Impact of environment regulation on the efficiency of regional construction industry: A 3-stage Data Envelopment Analysis (DEA)

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Impact of Environment Regulation on the Efficiency of Regional Construction Industry: a 3-stage Data Envelopment Analysis (DEA)

Abstract:

Although the impact of environmental regulation on industrial efficiency has been widely investigated in various industries, it remains largely unknown in the construction industry. Using 2011-2015 panel data of 30 provinces and cities in China, this paper aims to reveal whether environmental regulation has an impact on regional construction efficiency. A 3-Stage DEA Model is used to measure the technical efficiency of regional construction industries influenced by environmental regulations. Then Hansen's (Hansen, 1999) threshold regression model is used to analyse the threshold effect of environment regulation on the efficiency of regional construction industry. A single threshold value of 0.014 is identified to be used to group China's 30 provinces into high-regulation and low-regulation regions. The results show that environmental regulation has a significant impact on the efficiency of China's construction industry. Scale efficiency is the most affected. The technical efficiency of highly regulated provinces is less affected by environmental regulations. The findings provide a reference frame and analytical method for the analysis of construction efficiency of other developing countries, and provide practical implications for the implementation of environmental regulation policies and future policy formulation.

Key words: Environmental regulation, Construction Industry, Efficiency Measurement, 3-stage DEA

1 Introduction

The Chinese construction industry consumes half the global amount of construction cement and steel, and is responsible for approximately 30% of China's total energy use (China, 2014, 2015; China 2014). At the same time, China has promised to the world to reduce its carbon dioxide (CO_2) emissions by 45% by 2050 and therefore its pursuit of a low-carbon and high efficient construction industry is imminent. Environmental regulation is playing an important role in helping to achieve the goal, as it is extremely difficult to solve the increasingly harsh environmental problems by relying solely on the free market mechanism.

Environmental regulation provides an important means of policy control for dealing with climate change, ensuring energy security, and creating a resource saving and environmentally friendly society (Afsah, 2013; Goodstein, 2011; Hussen, 2012). It controls and regulates economic activities and their environmental pollution, promoting the environment and sustainable economic development. Moreover, it is also claimed that reasonable environmental regulations provide "innovation compensation" to the regulated entities involved (Porter, 2004; Porter and Montgomery, 1991; Porter and Nathan/Tyler Productions, 1988) and act as a suitable means of improving the industry's efficiency and low-carbon development (Li and Wei, 2014; Spigarelli et al.; Tang et al., 2016; Wang, 2016; Zhang et al., 2017). Empirical research aimed at understanding the impact of environmental regulation on industrial efficiency has gained popularity

(Busch and Shrivastava, 2011; Fontana et al., 2015; Lewis, 2013; Wang, 2014). However, only very limited studies have paid attention to the construction industry and few have focused on the industry in China.

In China, given the increasing importance of the industry in contributing to low-carbon development, a number of Chinese scholars have begun to examine the impact of environmental regulation on the efficiency of the industry (Ren and Li, 2016; Wang et al., 2011; Zhu, 2013). However, previous studies have a number of limitations. First, all the data used was collected before 2013, which does not reflect the current rapid development of regional environment regulations. In addition, each study used different input and output variables for measuring efficiency, which makes cross comparison of research findings very difficult. Similarly, no consensus has been reached on the measurement of environmental regulation. As a result, there is no clear answer yet to whether environmental regulation has any effect on the efficiency of the industry in China.

In response, this paper examines the effect of environmental regulation policy on regional construction efficiency using the three-stage Data Envelopment Analysis (DEA) method, as this provides a better means of evaluating the efficiency of decision-making units (Lovell et al., 2002). The remainder of the paper proceeds as follows. Section 2 provides a brief literature review of environmental regulation, the concepts and measurement involved, and its relationship with construction efficiency. The research method, data sources, and indicators are then described in Section 3, followed by the 3-stage DEA efficiency analysis in Section 4, and a comparison of the regional effect of high and low environmental regulations on efficiency in Section 5. A discussion of the main findings and concluding remarks are provided in Sections 6 and 7 respectively.

2. Materials and method

2.1 3-stage DEA

A 3-stage DEA model is adopted to evaluate the efficiency of the industry under environmental regulation. Compared with the traditional DEA model (Hokey et al., 2008; Masternak-Janus and Rybaczewska-Blazejowska, 2017), this can analyse the relationship between the input difference value and exogenous environment variables in Stage 1 using the stochastic frontier model. It not only effectively divests the environmental factors and impact of random errors, but can also reflect the real efficiency of the decision-making unit value (Cook and Zhu, 2005; Narasimhan et al., 2004; Shinn, 2004).

The 3-stage DEA model proposed by Fried et al. (1996) has been greatly improved with DEA technology (Färe et al., 1996). Its construction and applications comprise three stages.

Stage 1: The SBM-undesirable model

Compared with traditional production functions, environmental production functions must take into account environmental factors. Producing expected outputs requires the production of undesired outputs. Therefore, it is necessary to construct an environmental production function that contains both expected and undesired outputs.

Before proceeding, some notation must be introduced. Inputs are denoted by $x = (x_1, \dots, x_N) \in R_N^+$, expected outputs by $y = (y_1, \dots, y_N) \in R_M^+$ and undesirable outputs by $b = (b_1, \dots, b_J) \in R_J^+$. We define the outputs sets as

$$P(x) = \{(y, b): x\ can\ produce\ (y, b)\},\ x \in R_N^+,\ y \in R_M^+,\ b \in R_J^+ \tag{4}$$

In words, for each input vector x, the output set $\mathrm{P(x)}$ consists of the combinations of expected and undesired outputs $\mathrm{(y, b)}$ that can be produced by that vector. To reflect the real production conditions better, Faere et al (Faere et al., 1989) propose a method called "environment technology". This method incorporates weak disposability of outputs and null-jointness.

Based on the study of Faere et al (Faere et al., 1989), Tone et al (Tone, 2004) proposed the SBM-undesirable model. Compared with the traditional SBM model (Tone, 2001), this improved model effectively solves the defect that the slack of input factors and output factors has zero, and takes undesired output into account. The efficiency value measured by this method is more in line with the actual production conditions. Therefore, the SBM-undesirable model is widely used to measure the efficiency value of considering undesired outputs. Lozano et al (Lozano and Gutiérrez, 2011) used the SBM-undesirable model to measure efficiency of 39 Spanish airports for years 2006 and 2007, finding that the SBM model used has more discriminatory power than the common directional distance function approach. Chang et al (Chang et al., 2013) measure energy efficiency in China's regional economies between 2001 and 2010 with this method, finding that undesirable outputs had a significant effect on energy efficiency measurements. Song et al (Song et al., 2015) carried out a systematic analysis of integrated transportation efficiency in China from 1979 to 2012 based on the temporal evolution by introducing the SBM- undesirable model.

In stage 1, we used the SBM-undesirable model to measure the technical efficiency of the construction industry in 30 provinces in China from 2011 to 2015. Suppose there are *n* DMUs (decision-making units) each having three factors: inputs, expected outputs and undesired outputs, as represented by three vectors $\mathrm{x} \in R^m$, $\mathrm{y}^g \in R^{s1}$ and $\mathrm{y}^b \in R^{s2}$, respectively. We define the matrices X, $\mathrm{Y^g}$ and $\mathrm{Y^b}$ as follows. $X = [x_1, \dots, x_n] \in R^{m \times n}$, $Y^g = [y^{g1}, \dots, y^{gn}] \in R^{s1 \times n}$, and $Y^b = [y^{b1}, \dots, y^{bn}] \in R^{s2 \times n}$. We assume $X > 0$, $Y^g > 0$ and $Y^b > 0$. The production possibility set $\mathrm{(P)}$ is defined by

$$P = \left\{\left(x, y^g, y^b\right) \middle| x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \lambda \geq 0\right\} \tag{5}$$

Refer to the study of Tone et al (Tone, 2004), we modify the SBM-undesirable model as follows.

$$\rho^* = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s1}\frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s2}\frac{s_r^b}{y_{r0}^b}\right)} \tag{6}$$

Subject to

$$x_0 = X\lambda + s^- \tag{7}$$

$$y_0^g = Y^g\lambda - s^g \tag{8}$$

$$y_0^b = Y^b\lambda + s^b \tag{9}$$

$$s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0. \tag{10}$$

In the model, s represents the slack of inputs and outputs; λ represents a weight vector. The objective function strictly decreases with respect to s^-、s^g、s^b and the objective value satisfies $0 \leq \rho^* \leq 1$. The DMU_0 is efficient in the presence of undesirable outputs *if* $\rho^* = 1$, i.e., $s^- = 0$, $s^g = 0$, $s^b = 0$.

