodology and data were then described in Section 3 and Section 4 respectively, followed by the empirical results in Section 5, and the conclusion and policy implications in Section 6.

2. Literature review

Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are the main methods to measure energy efficiency. DEA is a non-parametric, linear and programming method to measure the productivity of comparable multiple-input and multiple-output decision-making units (DMUs). Compared with SFA, DEA does not require a priori assumptions on the underlying functional form and information on prices, so it is widely employed for the measurement of the energy efficiency. The first published paper used this approach in energy efficiency issues by Färe (Färe et al., 1983) in the field of electricity generation plants energy. During the 2010s, there are 524 articles on energy and environment applied the DEA methods (Toshiyuki et al., 2017), and this method has been adopted by more and more scholars. DEA model was widely employed to investigate energy efficiency or environmental performance in different countries and regions, and has been deeply modified and widely applied to many sectors such as agricultural sectors(Ullah and Perret, 2014; Fei and Lin, 2017; Li et al., 2017), industrial sectors(Liu et al., 2016; Liu and Wang, 2015; Wu et al., 2019), transportation sectors (Cui and Li, 2014, 2015; Feng and Wang, 2018), energy intensive industries (Lin and Tan, 2016), power generation industry (Liu et al.,2016), ecosystem (Susaeta et al., 2016), construction sectors(Xue et al., 2015), service sectors (Lin and Zhang, 2017) and commercial banks (Wang et al., 2014). These studies showed that DEA model provides an appropriate way in modeling the production with multiple-inputs and multiple-outputs, especially widely employed in the field of Energy and Environmental Economics.

DEA model has experienced a series of evolutions, from radial slacks to non- radial slacks, from Shepard Distance Function (SDF) to Directional Distance Function (DDF) and non-radial Directional Distance Function (NDDF) (Zhang and Choi, 2014). During the evolution of DEA model, the disposal of undesirable outputs and the impact of external factors and random error were two concerned issues and the argument around these two problems promoted the development of DEA model.

Traditional DEA model, such as BCC and CCR, are radial model hence cannot solve the coexistent of desirable and undesirable outputs. The endeavor to solve this problem promoted the improvement of DEA model from SDF to DDF and NDDF. Early scholars took undesirable outputs as inputs, or turned it into the desired outputs by SDF, implied the assumption that the desirable output changed in the same proportion as the undesirable output, which violated the actual production process. Some scholars proposed a more practical technology for weak disposability production, and employed DDF to improve the deficiency of SDF (Zhou et al., 2008). Furtherly, NDDF was employed to relax the constraints about undesirable output of DDF, making the measurement of efficiency more in line with reality (Zhou et al., 2012), then capital, labor and energy were all incorporated into the framework of NDDF, the calculation of total factor energy and environmental efficiency is realized (Zhang et al., 2014).

In addition to the improvement of DDF, a slack-based measurement (SBM) model proposed by Tone (2001) gave another way to deal with different inputs and outputs, which allowed input reduction and output expansion at the same time, and does not stick to a proportionate change of

input and output. And the duality form of SBM model was proposed to model the shadow price of pollution and the substitution between production factors (Zhang et al., 2014). Considering the treatment of undesirable outputs, the SBM-undesirable model proposed by Tone (2004), which is a new non-radial and non-oriented DEA approach and employed by a lot of studies to investigate the efficiency (Zhang and Choi, 2013; Apergis et al., 2015; Zhang et al., 2016). On this basis of SBM-DEA model, some new methods have been proposed in recent years. Considering the technological gaps between different DMUs and the movement of technological frontier, the meta-frontier slack-based efficiency measure (MSBM) and meta-frontier undesirable SBM were proposed to incorporates group heterogeneities (Zhang et al., 2014). On the contrary of SBM, which require a DMU was evaluated at maximum distance to the frontier, a minimum distance to the weak efficiency frontier method (MinDW) was proposed to evaluate DMU at minimum distance to the frontier, allowing a DMU to reach the frontier at a less adjustment of inputs and outputs (Wang et al., 2013). In addition, considering the different importance of each inputs and outputs, an epsilon-based measure (EBM) model was proposed by setting a series of parameters to express the relative importance of inputs, desirable and undesirable outputs(Tone and Tsutsui, 2010). Yu et al. (2019) synthetically studied these model (SBM, EBM and MinDW) and their meta-frontier forms, then employed them to investigate the eco-efficiency of cities in China, and found there were small difference of the measured eco-efficiency in different models.

Another argument which promoted the development of DEA model was that the traditional DEA method does not consider the impact of external environment and random error on the efficiency value, and the results obtained are not comparable. In response, the three-stage and four-stage DEA models were the most widely used approach to investigate energy efficiency. The four-stage model proposed by Fried et al. (1999) eliminates the influence of environmental factors on technical efficiency, but it cannot eliminate the influence of statistical noise. In recent years, the three-stage model proposed by Fried et al. (2002) has effectively eliminated the interference of environmental factors and managers' luck on the measurement of technical efficiency.

DEA model was also widely used to study the energy efficiency in construction industry. Xue et al. (2015) employed a DEA-based Malmquist productivity index (MPI) to measure the energy efficiency of construction industry in 26 provinces in China during 2004 to 2009. They found that energy efficiency gaps existed different regions and it's necessary for the Chinese government to develop policies to strengthen the energy management. Chen et al. (2016) employed a three-stage DEA and Discriminant Analysis (DA) model to measure the energy efficiency and trends of construction industry in 30 provinces during 2003 and 2011. A constant fluctuate in the efficiency was found in most of provinces during the sample years, for the overall efficiency decreased after the peak in 2004. In addition, they found that the regional economic level has no significant impact on the energy efficiency in construction industry and the gaps among the eastern, central and west regions were not obvious. Zhang et al. (2018) employed the undesirable SBM-DEA model to measure the provincial energy efficiency of construction industry from 2011 to 2015 and empirically reveal that environmental regulation has a significant impact the energy efficiency in construction industry.

In view of the studies about energy efficiency in China's construction industry, DEA model provides a good way to measure the energy efficiency and can help policy-makers to improve strategies of sustainable development in China. However, there were some gaps in current research. Firstly, various DEA model were employed in these research, while few of them considered the

disposal of undesirable outputs and the elimination of external influences simultaneously. Secondly, indirect CO_2 emissions from the production of building materials, which was an important source of emissions, were often overlooked when CO_2 emissions were considered as an undesirable output of the construction industry. Thirdly, existing studies were not comprehensive enough to examine the factors influencing energy efficiency in the construction industry. Therefore, this paper combined undesirable SBM-DEA and three stage DEA framework to accurately measure the energy efficiency of the China's construction industry, then distinguish and eliminate the impact of external factors.

3. Methodology

A three-stage SBM-DEA model was adopted to evaluate the energy efficiency of the construction industry. Compared with the traditional DEA model, this method can eliminate the impact of external environment and random error on the efficiency value and conduct input and output slacks at the same time. Considering other types of updated DEA models, such as meta-frontier slack-based efficiency measure (Zhang et al., 2014), which incorporates the movement of technological frontier caused by the technological gaps between different groups of DMU, and the duality form of SBM model was proposed to model the shadow price of pollution and the substitution between production factors (Zhang et al., 2014), the three-stage undesirable SBM-DEA was more consistent with our research goals. Further studies can be carried out on the basis of these updated DEA models.

