

## Retraction

# Retracted: Level and Drivers of China's Construction Industry Energy Efficiency under Carbon Dioxide Emissions

### Discrete Dynamics in Nature and Society

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### References

- [1] Y. Xie, "Level and Drivers of China's Construction Industry Energy Efficiency under Carbon Dioxide Emissions," *Discrete Dynamics in Nature and Society*, vol. 2022, Article ID 6972715, 8 pages, 2022.

## Research Article

# Level and Drivers of China's Construction Industry Energy Efficiency under Carbon Dioxide Emissions

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Taking the carbon dioxide emissions of energy utilization in construction industry (CI) as an unwanted output, this study builds an index system for construction industry energy efficiency (CIEE) under carbon dioxide emissions, adopts the super-SBM to assess the CI energy efficiencies (CIEEs) of 30 Chinese provincial administrative regions (PARs) in 2005–2018, and further examines the influencing factors of the CIEEs with the panel data model. The main results show that, during the study period, only a few PARs (e.g., Beijing, Heilongjiang, Zhejiang, and Tianjin) realized the optimal CIEEs and most PARs failed to optimize their CIEEs. After dividing China into three parts, the CIEEs of oriental, middle, and occidental parts followed a trend like an inverted U in the study period and their CIEEs first increased and then decreased with the elapse of time. There were significant differences in CIEE between the three parts: the oriental part realized the greatest CIEE, the middle part came at the second, and the occidental part ended up at the bottom. Empirical results demonstrate that CIEE is significantly promoted by enterprise scale, property right structure, and environmental regulation, greatly inhibited by economic growth and technical level and not greatly affected by production level or urbanization level.

## 1. Introduction

The rapid growth of the Chinese economy has fueled the boom of industrialization and urbanization. However, the fast expansion of industries and cities not only utilizes much energy but also discharges numerous pollutants, exerting immense pressures on China's resources and environment. Eleven years ago, China became the leading energy consumer for the first time. Since then, China has been consuming 20% of all energy consumed globally each year. The rising energy demand far outweighs the energy production, resulting in a growing energy gap in China. The large consumption of energy is attributable to the low efficiency of energy utilization [1], the huge population, and the fast-growing economy. The energy problem has bottlenecked China's pursuit of sustainable development. To realize coordinated development between population, resources, and environment, China must fully consider the energy utilization level to save energy and reduce emissions.

The construction industry (CI) is of great importance in creating economic benefits and job opportunities, bettering living environment, and maintaining social stability in China. However, this labor and resource-intensive industry is naturally a heavy energy consumer. In 2018, China's CI utilized as many as 86.85 million tons of carbon equivalent (TCE), with an increase of 149.14% from that (34.86 million TCE) in 2005. The rising energy use of the industry is accompanied by the heavy emission of carbon dioxide, which severely worsens the climate. Studies have shown that the CI emits 1/3 of the global total of carbon dioxide, second only to the manufacturing industry [2]. On the 75th Session of the UNGA, the Chinese government pledged to peak its carbon dioxide emissions prior to 2030 and realize carbon zero ahead of 2060. The pledge brings a high pressure of carbon reduction and raises stricter requirements on the green development of the CI. The improvement of China's CI energy efficiency (CIEE) is crucial for the country and the world to realize the goal of carbon peaking [3]. Therefore,

the healthy and sustained growth of China's CI hinges on the scientific CIEE assessment under carbon dioxide emissions.

## 2. Literature Review

Energy efficiency is a traditional hot topic in academia. The literature focuses on three areas. On assessment indices, energy efficiency is primarily divided into single-factor (SF) and total-factor (TF) dimensions. The SF energy efficiency is usually measured by energy intensity and energy consumption for each unit of the GDP [4, 5]. Although it is easy to compute, SF energy efficiency only demonstrates the proportionality between energy factors and financial output. It is impossible to precisely measure energy utilization efficiency with SF energy efficiency. On the contrary, TF energy efficiency reflects the joint effects of multiple inputs and manages to measure energy efficiency comprehensively and accurately [6, 7]. On assessment methods, the common approaches include SFA and DEA. Li and Liu (2010) [8] assessed the energy efficiency of each Chinese PAR through SFA. Lundgren et al. [9] resorted to SFA to estimate the energy efficiencies of 14 sectors of the Swedish manufacturing industry. Compared with SFA, DEA can handle multi-input and multi-output problems and achieve high flexibility. Hence, DEA gradually becomes the mainstream assessment strategy of energy efficiency. Vlontzos et al. [10] and Song et al. [11] all employed DEA to estimate state-level energy efficiency. On influencing factors, the existing research has shown that energy efficiency may be influenced by industrial structure [12], technical level [13], energy price [14], energy consumption structure [15], marketization level [16], geographical location [17], and environmental regulation [18].