Stage 2: Stochastic Frontier Analysis

The flaw of the Stage 1 DEA model is that it cannot separate the effects of external environmental factors, stochastic errors, and internal management factors on efficiency values, so the resulting efficiency estimates cannot accurately reflect the inefficiencies caused by internal management or external environmental factors and random errors. It is therefore necessary to divest the external environmental factors and random interference errors on the efficiency of the estimated value of the impact. Timmer and Los (2005) originally proposed the Stochastic Frontier Analysis (SFA) method for this (Timmer and Los, 2005). Let the *n*-th input value of the *i*-th decision-making unit (DMU) be x_{ni}, the slack variables, s_{ni}, are then

$$s_{ni} = x_{ni} \, , \, x_n\lambda > 0 \tag{11}$$

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

$$s_{ni} = f\left(Z_i \, , \, \beta^n\right) + V_{ni} + U_{ni} \tag{12}$$

$$\mathrm{n} = 1,2, \dots, \mathrm{N}; \mathrm{i} = 1,2, \dots, \mathrm{I}.(13)$$

where s_{ni} is the slack variable for the *n*-th input of the *i*-th decision-making unit, $f(Z_i, \beta^n)$ represents the effect of the environment variable on the slack variable. Let $f(Z_i, \beta^n) = Z_i\beta^n$ and $V_{ni} + U_{ni}$be the mixed error term.

Considering the investment cannot be negative, the regression result of the SFA model is used to adjust the DMU inputs. That is, to increase investment of the DMU in a better external environment, thereby stripping the environmental factors and the impact of random factors, with

$$x_{ni}^* = x_{ni} + \left[\max_i\{Z_i\beta^n\} - Z_i\beta^n\right] + \left[\max_i\{V_{ni}\} - V_{ni}\right] \tag{14}$$

$$\mathrm{n} = 1,2, \dots, \mathrm{N}; \mathrm{i} = 1,2, \dots, \mathrm{I}.(15)$$

where $x_{ni}^*$is the adjusted input amount, and $x_{ni}$is the input value from Stage 1.

Stage 3: The adjusted DEA model

In Stage 3, the adjusted input data and original output data obtained in Stage 2 are brought into the SBM-undesirable model again, and the efficiency values of each decision-making unit are calculated. The resulting pure technical efficiency value, based on the level of management, is free of environmental factors and stochastic factors.

2.2. Data sources and indicators

2.2.1 Data sources

The data used is mainly derived from the *China Statistical Yearbook* (2011-2015) (NBS, 2011-2015), *China Energy Statistical Yearbook* (2011-2015) (NBSMEP, 2011-2015), *China Architecture Statistical Yearbook* (2011-2015) (NBS, 2011-2015), and China provinces and autonomous regions' related statistical yearbooks. Other data are obtained through the website query http://cyfd.cnki.com.cn/. The Tibet Autonomous Region is excluded due to the lack of availability and integrity of data.

2.2.2 Input variables

The input indicators mainly cover the three aspects of manpower, material, and financial resources, comprising the Input of Energy Factors, Number of Engaged Persons, Total Wages of Construction Workers, Total Assets of the Construction Industry, and Total Power of Machinery and Equipment Owned. To take into account environmental factors, Capital, Labour, Technology Equipment, and Total Energy Consumption are used as input efficiency variables. In terms of capital investment variables, the general selection of the provinces[1]nationwide is the Total Assets of the Construction Industry, as this measures the material wealth of the current year and to some extent represents the material basis for the next year. Manpower is usually measured by the effective working hours of the practitioners involved, but there is no data for the average number of working hours of the construction industry in China. Instead, the Number of Engaged Persons in the Construction Industry is used to measure labour input. In terms of technical equipment, the difference in the quantity of raw materials is largely determined by the industry's machinery and equipment, and which largely reflects technical progress. Therefore, Total Power of Machinery and Equipment Owned is used to express technical equipment investment. In terms of environmental impact under the constraints of limited resources, combined with the industry's high-energy consumption, the Energy Consumption of the Construction Industry is used as an input measure as, under environmental regulation, the industry's economic growth should also control energy consumption.

2.2.3 Output variables

Potential output variables include Engineering Settlement Profits, Floor Space of Buildings under Construction, Gross Output Value of Construction and Total Profits of the Construction Industry. Of these, it is clear that "Total Profits of the Construction Industry" reflects the efficiency of the industry better than "Engineering Settlement Profits", while "Gross Output Value of Construction" not only considers total floor space but also the price of buildings under construction. "Total Profits of the Construction Industry" and "Gross Output Value of Construction" are therefore used as output variables, while CO_2 emissions (as an unpaid environmental cost) is used as an undesirable output.

2.2.4 The measurement of carbon dioxide

In the actual production process, after the input of a certain number of factors of production, the main output produced is called the expected output (good output), such as the "Total Profits of the Construction Industry" and "Gross Output Value of Construction". However, this also inevitably produces some pollution, known as undesirable output (bad output). The undesirable output in this study is the amount of CO_2 emitted, because CO_2 is the most important undesirable output and the world's most serious environmental pollutant. Because there is no official public record of CO_2 emissions in China, the official method in the 2006 United Nations Intergovernmental Panel on Climate Change (IPCC) *Guidelines for National Greenhouse Gas Inventories*

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[1] The term 'provinces' is used throughout to denote China's 30 provinces/metropolitan cities

is used to calculate the amount of CO_2 emissions from the industry's energy consumption (Böhringer et al., 2003; Cormos et al., 2014). The basic formula is

$$CO_2 = \sum_{i=1}^{n} Ei \times NCVi \times CEFi \times COFi \times \left(\frac{44}{12}\right) \tag{16}$$

where *Ei* represents the terminal consumption of the *i*-th energy, *NCVi* represents the average low calorific value of the *i*-th energy (Böhringer et al., 2003; Cormos et al., 2014), *CEFi* is the CO_2 emission factor, *COFi* is the carbon oxidation rate, and 44/12 is the carbon conversion coefficient.

This method of estimating CO_2 emissions has been recognised and widely used by international academia. Zhang, Yu and Guo (2010) combine the relevant calculation rules in China to obtain the amount of CO_2 emissions for each energy source, as shown in Table 1 (Zhang et al., 2010).

Table 1

Conversion table for various types of energy and CO2 emissions.

Energy	Heat value (kj/kg)	Carbon emission factor (kg/106 kj)	Carbon oxidation rate	Conversion factor	CO_2 emissions (kg)
Coal (1 kg)	20908	25.8	0.91	44/12	1.800
Coke (1 kg)	28435	29.2	0.928	44/12	2.285
Crude Oil (1 kg)	41816	20.0	0.979	44/12	3.002
Gasoline (1 kg)	43070	18.9	0.980	44/12	2.956
Kerosene (1 kg)	43070	19.6	0.986	44/12	3.052
Diesel Oil (1 kg)	43070	20.2	0.982	44/12	3.102
Fuel Oil (1 kg)	41816	21.1	0.985	44/12	3.187
Natural Gas (1 m^3)	38931	15.3	0.990	44/12	2.162
Liquefied petroleum gas (1 kg)	50179	17.2	0.980	44/12	3.101

Source: Zhang et al. (2010)

3. Results

3.1 Stage 1 - Using the SBM-undesirable model to calculate the results

This stage uses the SBM-undesirable model in the *MaxDEA6.18* software to measure the 2011-2015 technical efficiency of China's construction industry, and obtain the technical efficiency, pure technical efficiency, and scale efficiency of each province. Fig. 1 shows the trend, ignoring the effects of random factors and external environmental variables. The mean values for technical efficiency, pure technical efficiency and scale efficiency are 0.735, 0.784, and 0.938 respectively, indicating that, in general, technical inefficiency was more affected by pure technical efficiency, the impact of scale efficiency being relatively small. As shown in Fig. 1, without considering environmental factors, technical efficiency and pure technical efficiency generally gradually decreased after 2013, indicating that the application of technology was deteriorating. Scale efficiency was generally stable, with a value fluctuating at around 0.95. The main constraint on the reduction of CO_2 emissions most provinces is their relatively low technical efficiency due to a lack of resources.