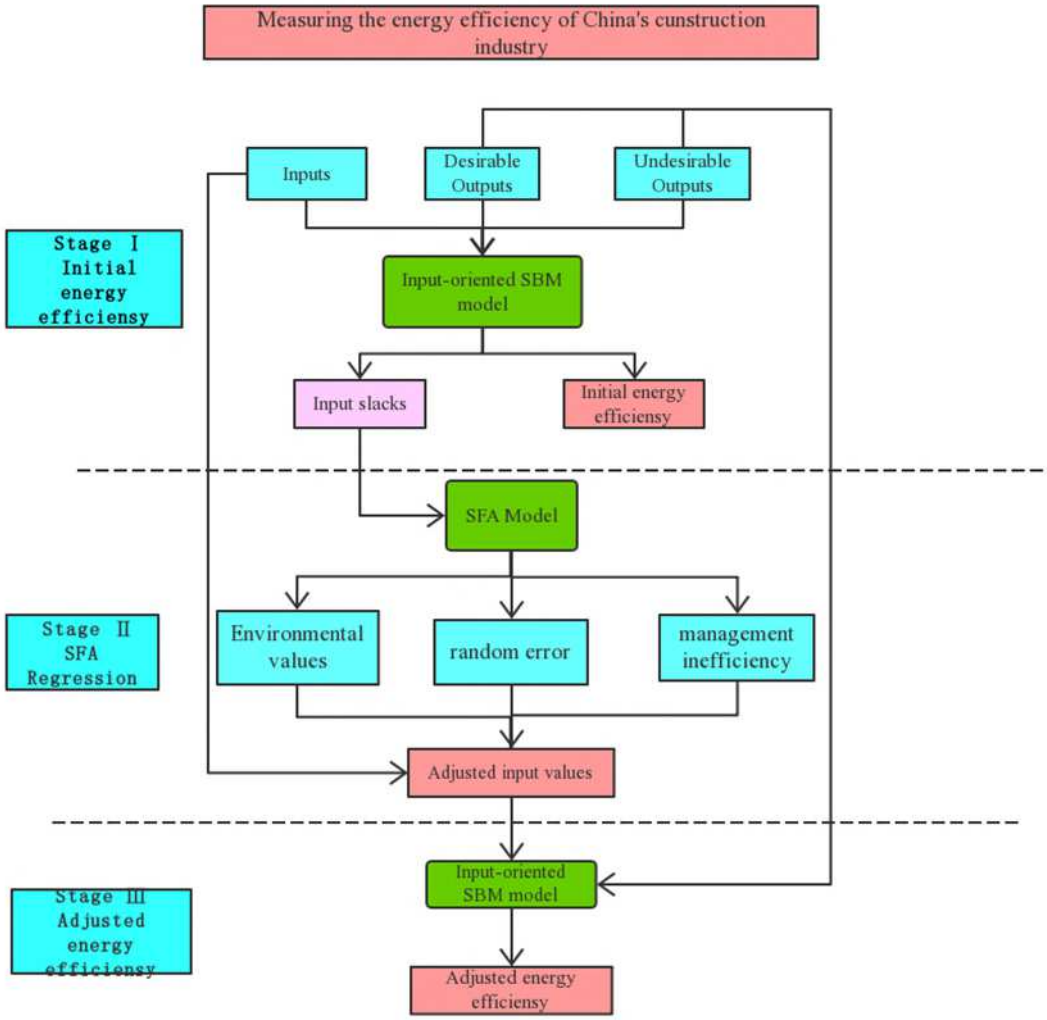

Figure 2: Methodological framework of the three-stage undesirable SBM-DEA model

The specific framework of three-stage undesirable SBM-DEA model were shown in Figure 2. In Stage I, the energy efficiency of each DMU is initially evaluated based on the SBM-DEA model. In Stage II, SFA method was employed to decompose the influence of environmental factors and random error factors, and then adjust the input variables according to the SFA results to exclude the influence of environmental factors and random error factors. In Stage III, the energy efficiency of each DMU was re-estimated using the adjusted input variables and the SBM-DEA model.

3.1 The SBM-undesirable model

The slack-based measurement (SBM) model proposed by Tone (2001) can deal with input reduction and output expansion at the same time, and does not stick to a proportionate change of input and output. However, the SBM model cannot deal with undesirable outputs. Tone (2004) proposed the SBM-undesirable model to deal with undesirable output. As a new non-radial and non-oriented DEA model, the SBM-undesirable model can conduct input and output slacks at the same time, while do not need strict proportional changes of inputs and outputs.

According to Tone's model, a system with n decision making units (DMUs) has three indicators: inputs, desirable outputs and undesirable outputs, represented by three vectors $\in R^m$, $y^g \in$

$R^{s1}, y^b \in R^{s2}$, respectively. Matrix X, Y^g, Y^b were defined as follows:

$$X = \left[x_1, ..., x_n\right] \in R^{m\times n}, Y^g = \left[y^{g1}, ..., y^{gn}\right] \in R^{s1\times n}, \quad Y^b = \left[y^{b1}, ..., y^{bn}\right] \in R^{s2\times n} \tag{1}$$

Where X, Y^g and Y^b are greater than 0.

Then, the production possibility set P was defined as:

$$P = \left\{\left(x, y^g, y^b\right) \middle| x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \lambda \geq 0\right\} \tag{2}$$

According to the production possibility set P, the energy efficiency of SBM-undesirable model was modified as follows:

$$\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s1}\frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s2}\frac{s_r^b}{y_{r0}^b}\right)}$$
$$s.t. \quad \begin{cases} X\lambda + s_i^- = x_d \\ Y^g\lambda - s_r^g = y^g \\ Y^b\lambda + s_r^b = y^b \\ \lambda \geq 0, s_i^- \geq 0, s_r^g \geq 0, s_r^b \geq 0 \end{cases} \tag{3}$$

In this model, ρ^* represent the energy efficiency value, s_i^-, s_r^g and s_r^b represent the slack of inputs and two various outputs,; λ represent a weight vector used to conduct the frontier; $0 \leq \rho^* \leq 1$ and it strictly decrease with respect to s_i^-, s_r^g and s_r^b. The DMU is efficient only when $\rho^*=1$ and s_i^-, s_r^g and s_r^b are equal to 0, this DMU is most efficient.

3.2 Stochastic Frontier Analysis

The energy efficiency value in Stage I can't eliminate the impact of external environment and random error, so it is not credible. In general, SFA and Tobit Model are commonly employed in Stage II to adjust input or output variables for more accurate efficiency values. However, Tobit Model can't eliminate the influence of random error, Fried et al. (2002) proposed a three stage DEA model and employ the cost function SFA model in Stage II, to separate the effects of management inefficiencies, environmental factors and random errors, they used environmental variables and a combined error term to regression the slack variables obtained in Stage I.

The regression equation for the slack variables and environmental variables can be set to:

$$S_{ni}^* = f\left(Z_i, \beta^n\right) + v_{ni} + U_{ni} \qquad (n = 1, \ldots, N\ ;\ i = 1, \ldots, I) \tag{4}$$

Where S_{ni}^* is the slack variable for the n-th input of the i-th DMU, $f^i(Z_i, \beta^n)$ represents the effect of the environment variable on the slack variable. Let $f^i(Z_i, \beta^n) = Z_i\beta^n$ and $v_{ni} + U_{ni}$ be the mixed error term. We assume that $v_{ni} \sim N(0, \sigma_{vn}^2)$ represents the impact of random error and $u_{ni} \sim N^+(\mu^n, \sigma_{un}^2)$ obey the truncated normal distribution, represents the impact of management inefficiencies, and the two error terms are independent. When $\gamma = \frac{\sigma_{un}^2}{\sigma_{un}^2 + \sigma_{vn}^2}$ tends to 1, indicates that management inefficiency dominates the slack variables; when γ tends to 0, indicates that random error dominates the slack variables.

Then the results of the SFA will be employed to adjust the inputs of each DMU by putting all DMU's in the same environment and luck. There are two ways of adjustment, the first way is to increase the inputs of DMUs in relatively good environment and good luck; the other way is to decrease the inputs of DMUs in relatively bad environment and bad luck. When the outputs are constant, increased inputs mean lower efficiency value while decreased inputs mean higher efficiency value. Considering the regional gaps in construction industry and some DMUs are at extreme disadvantages, the downward adjustment may make their inputs very small, even close to

0, the first approach was employed for the adjustment in the SFA regression. That is, put all DMUs under the worst environment and luck to increase the inputs of DMUs in relatively good environment and good luck, so their efficiency value will decrease.

The equation for adjusting input variables is:

$$X_{ni}^{*} = X_{ni} + \left[\max_{i} \left\{ Z_i \beta^n \right\} - Z_i \beta^n \right] + \left[\max_{i} \left\{ V_{ni} \right\} - V_{ni} \right] \qquad (n = 1, \ldots N;\ i = 1, \ldots, I) \tag{5}$$

Where, X_{ni}^{*} is the adjusted input, and X_{ni} is the input value from Stage I. The first brackets on the right hand side of the equation indicate that all DMU were adjusted to the worst observation environment in the sample. The second brackets indicate that all DMUs were adjusted to the most unfortunate observation state in the sample. Through this adjustment, all DMUs face the same operating environment and external luck, so it can be obtained that the impact of external environment and random error were eliminated when measuring the energy efficiency in Stage III.

4. Data description and variables

This paper collected the data of construction industry of China's 30 provinces over 2005-2016 (except Tibet, Hong Kong, Macao, Taiwan), which are mainly from China Statistical Yearbook, China Energy Statistical Yearbook, China Architecture Yearbook, China's provincial statistical yearbooks. Table 1 showed the descriptive statistics of the data, inputs and outputs variables are selected in the second half of this section.

4.1 Input

Considering about the existing literature on energy efficiency evaluation of China's construction industry, the input indicators mainly cover the four aspects of labor, capital, equipment and energy consumption (Xue et al., 2015; Chen et al., 2015; Zhang et al., 2018). In this paper, the labor of construction industry(Labor), total assets of construction industry(Capital), total power of machinery(Equipment) and energy consumption converted to standard coal(Energy) were used as inputs to investigate energy efficiency of construction industry.

Table 1 Descriptive statistics of input and output variables

Variable	Type	Unit	OBS	Min	Max	Mean	SD
Labor	Input	10 thousand	360	5.48	787.23	131.25	146.28
Equipment	Input	10 thousand kw	360	15.10	5390.10	702.81	723.00
Capital	Input	100 million Yuan	360	40.68	20263.67	3136.53	3348.77
Energy	Input	10 thousand ton standard coal	360	8.00	740.18	169.71	133.60
GDP	Desirable Output	100 million Yuan	360	59.69	25791.76	3682.32	4243.81
CO_2 Emission	Undesirable Output	10 thousand tons	360	87.81	109783.20	5539.28	9293.59

Note: Min, max, mean and SD represent the minimum value, maximum value, mean value and standard deviation of 360results of 30 provinces during 2005–2016.

4.2 Desirable Output

Gross output value of construction, the total profits and the completed floor area are the main indicators of outputs in construction industry and they are correlated with each other. In this paper, gross output value of construction industry (GDP) was selected as a desirable output in the process of measuring energy efficiency.

4.3 Undesirable Output

Carbon dioxide is a typical undesirable output of the construction industry. This paper needs to calculate the carbon dioxide emissions of the construction industry before calculating the energy efficiency of China's provincial construction industry.