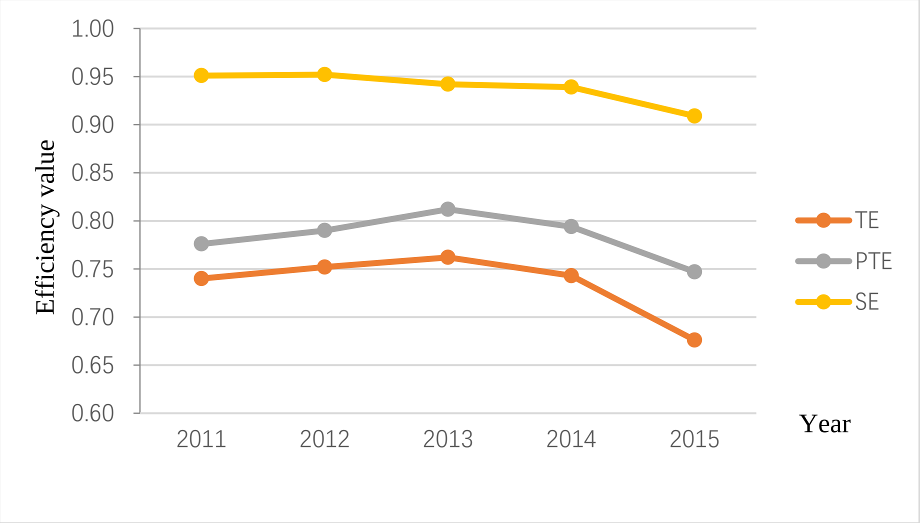


Fig. 1. 2011-2015 national construction industry Stage 1 efficiency

3.2 Stage 2 - Analysis of SFA model results

In this stage, the slack of each input variable in the DMU from Stage 1 is taken as the explained variable, with the degree of marketization, per capita GDP and Environmental Regulation as explanatory environmental variables. Frontier 4.1 is used to carry out the SFA model analysis (Table 2). The regression results show that the regression coefficients of the environmental variables with the four input slack variables, with such external environmental factors as environmental regulation having an obvious impact and a significant σ_2 for each year. γ is also significant, indicating that the management of non-efficiency factors accounted for a large proportion of the total variance.

In Table 2, a negative regression coefficient of the environment variable indicates that an increase of the environment variable is associated with a reduction of the slack variable, with smaller slack variables being associated with less waste of resources and higher relative efficiency. A positive coefficient indicates that the input slack variable increases with increases in the external environment variable; i.e., increasing the value of the external environment variable results in reduced output of the input variable.

Table 2
Stage 2 SFA model results.

	Number of employed persons		Total assets of the construction industry		Total power of machinery and equipment owned		Total energy consumption	
	Coefficient value	T value	Coefficient value	T value	Coefficient value	T value	Coefficien t value	T value
Constant term	-70.266*	-3.260	-33.591	-0.190	-176.267	-1.020	-51.957	-0.811
Marketizatio n degree	5.130	0.239	-15.809	-0.068	237.440	1.070	22.228	0.288

Per capita GDP	0.000	0.332	0.000	--0.689	0.000	-0.465	0.000	-0.227
Environmental regulation intensity	205.237	0.693	191.669*	11.708	-2789.374*	-132.756	1319.630	1.030
σ2	3210.179*	2.663	137151.950*	105642.400	125991.470*	107953.330	25071.392*	175.358
γ	0.954*	45.613	0.506*	8.381	0.618*	12.994	0.821*	36.669
Log likelihood function	-638.229		-1062.162		-1040.345		-872.072	
LR	27.916		22.352		35.942		93.007	

Note: The T value is an index of whether the explanatory variable has a significant effect on the explained variable, * represents a 1% significance.

(1) Marketization Degree

This variable is negatively correlated with the Total Assets of Construction Industry slack variables, and positively correlated with the Number of Employed Persons in the Construction Industry, the Energy Consumption of the Construction Industry and the Total Power of Machinery and Equipment Owned slack variables. Therefore, higher market levels of the industry are associated with higher utilisation rate of funds and energy. This can be explained as the higher the market level of the provinces, the greater the input, inevitably leading to redundancy; and that construction enterprises involved in the fierce competition of the market must improve their own efficiency.

(2) Per Capita GDP

This indicator represents the level of economic development in a region. It is generally believed that the development of the regional economy may drive the development of various industries including the construction industry and promote the improvement of its technical efficiency. Contrary to the expected result, the regression coefficients of this variable and the four input variables are close to zero, indicating that the change in per capita GDP has little effect on the slack of the four input variables. This showed that the increase in per capita GDP did not significantly improve the relative efficiency of each DMU.

(3) Environmental Regulation Intensity

Environmental Regulation Intensity represents the government's intensity of control of the environment. This variable is negatively correlated with the Total Power of Machinery and Equipment Owned and positive correlated with Number of Employed Persons in the Construction Industry, the Total Assets of Construction Industry, and Energy Consumption of the Construction Industry slack variables. This is in line with expectations in that industry productivity reduces with increased government regulation of the environment.

3.3 Stage 3 - Adjusted DEA empirical analysis

The input-output data in Stage 1 can be adjusted according to the results of the SFA model regression to provide new input-output data to Stage 3 for the *MaxDEA6.18* calculation. The average TE, PTE, and SE efficiencies are 0.607, 0.875, and 0.688

respectively. As can be seen from Fig. 2, in the case of environmental factors, the efficiency values have similar trends. During 2011-2013, there was a slow increase in technical efficiency and pure technical efficiency, and the scale efficiency fluctuated within a small range. During 2014-2015, all efficiency values dropped significantly. Pure technology efficiency is higher than scale efficiency and technical efficiency. Relatively low technology efficiency is the main factor associated with performance improvement.

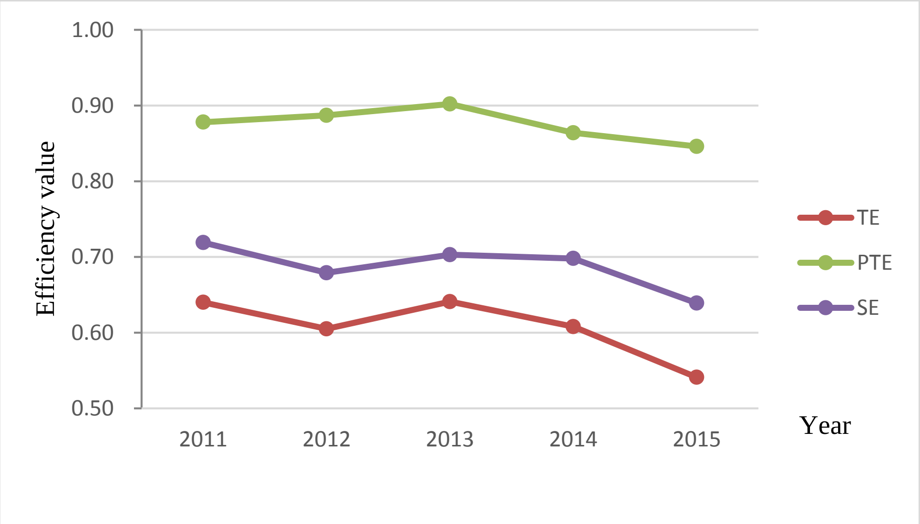
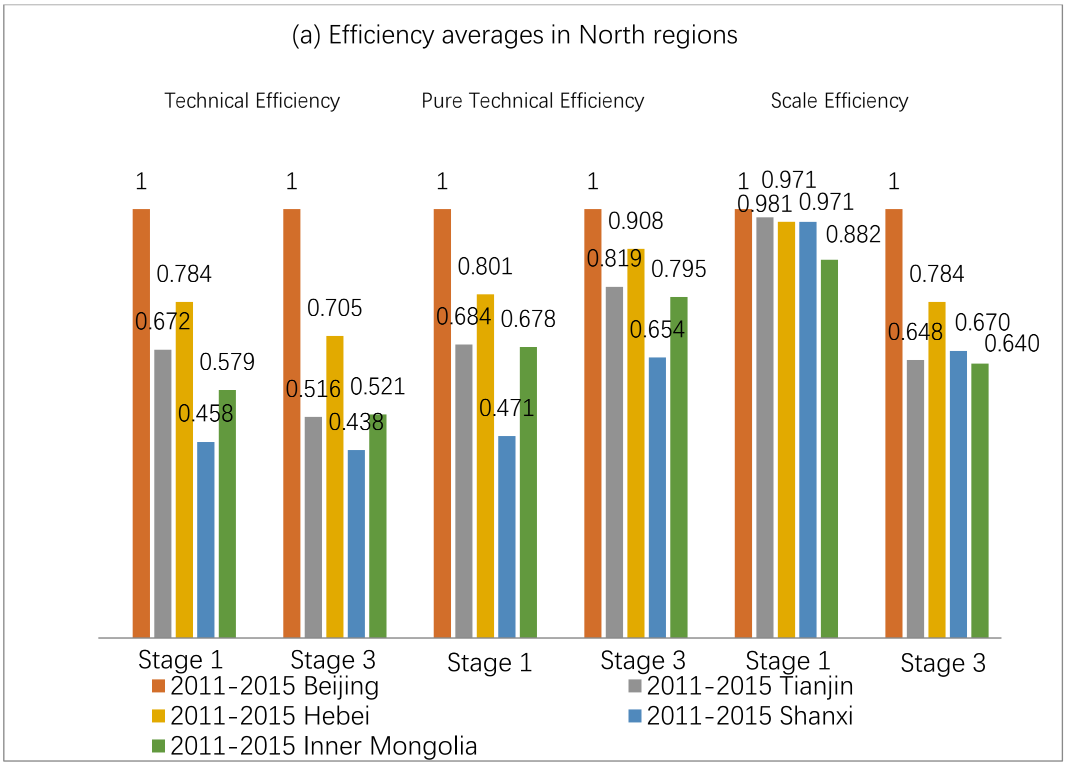


Fig. 2. 2011-2015 national construction industry Stage 3 efficiency measurement

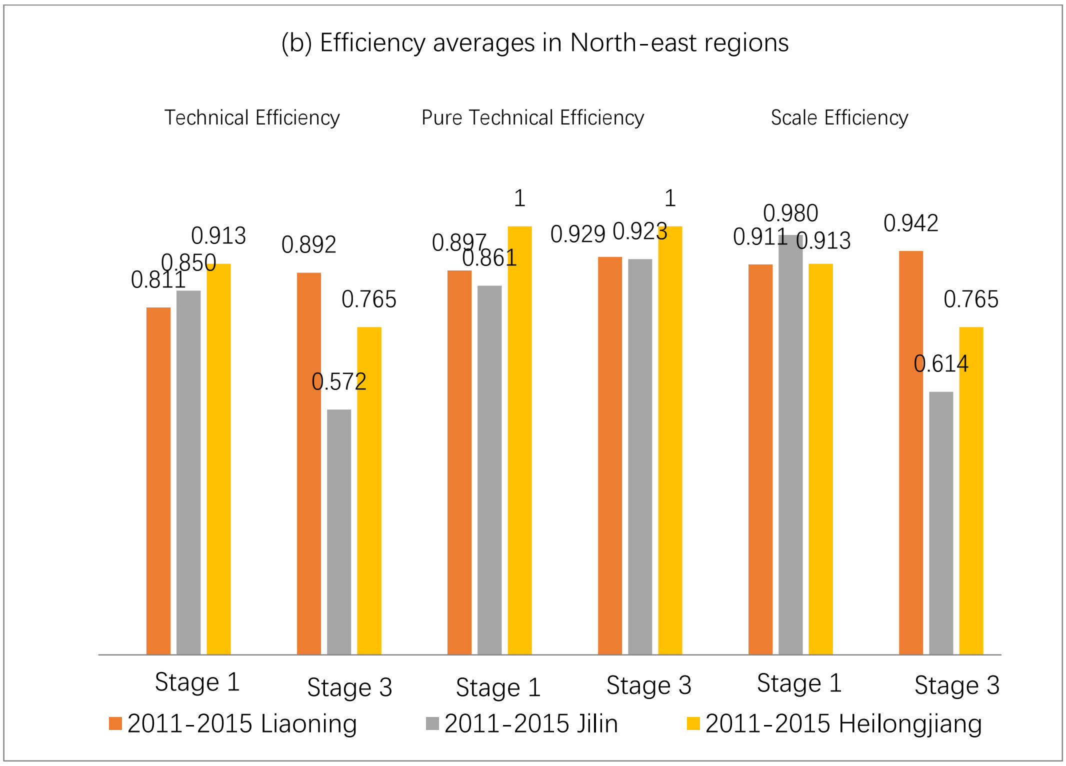
The national average technical efficiency value falls from 0.735 in Stage 1 to 0.607 in Stage 3 - a decrease of 0.128. Pure technical efficiency rose from 0.784 in Stage 1 to 0.875 in Stage 3 - an increase of 0.091, but scale efficiency falls sharply, from 0.938 in Stage 1 to 0.688 in Stage 3 – a decrease of 0.25. This shows that environmental variables have a significant impact on the technical efficiency of the construction industry, especially on scale efficiency.

3.4 Comparison of regional efficiencies

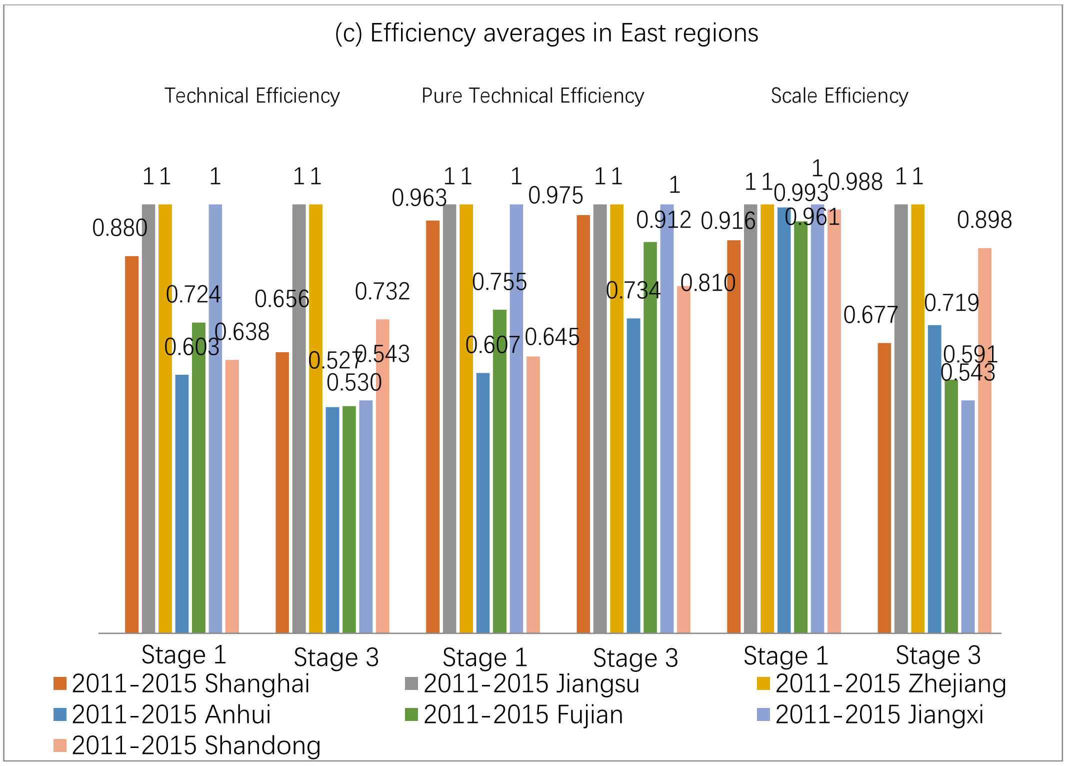
In order to facilitate comparison, the 30 provinces are grouped into north, northeast, east, south-central, southwest, and northwest China regions. North China comprises Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia; northeast is Liaoning, Jilin, and Heilongjiang; east is Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Anhui, and Jiangxi; south-central is Henan, Hubei, Hunan, Guangdong, Guangxi, and Hainan; southwest is Chongqing, Sichuan, Guizhou, and Yunnan; and northwest is Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The average of technical efficiency, pure technical efficiency and scale efficiency in each region from 2011 to 2015 is summarised in Fig. 3. Almost all provinces have a higher technical efficiency in stage 1 than stage 3 except Liaoning, Shandong, and Hubei, showing that technical efficiency is overestimated. In addition, all provinces have a higher pure technical efficiency in stage 3, which indicates that environmental factors do have a positive impact on the development of technological innovation. Scale efficiency is more affected than technical efficiency and pure technical efficiency.