It can be seen from the relevant literature (Yan et al., 2010; Acquaye and Duffy, 2010; Wu et al., 2012) that the measurement standards for carbon dioxide emissions of the construction industry have not been unified, and the current studies were always focused on the national level, and there was no comparative analysis of the carbon dioxide emissions of the construction industry in the provinces.

Carbon dioxide emissions of the construction industry are divided into direct emissions and indirect emissions. Direct carbon emissions refer to the carbon emissions generated by energy consumption in the activities of construction industry. Indirect carbon emissions refer to the carbon emissions generated from the production of building materials. Therefore, this paper take the concept of the whole life cycle of buildings for reference and, on the basis of measuring the direct carbon emissions of the construction industry, puts the carbon dioxide generated during the production of building materials into the carbon emission measurement framework of the construction industry. At the provincial level of the construction industry, considering the possibility of data acquisition and the practicability of model establishment, this paper calculated the indirect carbon emission of the construction industry caused by the production of steel, aluminum, wood, cement and glass, which are the most widely used building materials. The direct carbon emission of the construction industry caused by the consuming of twelve types of energy sources. Among them, raw coal, briquette coal, coke, gasoline, kerosene, diesel oil, fuel oil, lubricating oil, liquefied petroleum gas, natural gas and other ten kinds of energy sources are primary energy, and heat and electricity are secondary energy sources. Based on the above, this paper establishes the following carbon dioxide emission measurement approach of the construction industry:

$$E_{co_2} = \sum C_i \times \beta_i + \sum G_i \times \varepsilon_i \times (1-\alpha) \tag{6}$$

Where E_{co_2} is the total carbon dioxide emissions of the construction industry, C_i is the total energy consumption of energy i, β_i is the carbon dioxide emission factor of each kind of energy, G_i is the usage amount of building materials i, ε_i is the unit carbon dioxide emission coefficient of each kind of building material, α is the recovery coefficient of some metal material , for the steel, α is 0.8 and for aluminum is 0.85. Carbon dioxide emission factor comes from United States Department of Energy (1999), emission coefficient and recovery coefficient of each kind of building material come from the research of Yan et al (2010).

5. Empirical Results

5.1 The initial energy efficiency (Stage I)

This stage employed the SBM-undesirable model in the MaxDEA software to measure the initial energy efficiency of China's construction industry between 2005 and 2016. Table 2 showed the results, ignoring the effects of random errors and external environmental variables.

Table 2 The initial energy efficiency of China's construction industry in Stage I

Province	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	average
Anhui	0.72	0.71	0.69	0.75	0.71	0.62	0.69	0.65	0.66	0.65	0.73	0.71	0.69
Beijing	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Chongqing	0.72	0.71	0.69	0.75	0.71	0.62	0.69	0.65	0.66	0.65	0.73	0.71	0.69
Fujian	0.70	0.72	0.88	0.64	0.62	0.66	0.72	0.71	0.71	0.68	0.70	0.72	0.70
Gansu	0.38	0.37	0.47	0.35	0.41	0.53	0.54	0.58	0.61	0.56	0.62	0.59	0.50
Guangdong	0.58	0.63	0.63	0.61	0.68	0.61	0.62	1.00	0.63	0.63	0.61	0.62	0.65
Guangxi	0.52	0.55	0.58	0.65	0.70	0.72	0.84	0.85	1.00	1.00	1.00	1.00	0.78
Guizhou	0.47	0.46	0.47	0.46	0.55	0.54	0.59	0.63	0.64	0.63	0.62	0.55	0.55
Hainan	0.46	0.44	1.00	0.55	0.55	1.00	1.00	1.00	1.00	1.00	0.77	0.82	0.80
Hebei	0.56	0.54	0.57	0.57	0.62	0.62	0.66	0.63	0.74	0.79	0.71	0.72	0.64
Henan	0.62	0.75	0.71	0.86	0.76	0.66	0.71	0.68	0.71	0.70	0.63	0.67	0.70
Heilongjiang	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.69	0.78	0.96
Hubei	0.52	0.59	0.56	0.66	0.67	0.60	0.75	0.69	0.79	0.93	0.85	1.00	0.72
Hunan	0.57	0.58	0.63	0.62	0.63	0.68	1.00	1.00	1.00	1.00	0.69	0.76	0.76
Jilin	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.65	0.81	1.00	0.68	1.00	0.93
Jiangsu	1.00	1.00	1.00	1.00	1.00	0.79	0.77	0.78	1.00	1.00	1.00	1.00	0.95
Jiangxi	0.69	0.72	0.81	1.00	1.00	1.00	1.00	1.00	0.88	1.00	0.87	0.87	0.90
Liaoning	1.00	1.00	1.00	0.86	1.00	0.78	1.00	0.88	1.00	0.78	0.56	0.46	0.86
Inner Mongolia	0.58	0.62	0.67	0.57	0.60	0.61	0.61	0.56	0.58	0.52	0.49	0.51	0.58
Ningxia	0.50	0.53	0.60	0.57	0.68	0.71	0.72	0.71	0.73	0.74	0.64	0.67	0.65
Qinghai	0.43	0.46	0.43	0.44	0.53	0.68	0.60	0.49	0.56	0.55	0.55	0.50	0.52
Shandong	0.64	0.60	0.73	0.60	0.61	0.54	0.59	0.58	0.60	0.64	0.60	0.59	0.61
Shanxi	0.62	0.62	0.59	0.61	0.71	0.63	0.65	0.59	0.64	0.65	0.56	0.59	0.62
Shaanxi	0.67	0.70	0.76	0.69	0.75	1.00	1.00	0.80	0.77	0.74	0.75	0.82	0.79
Shanghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Sichuan	0.56	0.59	0.57	0.62	0.68	0.60	0.63	0.69	0.69	0.69	0.67	0.69	0.64
Tianjin	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.84	1.00	0.99
Xinjiang	0.65	0.60	0.64	1.00	1.00	1.00	0.83	0.83	1.00	1.00	1.00	1.00	0.88
Yunnan	0.47	0.46	0.48	0.48	0.58	0.60	0.63	0.54	0.64	0.61	0.60	0.60	0.56
Zhejiang	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

It can be seen that Beijing, Tianjin, Zhejiang, Jiangxi, Shanghai, Jiangsu Heilongjiang and Jilin have higher energy efficiency, the average efficiency value of these provinces are close to 1. Guizhou, Qinghai, Inner Mongolia, Gansu and Yunnan are less energy efficient for their average efficiency value below 0.6. Among them, the energy efficiency values of Beijing, Tianjin, Zhejiang, and Shanghai are almost 1 from 2005 to 2016, indicating that the energy efficiency of construction industry in these provinces is high and very stable. These four provinces constitute the frontier of energy efficiency of China's provincial construction industry. There are 113 DMUs with a efficiency value of 1, accounting for 31.4% of all the DMUs, only 21 DMUs are less than 0.5, the overall situation of energy efficiency of China's provincial construction industry is good but the gaps between regions are obvious. According to the estimation results, the energy efficiency of Gansu, Guangxi, Hainan, Hubei, Chongqing has been improved obviously, while other provinces have not experienced significant fluctuations. By comparing the energy efficiency of 30 provinces horizontally, it can be seen that the highest energy efficiency is 1.000 and the lowest is below 0.500, indicating that the provinces with low energy efficiency have potential for improvement.

Table 3 The division of China's six major regions

Region	Province

North China	Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia
Northeast China	Heilongjiang , Jilin , Liaoning
East China	Anhui, Zhejiang, Jiangsu, Shanghai, Fujian, Jiangxi, Shandong
Middle of South China	Hubei, Hunan, Henan, Guangdong, Guangxi, Hainan
Southwest China	Chongqing, Sichuan, Guizhou, Yunnan
Northwest China	Shanxi, Ningxia, Gansu, Qinghai, Xinjiang

To study the regional differences in energy efficiency of the construction industry, 30 provinces were divided into six regions: North China, Northeast, East China, Middle of South, Southwest, and Northwest. Table 3 showed the division of these regions and Figure 3 shows the regional differences and tendency of these regions. It is illustrated that the efficiency of construction industry in Northeast and East China is relatively higher, the efficiency value in Southwest and Northwest is at a lower level though it has been growing for these years. The Northeast has been declining in recent years while East China is relatively stable, efficiency gaps between regions are decreasing by year.

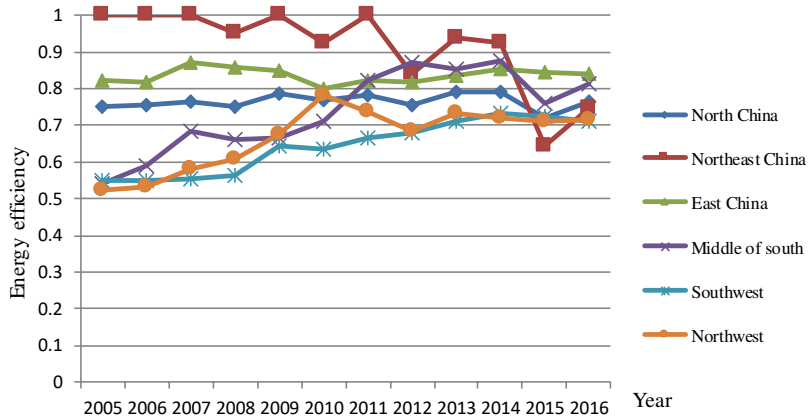

Figure 3: The initial regional energy efficiency in construction industry from 2005 to 2016

5.2 SFA regression (Stage II)

In Stage Ⅱ, a SFA model was employed to eliminate the influence of external environment as well as statistical noise. Urbanization, per capita GDP, environmental regulation, government public investment, human capital, and industrial structure were selected as environmental variables. The description of each variable and the indicators for selecting the variable were listed in the table below.