(a) Efficiency averages in North regions
Technical Efficiency
Pure Technical Efficiency
Scale Efficiency
1
0.672
0.784
0.458
0.579
1
0.516
0.705
0.438
0.521
1
0.684
0.801
0.471
0.678
1
0.819
0.908
0.654
0.795
1
0.981
0.971
0.971
0.882
1
0.648
0.784
0.670
0.640
Stage 1
Stage 3
Stage 1
Stage 3
Stage 1
Stage 3
2011-2015 Beijing
2011-2015 Tianjin
2011-2015 Hebei
2011-2015 Shanxi
2011-2015 Inner Mongolia

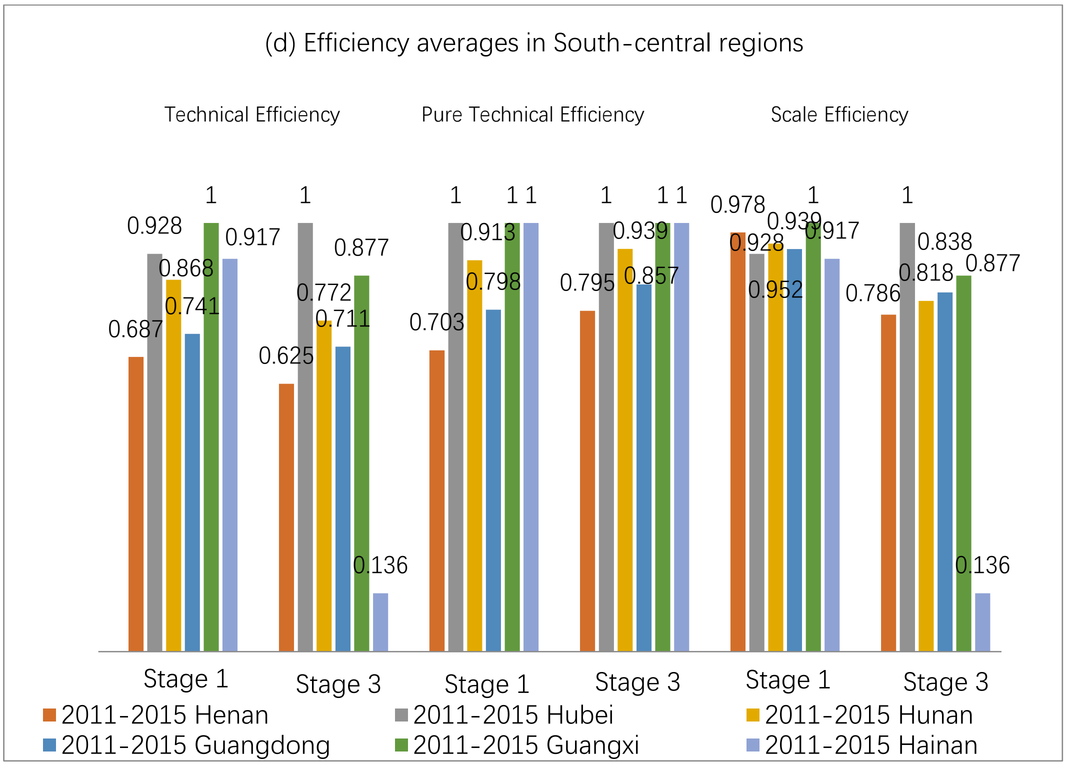
(a)


(b) Efficiency averages in North-east regions
Technical Efficiency
Pure Technical Efficiency
Scale Efficiency
0.811
0.850
0.913
0.892
0.572
0.765
0.897
0.861
1
0.929
0.923
1
0.911
0.980
0.913
0.942
0.614
0.765
Stage 1
Stage 3
Stage 1
Stage 3
Stage 1
Stage 3
2011-2015 Liaoning
2011-2015 Jilin
2011-2015 Heilongjiang

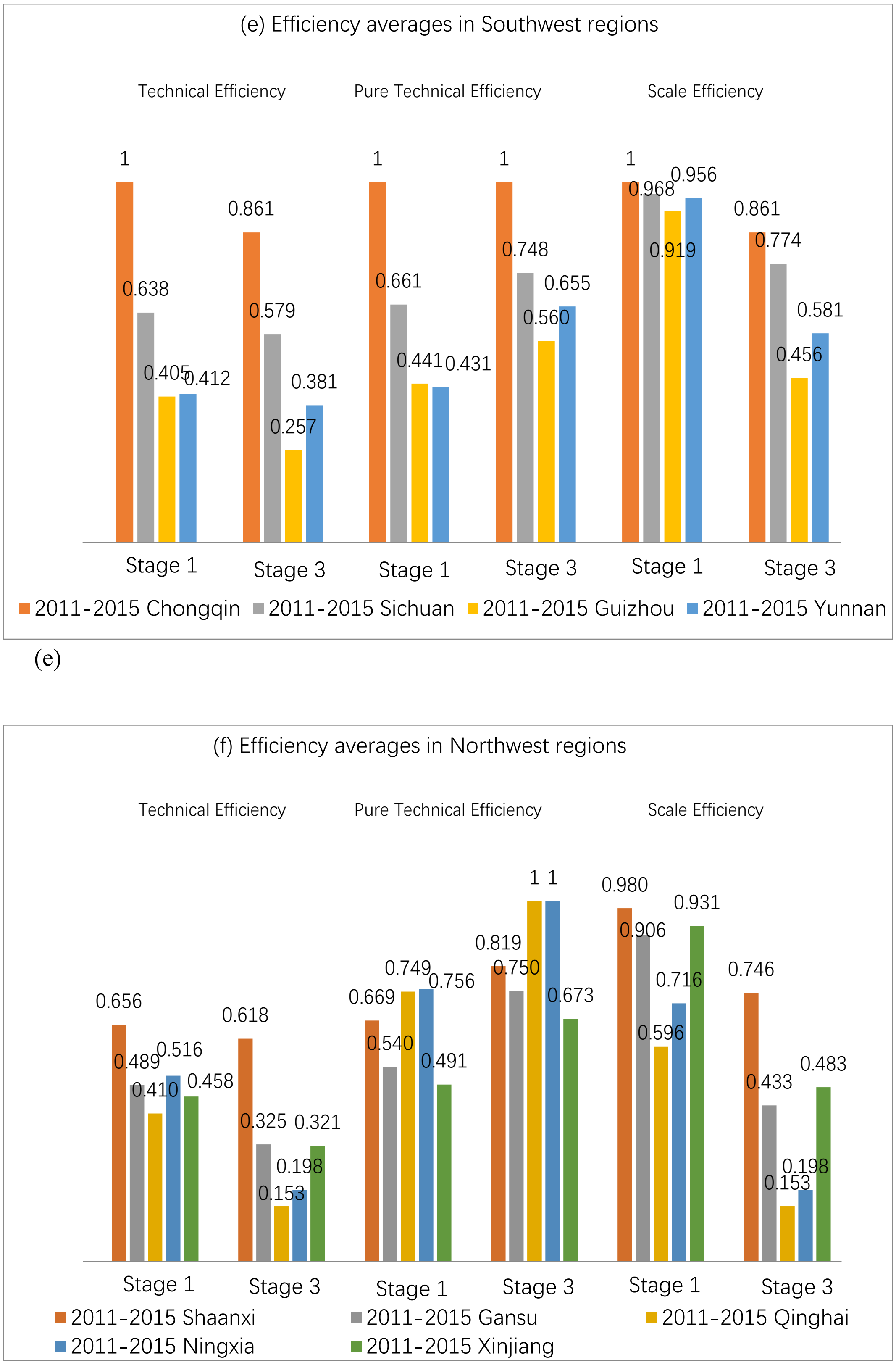
(b)


(c) Efficiency averages in East regions
Technical Efficiency
Pure Technical Efficiency
Scale Efficiency
0.880
1 1
1
0.724
0.603
0.638
0.656
1 1
0.527
0.530
0.543
0.732
0.963
1 1
1
0.755
0.607
0.645
0.975
1 1
1
0.734
0.912
0.810
0.916
1 1
0.993
1
0.961
0.988
0.677
1 1
0.719
0.591
0.543
0.898
Stage 1
Stage 3
Stage 1
Stage 3
Stage 1
Stage 3
2011-2015 Shanghai
2011-2015 Jiangsu
2011-2015 Zhejiang
2011-2015 Anhui
2011-2015 Fujian
2011-2015 Jiangxi
2011-2015 Shandong

(c)


(d) Efficiency averages in South-central regions
Technical Efficiency
Pure Technical Efficiency
Scale Efficiency
0.687
0.928
0.868
0.741
1
0.917
0.625
1
0.772
0.711
0.877
0.136
0.703
1
0.798
0.913
1 1
0.795
1
0.857
0.939
1 1
0.978
0.928
0.952
0.939
1
0.917
0.786
1
0.818
0.838
0.877
0.136
Stage 1
Stage 3
Stage 1
Stage 3
Stage 1
Stage 3
2011-2015 Henan
2011-2015 Hubei
2011-2015 Hunan
2011-2015 Guangdong
2011-2015 Guangxi
2011-2015 Hainan

(d)



(e)

(f)

Fig. 3. Regional efficiencies by type

Without considering the impact of environmental factors, the north region's highest technical efficiency is 1.000, the lowest 0.458, and Beijing is at the frontier of production, while Shanxi has the lowest technical efficiency. Considering the impact of environmental factors, the north region’s technical efficiency has experienced a significant decrease. Of these provinces, at a decrease of 23.2%, Tianjin is the most affected province in north regions.

Technical efficiency of all three provinces is greater than 0.8, which indicates the northeast region to be at a relatively high level in the country. Considering the impact of environmental factors, all Liaoning’s efficiencies have increased significantly; Jilin and Heilongjiang's technical efficiency and scale efficiency have both declined significantly, while only pure technological efficiency has increased slightly. This shows that Liaoning’s efficiency is less affected by environmental factors, while the technical efficiency of Jilin and Heilongjiang are greatly affected.

In the east regions, the efficiency of Jiangsu and Zhejiang is at the frontier of production. Considering the impact of environmental factors, the technical efficiency of other provinces except Jiangsu, Zhejiang, and Shandong has experienced a significant decrease. Of these, Jiangxi’s technical efficiency has the largest decrease of 45.7%. This shows that the efficiency of the construction industry in east regions was significant polarized, and the efficiency of some provinces is seriously overestimated.

In the south-central regions, the efficiency values of Hubei and Guangxi were highest. Considering the impact of environmental factors, the technical efficiency of Hubei has risen to the frontier of production, while other provinces have different decreases. Of these, the technical efficiency of Hainan decreases from 0.917 to 0.136, a drop of 85.2%, which indicates a serious overestimation.

In the southwest regions, Chongqing's efficiency is at the forefront, and pure technical efficiency is at the frontier of production, while the technical efficiency of the other provinces is less than 0.6. This shows that the technical efficiency of Chongqing is the highest in China, but that its influence of the surrounding areas is quite small.

In the northwest region, Shaanxi is highest with a technical efficiency of 0.656. After considering the impact of environmental factors, the technical efficiency of each province has decreased significantly. Other provinces except Shaanxi have a decrease of more than 30%, with Qinghai and Xinjiang decreasing more than 60%. This shows that the construction industry in the northwest is inefficient and its technical efficiency seriously overestimated.

3.5 Classification of high and low environmentally regulated provinces

Previous studies have showed that environment regulation may have a threshold effect on the technical efficiency of regional construction industry. Based on the work of Hansen (Hansen, 1999), we denote the environment regulation intensity both as the key variable and threshold variable, and later establish the single threshold, double threshold, and triple threshold models respectively, i.e.,

$$ECI = \alpha + \beta_1 ER^2(ER < \gamma_1) + \beta_2 ER^2(ER \geq \gamma_1) + \theta X + \varepsilon \tag{17}$$

$$\begin{aligned} ECI = \alpha + \beta_1 ER^2(ER < \gamma_1) + \beta_2 ER^2(\gamma_1 \leq ER < \gamma_2) \\ + \beta_3 ER^2(ER \geq \gamma_2) + \theta X + \varepsilon \end{aligned} \tag{18}$$

$$\begin{aligned} ECI = \alpha + \beta_1 ER^2(ER < \gamma_1) + \beta_2 ER^2(\gamma_1 \leq ER < \gamma_2) \\ + \beta_3 ER^2(\gamma_2 \leq ER < \gamma_3) + \beta_3 ER^2(ER \geq \gamma_3) + \theta X + \varepsilon \end{aligned} \tag{19}$$

where *ECI* denotes construction industry efficiency and *ER* environment regulation intensity. *X* represents a set of environmental variables that may have an impact on construction industry efficiency, while each column of β_i and θ represents the corresponding coefficients. Regional effect is denoted as α; random error as ε; and the threshold as γ_j.

Estimates are made using the single threshold, double threshold, and triple threshold models successively. The F test statistics, along with their bootstrap *p*-values, are shown in Table 3. We find that the test for a single threshold F is strongly significant with a bootstrap p-value of 0.027, and the test for a double threshold F is also significant with a bootstrap *p*-value of 0.060. However, the test for a triple threshold F is not significant. Comparing the *p*-values indicates that there is one threshold in the regression relationship, where $\gamma_1$is 0.014（1.4%) and the asymptotic 99% confidence interval is [0.006，0.028].

Table 3
Tests for threshold effects

Threshold	*F*	*P*-value	Critical values		
			1%	5%	10%
Test for single threshold	6.674	0.027	9.047	4.638	3.806
Test for double threshold	4.647*	0.060	8.504	5.029	3.751
Test for triple threshold	2.992	0.200	11.474	6.076	4.552

Note: 300 bootstrap replications were used for each of the three bootstrap tests. The *F* value is an index of whether the threshold effect is significant, *, and * represent 1%, 5% and 10% significance respectively.

In line with above identified threshold *ER*=1.4, the influence of environmental regulation intensity on efficiency was analysed, the 30 provinces being grouped into high (*ER*≥1.4) and low (*ER*<1.4) environmentally regulated provinces by year. As shown in Table 4, Shandong and Jiangxi moved from high to low regulated provinces in 2015, Guangxi and Chongqing in 2014. Beijing is in a highly regulated province from 2012 to 2015. The final composition of the high and low regulated provinces is shown in Table 5.

Table 4
2011-2015 low and high environmentally regulated provinces.

Year	High environmentally regulated provinces	Low environmentally regulated provinces
2011	Shandong, Guangxi, Tianjin, Qinghai, Liaoning, Anhui, Xinjiang, Jiangxi, Shanxi, Hebei, Chongqing, Ningxia, Inner Mongolia	Henan, Hunan, Guangdong, Zhejiang, Sichuan, Shanghai, Jilin, Fujian, Hainan, Guizhou, Heilongjiang, Jiangsu, Shaanxi, Beijing, Hubei, Yunnan
2012	Shandong, Guangxi, Heilongjiang, Hainan, Chongqing, Hebei, Beijing, Anhui, Jiangxi, Ningxia, Shaanxi, Inner Mongolia, Liaoning, Xinjiang	Guangdong, Shanghai, Henan, Sichuan, Jilin, Hunan, Gansu, Guizhou, Zhejiang, Fujian, Tianjin, Jiangsu, Hubei, Yunnan, Shanxi, Qinghai

2013	Chongqing, Guizhou, Shaanxi, Jiangsu, Shandong, Guangxi, Hebei, Jiangxi, Yunnan, Qinghai, Heilongjiang, Beijing, Anhui, Shanxi, Ningxia, Inner Mongolia, Xinjiang	Gansu, Guangdong, Jilin, Hainan, Shanghai, Henan, Hunan, Sichuan, Zhejiang, Hubei, Tianjin, Fujian, Fujian
2014	Jiangsu, Shandong, Hebei, Jiangxi, Shaanxi, Tianjin, Guizhou, Anhui, Shanxi, Beijing, Ningxia, Inner Mongolia, Xinjiang	Gansu, Guangdong, Hainan, Jilin, Fujian, Henan, Hunan, Liaoning, Sichuan, Shanghai, Heilongjiang, Zhejiang, Hubei, Chongqing, Yunnan, Guangxi, Qinghai
2015	Hebei, Tianjin, Anhui, Guizhou, Shanxi, Beijing, Ningxia, Inner Mongolia, Xinjiang	Gansu, Guangdong, Hainan, Jilin, Fujian, Hunan, Henan, Liaoning, Shanghai, Hubei, Chongqing, Sichuan, Zhejiang, Guangxi, Yunnan, Shaanxi, Jiangsu, Qinghai, Heilongjiang, Jiangxi, Shandong

Table 5
High and low environmentally regulated provinces.