Table 4 Selection and description of environment variables

Variable name	Definition of variables
Urbanization	Proportion of urban population
Per capita GDP	Per capita GDP of each province
Environmental regulation	The proportion of environmental management input to GDP
Government public investment	The proportion of fixed assets investment to GDP
Human capital	The proportion of employees with professional certificates
Industrial structure	Proportion of tertiary industry

Frontier 4.1 was used to carry out the SFA analysis and Table 5 showed the results. It was illustrated that there was a significant σ^2 for each year and γ was also significantly bigger than 0.5, indicating that the impact of external factor accounted for a large proportion of the total variance,

means the adjustment in this stage is necessary to eliminate the impact of external environment and random error. Based on the results, the impact of each environmental variables were discussed as bellow.

Table 5 The results of SFA regression

Environmental variables	Dependent variables			
	Slack of labor	Slack of equipment	Slack of capital	Slack of energy
constant	58.70***	142.58***	-431.40***	-45.93***
Urbanization	-0.65***	-5.52**	-7.49*	-0.27**
Environmental regulation	0.78**	-47.86***	96.31**	-1.67***
Per capita GDP	0.00	0.00	-0.01	0.00
Industrial structure	-0.64***	2.20**	13.09***	1.68*
Government public investment	-0.07*	1.90***	5.93**	0.85***
Human capital	-0.31***	-11.99**	-24.29**	-4.32**
σ^2	913.46***	158716.33***	483589.07***	16156.15***
γ	0.71***	0.69***	0.65***	0.82***
log likelihood function	-4867.36	-5813.02	-6039.88	-5307.04
LR	180.29	153.46	154.07	306.68

Note: ***, ** and * represent 1%, 5%, 10% significance respectively

(1) Urbanization

Table 5 showed that the level of urbanization is significantly negatively correlated with all of the four slack variables, especially the slack of equipment and capital, for the coefficients are -5.52 and -7.49, respectively. Therefore, the higher degree of urbanization will reduce the use of production factors and increase the efficiency of construction industry. It can be explained that higher urbanization level was benefit to the efficient use of labor, equipment, capital and energy in construction industry.

(2) Environmental regulation

It is showed that environmental regulation is negatively correlated with the slack of equipment and energy, while positively correlated with slack of labor and capital. In other words, environmental regulation will limit the use of equipment and energy in construction industry, which produce more pollution and consume more energy, make construction firms to substitute equipment and energy with cleaner production factors such labor and capital. Environmental regulation is generally believed to improve the total and industrial energy efficiency (Manda, 2010; Bi et al.,2014; Zhang et al., 2016), but the promotion effect may not exist due to specific environmental regulation policies and the enforcement force (Dirckinck, 2015; Lin and Xu, 2017), and this impact have regional differences (Lin and Xu, 2017). This section studies the correlation between environmental regulation and energy efficiency by investigate its impact on the slack variables, however, the measurement of energy efficiency in this paper was based on the frame of total factor energy efficiency (TFEE), so the substitution between these production factors resulted in the uncertain effect of environmental regulation on energy efficiency in construction industry.

(3) Per capita GDP

It is shown that Per capita GDP do not has significant impact on each input slacks, indicates that economic development will not promote energy-environment efficiency in construction industry, which is different form general belief. It may be explained that with the improvement of economic, the construction industry's dependence on energy has not weakened, and the energy structure of the

construction industry has not been well optimized.

(4) Industrial structure

It is illustrated from Table 5 that industrial structure is negatively correlated with the slack of labor, while positive correlated with slack of equipment, capital and energy, indicating that the proportion of tertiary industry is higher, the labor in the construction industry will decrease, and construction companies tend to use more equipment, capital and energy to cover the decline in labor. This may be explained that the increase of the proportion of the tertiary industry will lead to the increase of the price of labor and the expansion of financing channels at the same time, so construction firms tend to substitute labor with relatively inexpensive production factors and it is easier for them to raise their capital through financing and loans. So the influence of industrial structure on the efficiency of construction industry is uncertain due to the substitution between these production factors. At present, the impact of industrial structure on energy efficiency is mostly concerned on the provincial level and industrial sector (Li and Lin, 2014; Xiong et al., 2019), the influence of industrial structure on energy efficiency in construction industry needs to be further studied.

(5) Government public investment

This variable is positive correlated with all of the four slack variables, indicating the government fixed asset investment is not conducive to the reduction of waste of construction resources and the improvement of efficiency. This is a bit of a deviation from people's expectations. It can be explained from another perspective, that is, the production of the construction industry is greatly affected by policies, and the government's regulatory policies will have an important impact on the development of the construction industry. At present, the main body of the construction industry is still the government and large construction state-owned enterprises, the market economy requires the government to reduce its intervention in the market, and the government public investment to infrastructure construction or public buildings is not conducive to the improvement of the relative efficiency of the construction industry in China in the long term, indicating that construction industry may get better performance in energy and environment when government relax the intervention towards construction and give them more market incentives. The conclusion was conformed to the research on stated-owned power plants (Zhang and Choi, 2013; Zhang et al., 2014).

(6) Human capital

It is illustrated that human capital is negatively correlated with all of the four slack variables, indicating that the improvement of human capital will reduce various input indicators, so as to improve the efficiency of the construction industry.

Based on the discussion for the impact of some external factors, it can be found that these factors, expect Per capita GDP, would have an impact on the energy efficiency of construction industry. Among the environmental factors, urbanization and human capital have a positive impact on energy efficiency, while government direct investment has a negative impact on energy efficiency. The impact of environmental regulation and industrial structure was uncertain on different provinces due to the substitution of production factors. Environmental regulation does not necessarily improve environmental efficiency and may have a negative impact on the development of the construction industry. Economic development has little impact on energy efficiency in construction industry, possibly because that the energy structure and technological innovation in construction industry are not significantly promoted in the process of economic development in recently years.

Therefore, external environment has a certain impact on energy efficiency, when the external

environment became relatively equitable, the real energy efficiency will better reflect the internal management efficiency of the construction industry. Specially, the efficiency value of construction industry in provinces facing better external environment and good luck may be higher, while provinces facing a poor external environment and luck will have lower construction efficiency. When evaluating the efficiency of the construction industry, it is necessary to adjust the external environment factors and random error factors, making all DMUs are under the influence of unified external environment and random error, then its real efficiency level is investigated more accurately in Stage III.

5.3 Environmental-adjusted energy efficiency (Stage III)

The input-output data in Stage I can be adjusted according to the results of the SFA model regression to provide new input output data to Stage III for the evaluation and Table 6 shows the efficiency of each DMU in Stage III. It is illustrated that when all provinces are facing the worst external environment and luck, there has been a decrease in overall efficiency. Among the eight provinces with higher efficiency in Stage I, Beijing, Zhejiang, Shanghai and Jiangsu are still at the frontier with the efficiency value of 1, while the efficiency value Tianjin, Jiangxi, Heilongjiang and Jilin have a significant decline. This phenomenon indicated that the management level of the construction industry in these provinces is not well and their efficiency were high in Stage I because they faced with better external environment, while traditionally developed provinces Beijing, Zhejiang, Shanghai and Jiangsu have a high level of management in construction industry so their efficiency did not decrease after adjustment. There are 73 DMUs with an efficiency value equals to 1, 40 less than the number of Stage I and DMUs with an efficiency below 0.5 is more than 50%, shows that management inefficiency is widespread in the construction industry.

Figure 4 shows the change of energy efficiency of China's construction industry in six regions of China. It is illustrated that the efficiency of construction industry in Northeast and East China is relatively higher; the efficiency value in Northwest China is at a lowest level. Energy efficiency in East China, Middle of China and North China was on the rise, while other regions clearly fluctuating, and there was a sharp drop after 2011 in Northeast China, indicating that the management level of its construction industry has deteriorated.

Figure 5 shows the changes of average efficiency in Stage I and Stage III. When all DMUs are faced with the worst external environment and luck, the average efficiency has decreased in most provinces. In terms of the "high-low" provinces, such as Hainan, Ningxia and Qinghai, the dramatic decrease of energy efficiency when facing the poorest external environment and luck showed that their relatively higher energy efficiency in Stage Ⅰ were benefit from their superior external environment, but the management level in their construction industry limits the potential to be realized. The "high-high" provinces, especially Beijing, Zhejiang and Shanghai, has an efficiency value of 1 in both Stage Ⅰ and Stage Ⅲ, indicating that their environmental conditions and management level reached a high level. In terms of limited "low-high" provinces(Jiangsu, Hubei and Guangdong), there was a slight increase after the adjustment, indicating that the external environment limits the contributions of the management level in their construction industry, and the improvement of energy efficiency need to start from improving external environment.

At the regional level, in the Eastern region, the construction industry management level is high and the environmental conditions are good, so the efficiency level is very high, of Central and Northern management level has also been gradually improve, the Western region construction

efficiency is low not only because of its natural and social environment, the management level of the construction industry itself is also the important reasons of the low efficiency. Although the natural and social environment in Northeast China is better, but its management level is low, which limits its efficiency in construction industry.