Types	High regulated provinces	Low regulated provinces
Province	Anhui, Xinjiang, Shanxi, Hebei, Ningxia, Inner Mongolia, Shandong, Jiangxi, Guangxi, Chongqing, Beijing	Henan, Hunan, Guangdong, Zhejiang, Sichuan, Shanghai, Jilin, Fujian, Gansu, Hubei, Tianjin, Heilongjiang, Jiangsu, Guizhou, Yunnan, Shaanxi, Qinghai, Liaoning, Hainan

3.6 Comparison of construction industry efficiency between high and low environmentally regulated provinces

The 2011-2015 high and low regulatory efficiency measures for China's construction industry are summarised in Table 6. This shows 6 provinces with a technical efficiency of 1.000 in stage 1 throughout the five years involved. Of these, four are in high-regulated provinces and two in low regulated provinces. The efficiency of the construction industry in Beijing, Jiangsu, and Zhejiang is at the frontier of production in both first and third stages, indicating that these provinces are less affected by environmental variables. Taking 0.5 efficiency as the threshold, the six provinces with the lowest technical efficiency were high-regulated Shanxi and Xinjiang and low-regulated Guizhou, Yunnan, Gansu, and Qinghai. In addition, by comparing the efficiency values of the first and third stage of these six provinces, it can be found that the efficiency of the construction industry in the low environmental regulation provinces is more affected by environmental variables.

Table 6

2011-2015 construction industry efficiency of China's high and low regulated provinces (Stages 1 and 3).

Region	Province	2011-2015					
		Stage 1			Stage 3		
		TE	PTE	SE	TE	PTE	SE
High regulated provinces	Beijing	1	1	1	1	1	1
	Hebei	0.784	0.801	0.971	0.705	0.908	0.784
	Shanxi	0.458	0.471	0.971	0.438	0.654	0.670
	Inner Mongolia	0.579	0.678	0.882	0.521	0.795	0.640
	Anhui	0.603	0.607	0.993	0.527	0.734	0.719
	Jiangxi	1	1	1	0.543	1	0.543
	Shandong	0.638	0.645	0.988	0.732	0.810	0.898
	Guangxi	1	1	1	0.877	1	0.877
	Chongqing	1	1	1	0.861	1	0.861
	Ningxia	0.516	0.756	0.716	0.198	1	0.198
	Xinjiang	0.458	0.491	0.931	0.321	0.673	0.483
	Mean	0.731	0.768	0.950	0.611	0.870	0.698
Low regulated provinces	Tianjin	0.672	0.684	0.981	0.516	0.819	0.648
	Liaoning	0.811	0.897	0.911	0.892	0.929	0.942
	Jilin	0.850	0.861	0.980	0.572	0.923	0.614
	Heilongjiang	0.913	1	0.913	0.765	1	0.765
	Shanghai	0.880	0.963	0.916	0.656	0.975	0.677
	Jiangsu	1	1	1	1	1	1
	Zhejiang	1	1	1	1	1	1
	Fujian	0.724	0.755	0.961	0.530	0.912	0.591
	Henan	0.687	0.703	0.978	0.625	0.795	0.786
	Hubei	0.928	1.000	0.928	1	1	1
	Hunan	0.868	0.913	0.952	0.772	0.939	0.818
	Guangdong	0.741	0.798	0.939	0.711	0.857	0.838
	Hainan	0.917	1	0.917	0.136	1	0.136
	Sichuan	0.638	0.661	0.968	0.579	0.748	0.774
	Guizhou	0.405	0.441	0.919	0.257	0.560	0.456
	Yunnan	0.412	0.431	0.956	0.381	0.655	0.581
	Shaanxi	0.656	0.669	0.980	0.618	0.819	0.746
	Gansu	0.489	0.540	0.906	0.325	0.750	0.433
	Qinghai	0.410	0.749	0.596	0.153	1	0.153
	Mean	0.737	0.793	0.932	0.605	0.878	0.682

4. Discussion

By reviewing existing research on the efficiency of China's regional construction industry, the results of the study identify obvious regional differences, with the eastern part of China is better than its central and western regions. For example, Chancellor and Lu (Chancellor and Lu, 2016) focus on describing the regional differences of Chinese construction industry while Feng and Wang (Feng and Wang, 2017) evaluated economy-wide energy efficiency values of each province. At the same time, the result of this research using the 3-stage approach is in line with Zhong et al.'s (Zhong et al., 2017) study, showing the effect of random errors on efficiency, and that efficiency after eliminating the influencing factors is closer to the real situation. Compared with existing research, the innovation of this paper are from (a) using the SBM-undesirable model to measure the impact efficiency of environmental regulation on regional construction industry; and (b) identifying the single threshold value of 0.014 by applying Hansen's (Hansen, 1999) threshold regression model to group the high/low environmental regulation provinces in terms of the efficiency of Chinese regional construction industry.

As Fig. 2 shows, the average efficiency value in each province is changed slightly due to external environment regulation variables and stochastic factors. The national average technical efficiency value and scale efficiency value decrease while pure technical efficiency increases. Pure technical efficiency in 2013-2015 had a small average increase of 3%, while technical efficiency and scale efficiency fluctuate over a small range. After 2013, technical efficiency, pure technical efficiency, and scale efficiency all fell sharply, with technical efficiency having the biggest decrease of 15%. In addition, the average efficiency trend is highly consistent with the trend of environmental regulation intensity. The results therefore show that (1) environmental variables and stochastic factors do have a certain impact on the efficiency of China's construction industry, and (2) the scale efficiency of China's construction industry is overestimated - the magnitude is greater than the extent of technical efficiency being overestimated.

As can be seen from Tables 4 and 7, the adjusted efficiency of the construction industry in China is:

(1) Almost all provinces have a higher technical efficiency in stage 1 than stage 3, showing that technical efficiency is overestimated. In addition, all provinces have a higher pure technical efficiency in stage 3, which indicates that the environmental factors do have a positive impact on the development of technological innovation. Scale efficiency is more affected than technical efficiency and pure technical efficiency,

(2) The technical efficiency of the construction industry varies significantly between regions. It is higher in the northeast, north, and east regions than the south-central, southwest, and northwest regions. In addition, there is a significant polarization in the east and southeast regions.

In summary, such environmental factors as environmental regulation have had a significant impact on the efficiency of China's construction industry, especially the effects of scale efficiency. To further analyse this, the Stage 1 technical efficiency values in Table 6 are taken as the abscissa and Stage 3 technical efficiency as the ordinate (as shown in Figs 4 and 5) together with the simple regression equation for the influence of environmental regulation. The dashed diagonal denotes the situation where the third technical efficiency is the same as the first technical efficiency, while the solid line denotes the position of the linear regression line. When the constant term of the environmental regulation influence equation is very close to zero, the coefficient of the trend equation x represents the ratio of the first efficiency to the third efficiency. Therefore, the closer the coefficient is to unity, the closer the regression line is to the diagonal, and the smaller the effect of the environment variable on the third efficiency.