Table 6 The energy efficiency of China's construction industry in Stage III

Province	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	average
Anhui	0.52	0.50	0.52	0.54	0.56	0.58	0.63	0.69	0.66	0.64	0.72	0.65	0.60
Beijing	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Chongqing	0.44	0.44	0.46	0.52	0.56	0.58	0.63	0.75	0.78	0.87	1.00	1.00	0.67
Fujian	0.48	0.53	0.63	0.55	0.53	0.58	0.63	0.62	0.63	0.63	0.65	0.67	0.59
Gansu	0.26	0.24	0.30	0.24	0.27	0.38	0.36	0.47	0.47	0.44	0.50	0.45	0.36
Guangdong	0.62	0.64	0.65	0.63	0.66	0.61	0.60	1.00	0.67	0.64	0.65	0.68	0.67
Guangxi	0.33	0.36	0.37	0.41	0.42	0.49	0.56	0.56	0.79	0.75	1.00	1.00	0.59
Guizhou	0.32	0.32	0.31	0.32	0.37	0.38	0.38	0.43	0.44	0.44	0.45	0.43	0.38
Hainan	0.09	0.08	0.10	0.12	0.13	0.19	0.20	0.20	0.21	0.23	0.27	0.24	0.17
Hebei	0.51	0.48	0.52	0.52	0.57	0.63	0.65	0.73	0.80	1.00	0.62	0.64	0.64
Henan	0.47	0.53	0.54	0.62	0.64	0.65	0.74	0.64	0.74	0.64	0.74	0.65	0.64
Heilongjiang	0.44	0.45	0.50	0.49	0.57	1.00	1.00	1.00	1.00	0.69	0.51	0.51	0.68
Hubei	0.46	0.54	0.52	0.62	0.66	0.81	0.90	1.00	1.00	1.00	1.00	1.00	0.79
Hunan	0.49	0.49	0.53	0.55	0.55	0.61	1.00	1.00	1.00	1.00	0.68	0.75	0.72
Jilin	1.00	0.46	0.56	0.54	0.60	0.61	0.70	0.48	0.55	0.60	0.55	1.00	0.64
Jiangsu	1.00	1.00	1.00	1.00	1.00	1.00	0.78	0.81	1.00	1.00	1.00	1.00	0.97
Jiangxi	0.39	0.41	0.45	0.52	0.55	0.61	0.59	0.72	0.74	1.00	0.70	0.74	0.62
Liaoning	0.73	0.69	0.72	0.68	0.74	1.00	1.00	1.00	1.00	0.75	0.53	0.40	0.77
Inner Mongolia	0.35	0.34	0.42	0.36	0.42	0.43	0.46	0.43	0.44	0.38	0.27	0.27	0.38
Ningxia	0.13	0.14	0.14	0.17	0.20	0.24	0.23	0.26	0.24	0.24	0.22	0.20	0.20
Qinghai	0.15	0.15	0.15	0.14	0.18	0.22	0.25	0.22	0.25	0.25	0.23	0.19	0.20
Shandong	0.65	0.59	0.64	0.59	0.59	0.59	0.64	0.56	0.62	0.64	0.63	0.63	0.61
Shanxi	0.52	0.49	0.45	0.47	0.57	0.56	0.53	0.53	0.55	0.51	0.44	0.47	0.51
Shaanxi	0.49	0.51	0.59	1.00	0.66	1.00	1.00	1.00	0.73	0.75	0.65	0.67	0.75
Shanghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Sichuan	0.51	0.52	0.53	0.58	0.62	0.56	0.59	0.67	0.66	0.68	0.69	0.74	0.61
Tianjin	0.65	0.64	0.64	0.59	0.62	0.70	0.79	0.68	0.67	0.69	0.69	0.79	0.68
Xinjiang	0.43	0.36	0.39	0.49	0.54	0.55	0.55	0.59	1.00	0.70	0.66	0.62	0.57
Yunnan	0.39	0.38	0.39	0.41	0.47	0.49	0.57	0.57	0.55	0.51	0.57	0.60	0.49
Zhejiang	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

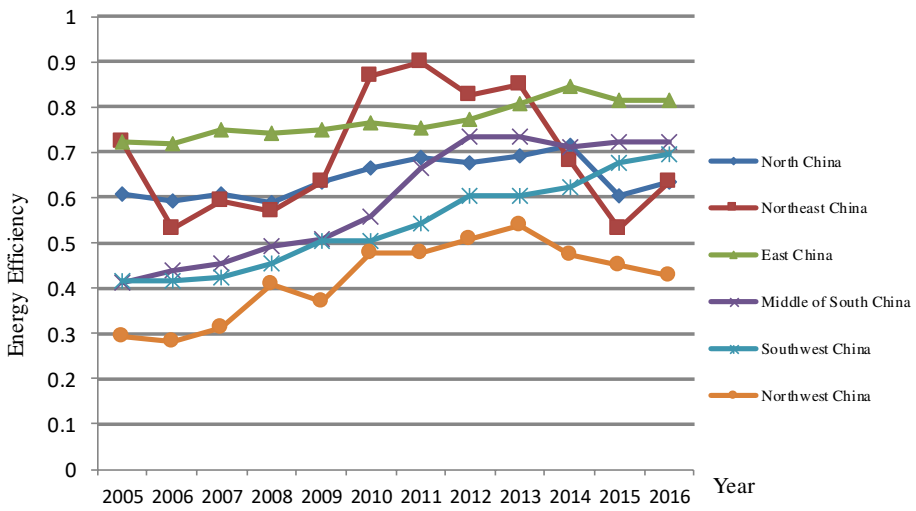

Figure 4: China's regional energy efficiency in construction industry after adjusted from 2005 to 2016

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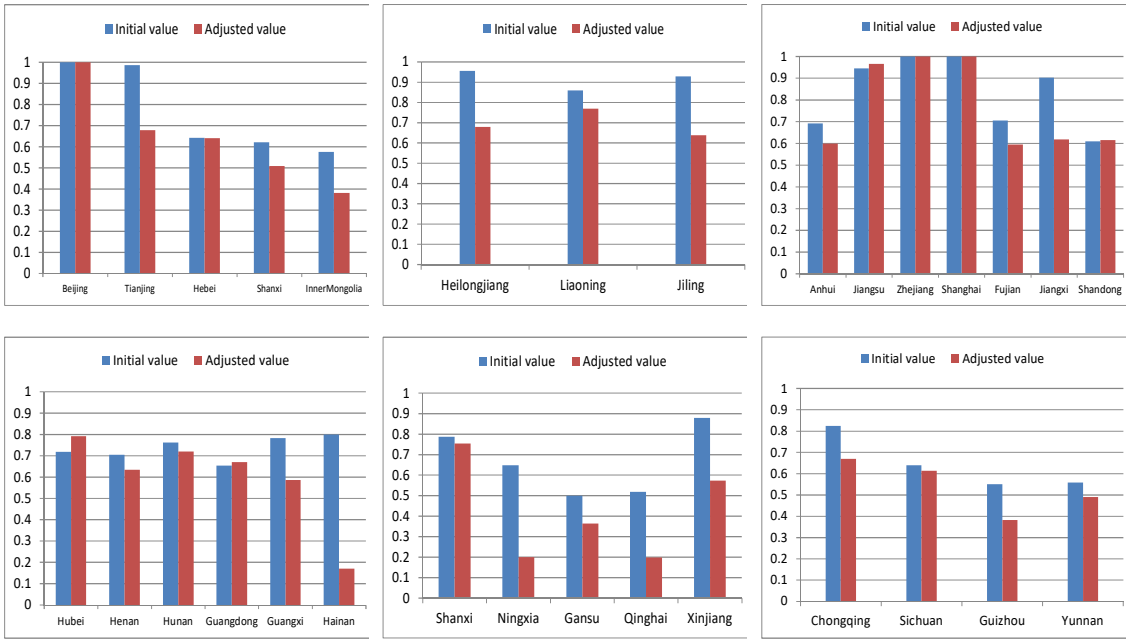

Figure 5: The comparison of China's regional average energy efficiency in construction industry

6. Conclusion and policy implications

This paper employed three-stage undesirable SBM-DEA to evaluate the energy efficiency of construction industry of 30 provinces in China from 2005 to 2016 and discussed the influence of external factors by SFA approach in Stage Ⅱ. Following conclusions could be obtained through the empirical results. Firstly, after the adjustment which let each DMU facing the poorest external factors and random error, the energy efficiency of China's construction industry showed a significant decline, indicating that the low efficiency of management in the construction industry is an important factor leading to the low level of energy efficiency in China's construction industry. Secondly, compared with the "high-high" provinces, which has made full use of the superior external environment by their high management level, the "high-low" provinces needs to fully

realize the potential in promoting energy efficiency of its external environment by improving its own management of construction. On the contrary, the “low-high” provinces need to improve the external environment to ease its restrictions on the level of management in the construction industry. Thirdly, among the external environmental factors, urbanization and human capital have a positive impact on energy efficiency, while government direct investment has a negative impact on energy efficiency. The impact of environmental regulation and industrial structure was uncertain on different provinces due to the substitution of production factors. Environmental regulation does not necessarily improve environmental efficiency and may have a negative impact on the development of the construction industry. Economic development has little impact on energy efficiency in construction industry, possibly because that the energy structure and technological innovation in construction industry are not significantly promoted in the process of economic development in recently years.In response to the above conclusions, some policy applications were proposed. (1) The promotion of the energy efficiency of the construction industry should not only rely on improving the external environment, but also take full account of the internal management level. The potential to improve the energy efficiency rely on improving the management level in Northeast China, while in “low-high” province should shed light on improving external environment. (2) Improving the urbanization level and the technical level of the construction industry will promote the improvement of the energy efficiency of the construction industry. (3) The government should reduce intervention in the construction industry and focus on ensuring fair competition in the market. At the same time, the characteristics of the construction industry should be taken into account when carrying out environmental regulation. (4) In the process of economic development, construction enterprises need to optimize the energy structure and enhance the human capital investment, which will help Chinese construction industry to improve energy efficiency and achieve the goal of energy conservation and emission reduction.