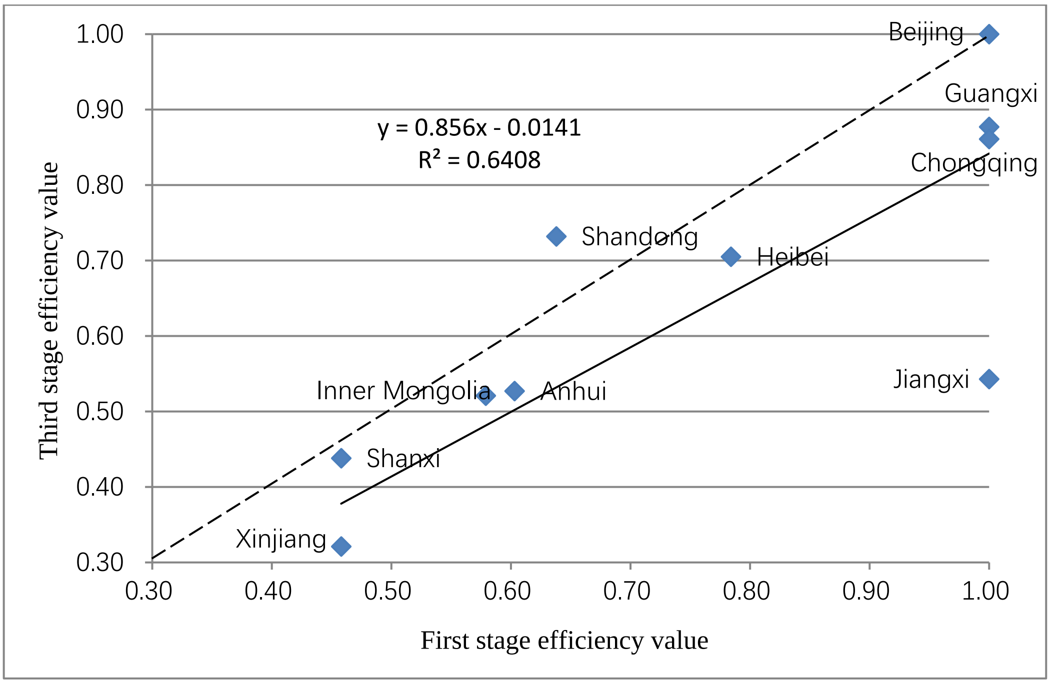


Fig. 4. 2011-2015 influence of environmental regulation (high regulated provinces).

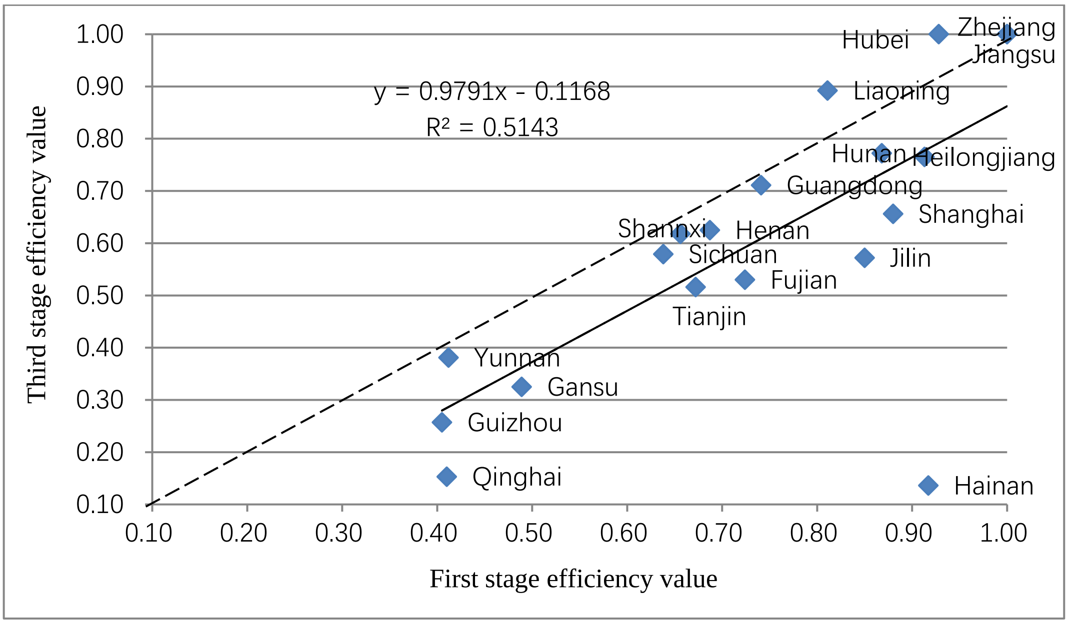


Fig. 5. 2011-2015 influence of environmental regulation (low regulated provinces).

The environmental regulation influence equation shows that construction efficiency in the high and low environmentally regulated provinces has an obvious short-term equilibrium relationship with environmental regulation (Manson et al., 1997; Wang, 2016). As can be seen, almost all the points on the curve are below the diagonal, indicating that efficiency is overestimated without regard to environmental regulation. The coefficients of both high and low regulated provinces is less than 1.000, indicating that environmental regulation has a negative impact on the efficiency of construction in most provinces. However, as the constant term of the environmental regulation influence equation in low regulated provinces is 0.1168, it is no longer applicable to determine the impact of environmental regulation between the high and low regulated provinces by comparing the coefficients. Hence, we use the *T* test to do this work here. Table 7 shows that the environment regulation of low regulated provinces (p<1%) is more effective than the high regulated provinces (p<5%).

Table 7
T test for high and low environment regulated provinces

		Pair of difference					t	df	Sig. (two sided)
		Average	Standard deviation	Mean of Standard deviation	95%				
					Lower	upper			
# 1	Stage 1-3 in high environment regulated provinces	0.1194	0.15201	0.04583	0.0172	0.2215	2.604	10	0.026
# 2	Stage 1-3 in low environment regulated provinces	0.1323	0.18788	0.04310	0.0417	0.2228	3.069	18	0.007

The possible reasons for the existence of high environmentally regulated provinces in the governance environment are that the technology is more mature and therefore there is little impact on the efficiency of the industry. In contrast, increasing the intensity of environmental regulation in low regulated provinces would make enterprises have to take corresponding measures to reduce or control the resulting environmental pollution. On the one hand, this would force enterprises to increase the cost of their original environmental management to deal with changes in environmental regulation (Bu and Yang; Castro-Lacouture et al., 2014; Fontana et al., 2015; Welfens and SpringerLink (Online service), 2001); while, the other hand, also forcing enterprises to strengthen their environmental awareness and reduce pollution sources in the selection and production process (Lewis, 2013; Simpson et al., 2013). Therefore, the efficiency of the industry in low regulated provinces is greatly affected by environmental regulation.

5. Conclusion

Based on the 3-stage DEA model, this paper measures and analyses national panel data during the "12th five-year plan" period to determine the efficiency of China's construction industry and the effect of environmental regulation on regional construction efficiency. Based on the intensity of environmental regulation, the national construction industry can be divided into high and low regulated regional provinces. The major conclusions of the study are as follows.

(1) After applying the SFA model to eliminate the influence of environmental regulation in the industry, the measurement of technical and scale efficiency decreased in different degrees. Scale efficiency is mostly affected, being overestimated by an annual minimum of 24.4% and maximum of 29.7% during the period. Pure technical efficiency is improved, with the biggest gap being 13.3% in 2014.

(2) The SFA regression study shows that only environmental regulation had a significant impact on construction efficiency. Environmental regulation is negatively correlated with the Total Power of Machinery and Equipment Owned and positive correlated with Number of Employed Persons in the Construction Industry, the Total Assets of Construction Industry, and Energy Consumption of the

Construction Industry slack variables. This is in line with expectations, in that industry productivity reduces with increased government regulation of the environment.

(3) Technical efficiency of the construction industry varies significantly between regions. For example, it is higher in the northeast, north, and east regions than the southwest and northwest regions. In such economically developed areas as Beijing, Jiangsu, and Zhejiang, technical efficiency is at the forefront of technology, while Qinghai, Guizhou, Ningxia, and Xinjiang for example, need to increase in future in both pure technical efficiency and scale efficiency.

(4) The underestimation of China's construction industry technical efficiency is mainly caused by the low efficiency of technology, indicating the need to improve the technical level of the industry and technological transformation efficiency. While scale efficiency is relatively high, it is mostly well below its potential - indicating the scale of the industry is in urgent need of upgrading.

The impact of environmental regulation in low environmentally regulated provinces has a greater impact on the efficiency of the industry than otherwise. Thus, this research has sound practical implications in strongly suggesting the need continue to improve environmental management technology, and strengthen investment in the environment in low environmentally regulated provinces. Future research would benefit from using a larger data set to explore the specific reasons for the low efficiency of technology in high/low regulated provinces, and compare the impact of environment regulation on the efficiency of the construction industry of China and developed countries.

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