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Authors' contributions:

Yufeng Chen: Conceptualization; Methodology; Software; Writing- Reviewing and Editing.

Lihua Ma: Data curation; Writing- Original draft preparation; Visualization.

Zhitao Zhu: Formal analysis; Writing- Reviewing and Editing.

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Competing interests:
The authors declare that they have no competing interests.

Availability of data and materials:
The datasets analyzed during the current study are available from China National Bureau of Statistics.

References

Acquaye, A. A. & Duffy, A. P.(2010) Input-output analysis of Irish construction sector greenhouse gas emissions. Building and Environment, 45(3), 784-791.

Apergis, N., Aye, G. C., Barros, C. P., Gupta, R., & Wanke, P. (2015). Energy efficiency ofselected OECD countries: A slacks based model with undesirable outputs. Energy Economics, 51, 45–53.

Bi, G.B., Song, W., Zhou, P., Liang, L. (2014). Does environmental regulation affect energy efficiency in china's thermal power generation? Empirical evidence from a slacks- based DEA model. Energy Policy, 66, 537–546.

Chen, Y., Liu, B., Shen, Y., & Wang, X. (2016). The energy efficiency of China’s regional construction industry based on the three-stage DEA model and the DEA-DA model. KSCE Journal of Civil Engineering, 20(1), 34–47.

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.

Cui, Q., & Li, Y. (2015). Evaluating energy efficiency for airlines: An application of VFB-DEA. Journal of Air Transport Management, 44–45, 34–41.

Färe, R., Grosskopf, S., & Logan, J. (1983). The relative efficiency of Illinois electric utilities. Resources and Energy, 5(4), 349–367.

Feng, C., & Wang, M. (2018). Analysis of energy efficiency in China’s transportation sector. Renewable and Sustainable Energy Reviews, 94(June), 565–575.

Fei, R., & Lin, B. (2017). Technology gap and CO2 emission reduction potential by technical efficiency measures: A meta-frontier modeling for the Chinese agricultural sector. Ecological Indicators, 73, 653–661.

Feng, F., Li, Z., Ruan, Y., & Xu, P. (2016). An empirical study of influencing factors on residential building energy consumption in Qingdao City, China. Energy Procedia, 104, 245–250.

Fried, H., Lovell, C., Schmidt, S., & Yaisawarng, S. (2002). Accounting for environmental effects and statistical noise in Data Envelopment Analysis. Journal of Productivity Analysis, 17， 157–174.

Fried, H., Schmidt, S., & Yaisawarng, S. (1999). Incorporating the operating environment into a nonparametric measure of technical efficiency. Journal of Productivity Analysis, 12, 249–267.

Li, K., & Lin, B. (2014). The nonlinear impacts of industrial structure on China’s energy intensity.

Energy, 69, 258–265.
Li, N., Jiang, Y., Yu, Z., & Shang, L. (2017). Analysis of agriculture total-factor energy efficiency in China based on DEA and Malmquist indices. Energy Procedia, 142, 2397–2402.
Lin, J., & Xu, C. (2017). The impact of environmental regulation on total factor energy efficiency: A cross-region analysis in China. Energies, 10(10), 1578.
Lin, B., & Tan, R. (2016). Ecological total-factor energy efficiency of China's energy intensive industries. Ecological Indicators, 70, 480–497.
Liu, Z., Qin, C.-X., & Zhang, Y.-J. (2016). The energy-environment efficiency of road and railway sectors in China: Evidence from the provincial level. Ecological Indicators, 69, 559–570.
Lin, B., & Zhang, G. (2017). Energy efficiency of Chinese service sector and its regional differences. Journal of Cleaner Production, 168, 614–625.
Liu, J., Liu, H., Yao, X.-L., & Liu, Y. (2016). Evaluating the sustainability impact of consolidation policy in China's coal mining industry: a data envelopment analysis. Journal of Cleaner Production, 112, 2969–2976.
Liu, Y., & Wang, K. (2015). Energy efficiency of China's industry sector: An adjusted network DEA (data envelopment analysis)-based decomposition analysis. Energy, 93, 1328–1337.
Lu, Y., Cui, P., & Li, D. (2016). Carbon emissions and policies in China's building and construction industry: Evidence from 1994 to 2012. Building and Environment, 95, 94–103.
Mukherjee, K. (2010). Measuring energy efficiency in the context of an emerging economy: The case of indian manufacturing. European Journal of Operational Research, 201(3), 933–941.
Susaeta, A., Adams, D. C., Carter, D. R., Dwivedi, P., Adams, D. C., & Carter, D. R. (2016). Climate Change and Ecosystem Services Output Efficiency in Southern Loblolly Pine Forests. Environmental Management, 58(3), 417–430.
Sueyoshi, T., Yuan, Y., & Goto, M. (2017). A literature study for DEA applied to energy and environment. Energy Economics, 62, 104–124.
Tone, K. (2001). Theory and Methodology A slacks-based measure of efficiency in data envelopment analysis. European Journal of Operational Research, 130, 498–509.
Tone, K. (2004). Dealing with undesirable outputs in DEA: A Slacks-based Measure (SBM) Approach. North American Productivity Workshop 2004, Toronto, 23-25 June 2004, 44-45.
Ullah, A., & Perret, S. R. (2014). Technical- and Environmental-Efficiency Analysis of Irrigated Cotton-Cropping Systems in Punjab , Pakistan Using Data Envelopment Analysis. Environmental Management, 54(2), 288–300.
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, T. H., Chen, Y. S., Shang, W., & Wu, J. T. (2018). Measuring energy use and CO2 emission performances for APEC economies. Journal of Cleaner Production, 183, 590–601.
Wu, J., Li, M., Zhu, Q., Zhou, Z., & Liang, L. (2019). Energy and environmental efficiency measurement of China's industrial sectors: A DEA model with non-homogeneous inputs and outputs. Energy Economics, 78, 468–480.
Xue, X., Wu, H., Zhang, X., Dai, J., & Su, C. (2015). Measuring energy consumption efficiency of the construction industry: The case of China. Journal of Cleaner Production, 107, 509–515.
Xiong, S., Ma, X., & Ji, J. (2019). The impact of industrial structure efficiency on provincial industrial energy efficiency in China. Journal of Cleaner Production, 215, 952–962.
Yan H，Shen Q，Fan L C H, et al. (2010) Greenhouse gas emissions in building construction：A

case study of One Peking in Hong Kong. Building and Environment, 45(4), 949-955.

Yu, Y., Huang, J., & Zhang, N. (2019). Modeling the eco-efficiency of Chinese prefecture-level cities with regional heterogeneities: A comparative perspective. Ecological Modelling, 402(March), 1–17.

Zhang, C., He, W., Hao, R. (2016) . Analysis of environmental regulation and total factor energy efficiency. Current Science, 110 (10), 1958–1968.

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). Journal of Cleaner Production, 200, 770–780.

Zhang, N., & Choi, Y. (2013). Environmental energy efficiency of China's regional economies: A non-oriented slacks-based measure analysis. Social Science Journal, 50(2), 225–234.

Zhang, N., & Choi, Y. (2013). Total-factor carbon emission performance of fossil fuel power plants in China: A metafrontier non-radial Malmquist index analysis. Energy Economics, 40, 549–559.

Zhang, N., & Choi, Y. (2014). A note on the evolution of directional distance function and its development in energy and environmental studies 1997-2013. Renewable and Sustainable Energy Reviews, 33, 50–59.

Zhang, N., Kong, F., Choi, Y., & Zhou, P. (2014). The effect of size-control policy on unified energy and carbon efficiency for Chinese fossil fuel power plants. Energy Policy, 70, 193–200.

Zhang, N., Kong, F., & Kung, C. C. (2015). On Modeling Environmental Production Characteristics: A Slacks-Based Measure for China's Poyang Lake Ecological Economics Zone. Computational Economics, 46(3), 389–404.

Zhang, N., Kong, F., & Yu, Y. (2015). Measuring ecological total-factor energy efficiency incorporating regional heterogeneities in China. Ecological Indicators, 51, 165–172.

Zhang, Q., & Crooks, R. (2012). Toward an Environmentally Sustainable Future:Country Environmental Analysis of the People's Republic of China. Asian Development Bank,Manila, the Philippines.

Figures

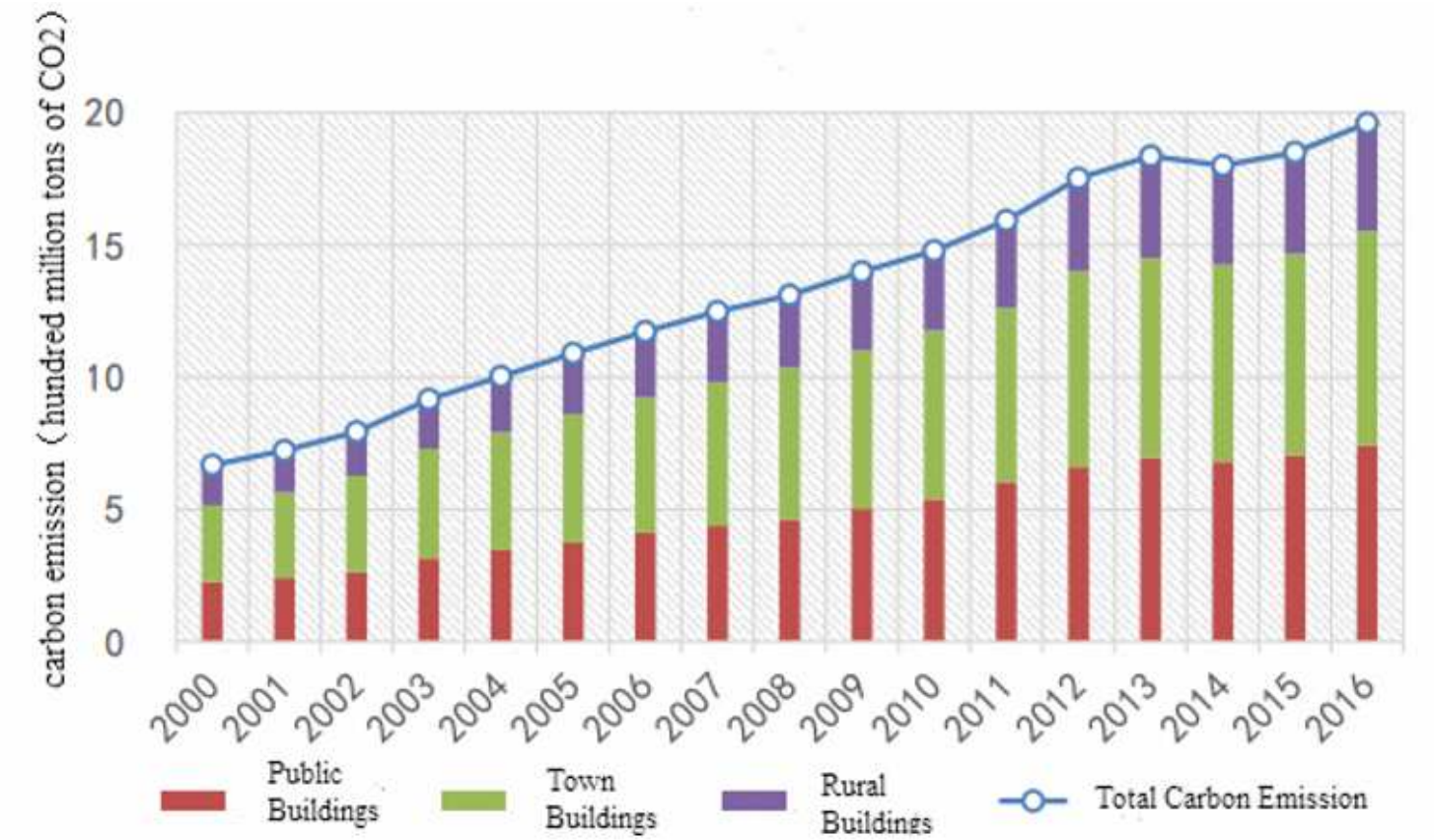

Figure 1

Carbon emission of construction industry during from 2000 to 2016

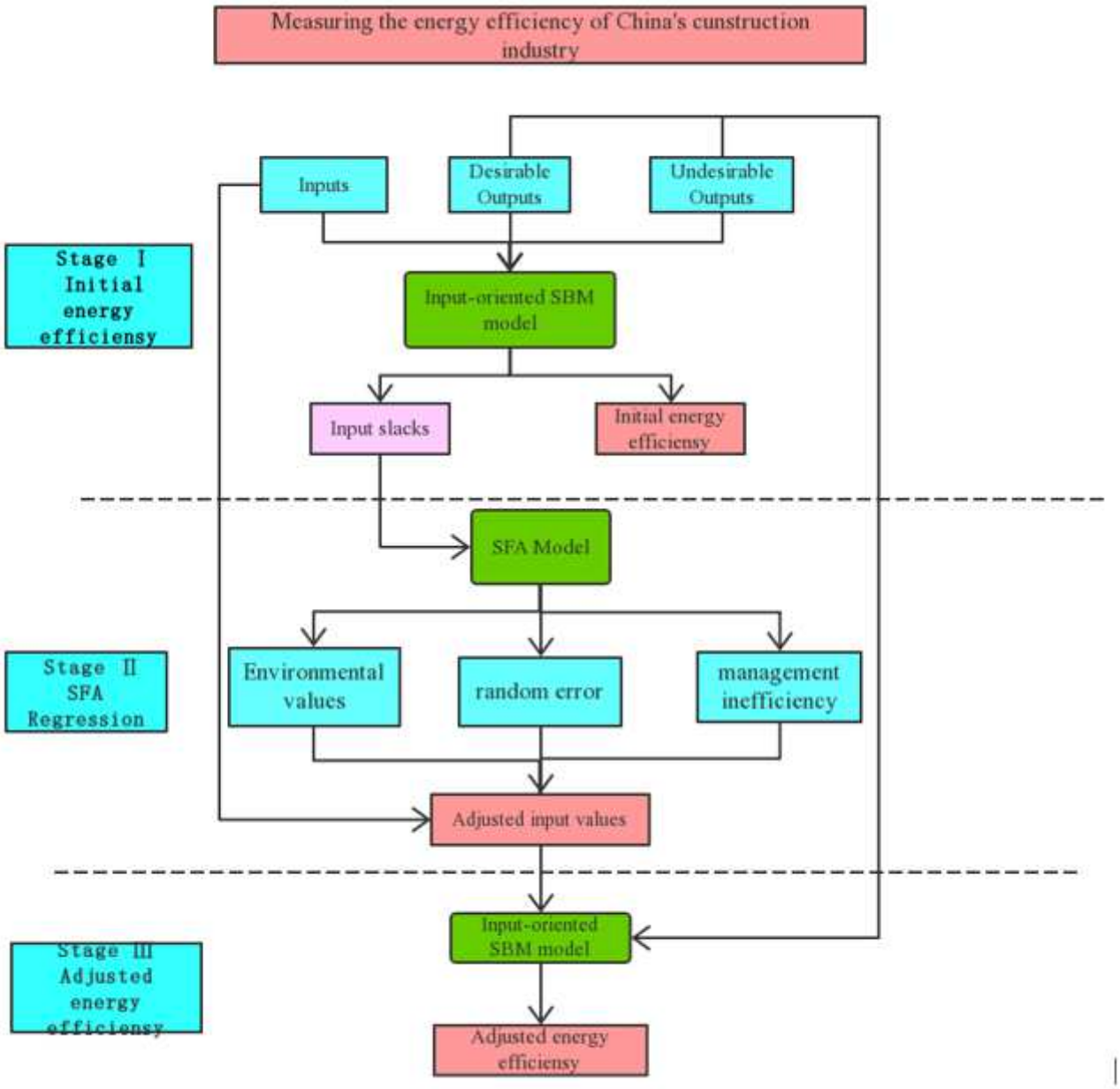

Figure 2

Methodological framework of the three-stage undesirable SBM-DEA model

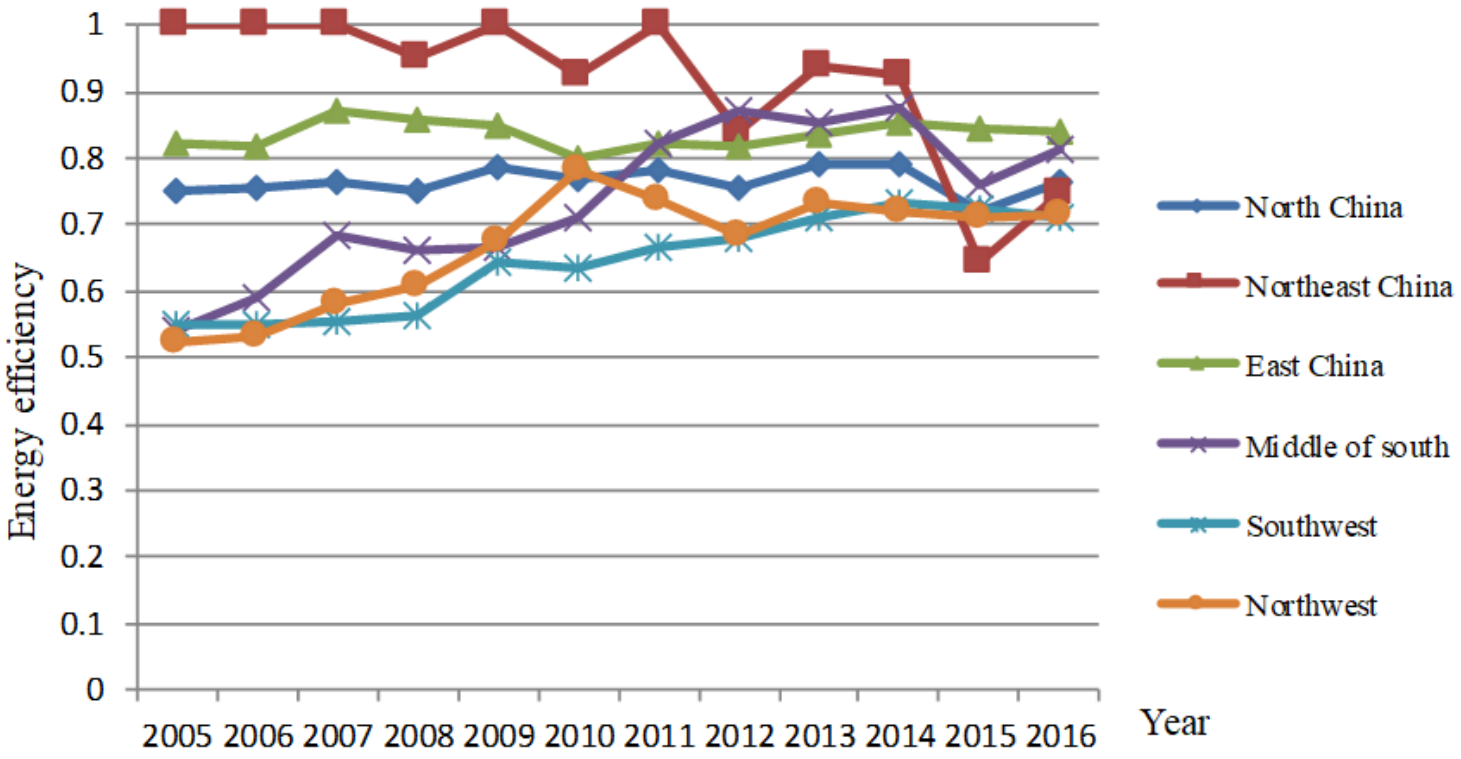

Figure 3

The initial regional energy efficiency in construction industry from 2005 to 2016

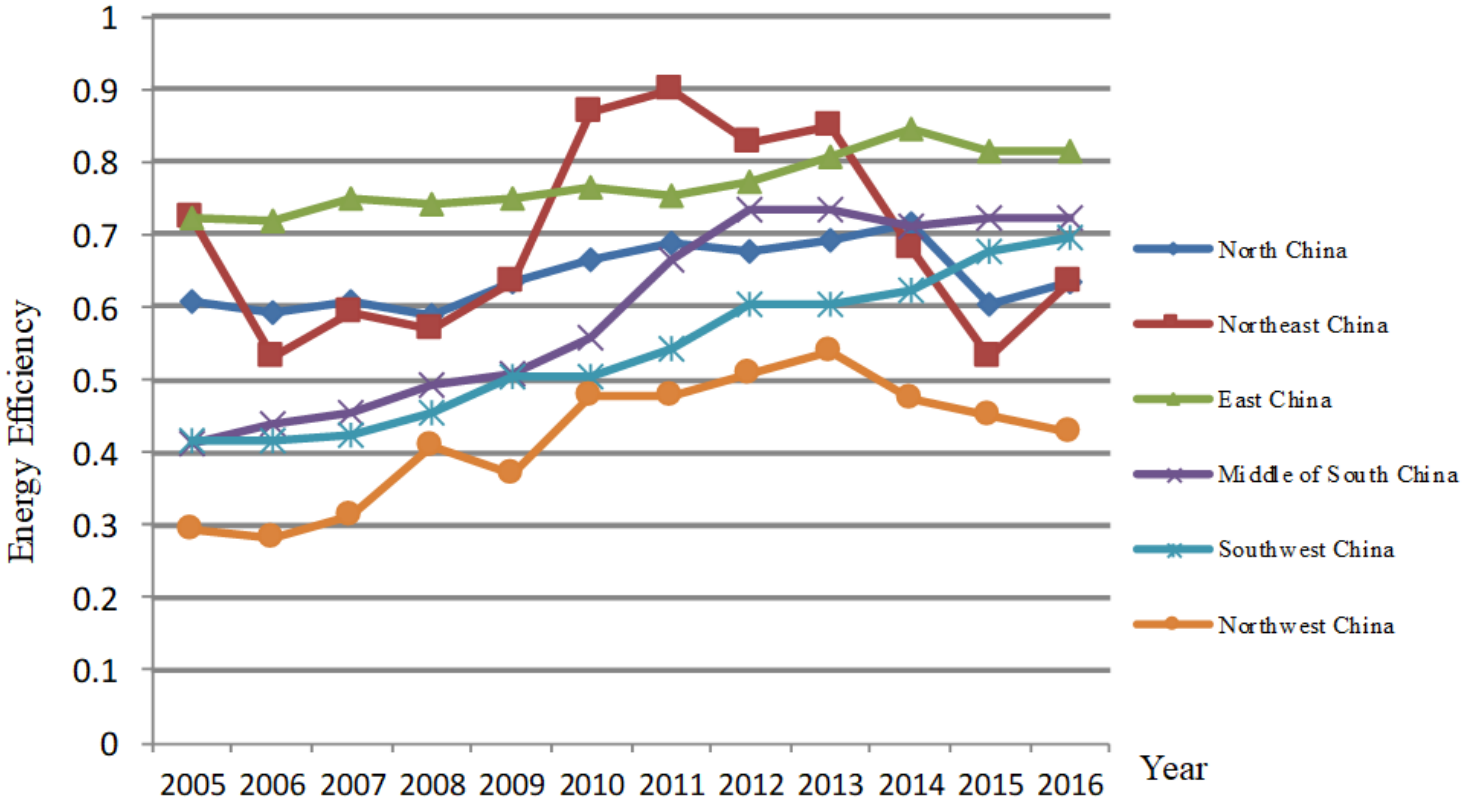

Figure 4

China’s regional energy efficiency in construction industry after adjusted from 2005 to 2016

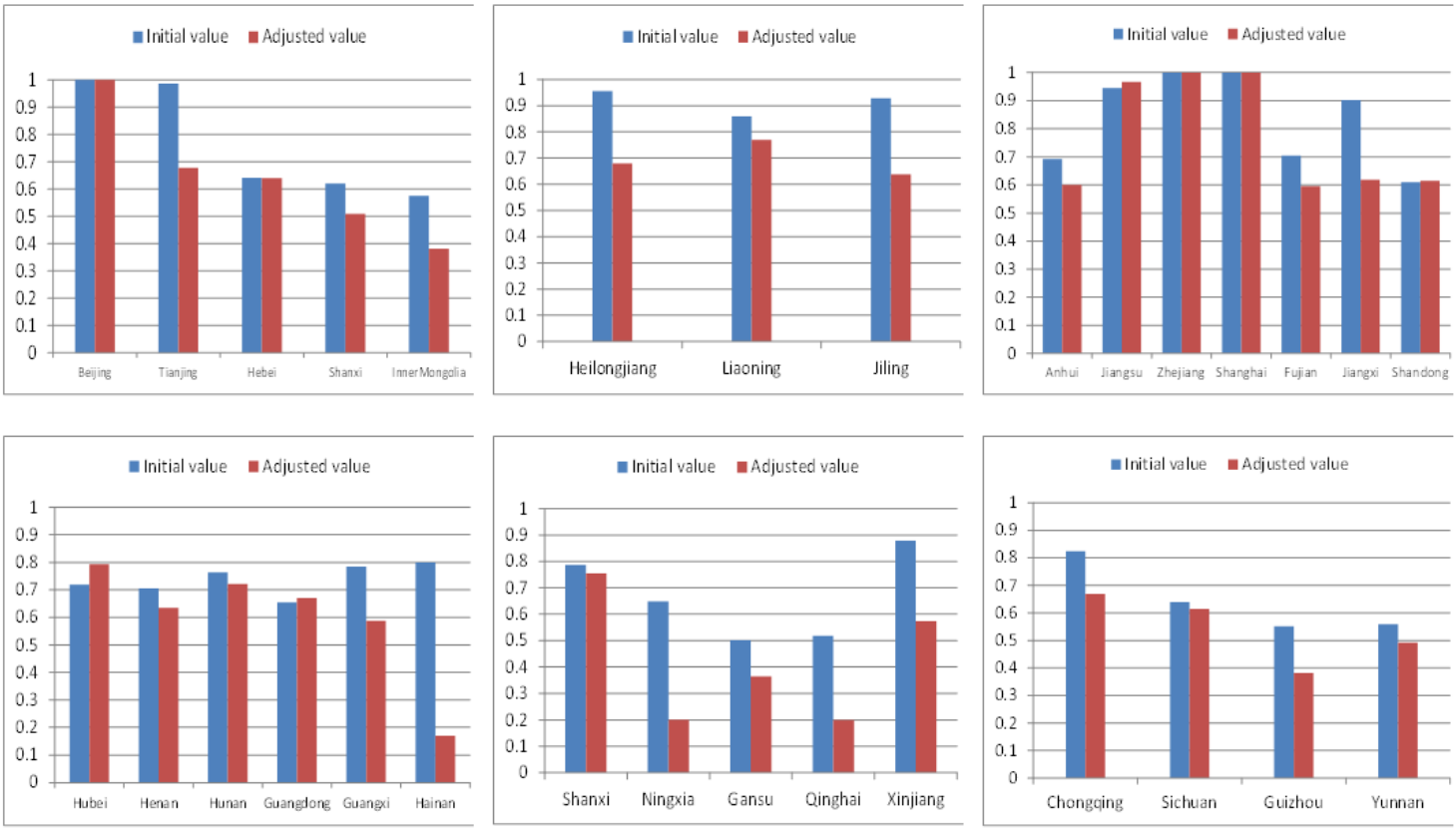

Figure 5

The comparison of China’s regional average energy efficiency in construction industry