The CI is an important department engaged in material production. Recognizing the importance of the CI to economic growth and social advancement, academia has paid lots of attention to CIEE. The relevant studies concentrate on TF productivity [19], industrial efficiency [20], and technical efficiency [21] of the industry. With the steady increase of energy consumption of the industry, a few scholars turned their attention to CIEE. For example, Lin and Liu [22] analyzed the relationship between urbanization and CIEE. Huo et al. [23] evaluated the actual TF energy efficiency of CI in China through DEA. Nevertheless, the above studies on CIEE assessment fail to consider the pollutants emitted during the CI's energy utilization. The efficiency assessment may be biased when the "environmental cost" is not taken into account [24].

Several important problems remain unanswered. How high is the CIEE of each province in China? What are the factors that greatly affect the CIEE? To solve the problem, the study treats the carbon dioxide generated during the CI's energy use as an unwanted output and incorporates the

unwanted output into the assessment index system of CIEE. On this basis, the super-SBM was introduced to assess the CIEE of each Chinese PAR, aiming to realize accurate and truthful assessment of energy efficiency.

## 3. Methodology

*3.1. Model.* The study adopts DEA to measure the CIEE of each Chinese PAR. Different from traditional energy efficiency, the CIEE includes carbon dioxide as the unwanted output. DEA needs to meet a prerequisite: maximize the outputs with the minimal inputs. In the early days, linear segmentation and radial theory were adopted to measure efficiency by CCR model with constant returns to scale (RS) [25] and BCC model with variable RS [26]. These traditional DEA methods lead to the slackness of inputs and outputs, which results in biased measurements. What is worse, radial models like CCR and BCC only follow the output maximization principle in efficiency measurement. By contrast, the actual production generates not only products and values but also unwanted outputs like various pollutants. When the efficiency assessment task involves unwanted outputs, the radial models cannot include the slackness of the unwanted outputs into the efficiency measurement framework. To solve the problem, Morita et al. [27] proposed the nonradial, nonangular SBM. Unlike the traditional CCR and BCC, the SBM solves the slackness of inputs and outputs by incorporating it into efficiency measurement and clarifies the gap between the actual and target values of invalid decision-making units (DMUs), laying the basis for efficiency improvement. In addition, the SBM takes account of unwanted outputs and thereby eliminates the efficiency bias induced by the selection between radial directions and angles.

Admittedly, the SBM has a large advantage in measuring the DMU efficiency, which involves outputs that are undesirable. Yet there is a defect with the SBM: the efficiency measured by SBM is below 1. If all DMUs have the efficiency of 1, they cannot be ranked. In this case, the measured results are not comparable, for the SBM only measures relative efficiency. To overcome the defect, Tone [28] drew on the superefficient programming of Andersen and Petersen [29] and developed the super-SBM to overcome the upper bound of DMUs and sort all DMUs accurately. The operation of super-SBM is explained as follows.

First, it is necessary to set up an  $n$ -DMU production system. During operation, each DMU is given some inputs and yields some outputs. It is assumed that a DMU needs  $i$  types of inputs to generate  $u$  types of wanted outputs and  $v$  types of unwanted outputs. The inputs, wanted outputs, unwanted outputs, and the  $m$ -th DMU are denoted as  $X = (x_1, x_2, \dots, x_n) \in R_+^{i \times n}$ ,  $Y = (y_1, y_2, \dots, y_n) \in R_+^{u \times n}$ ,  $B = (b_1, b_2, \dots, b_n) \in R_+^{v \times n}$ , and  $DMU_m$ , respectively. The set of possible production scenarios is defined as

$T = \{(x, y, b): x \text{ can produce } y \text{ and } b\}$ . On this basis, the super-SBM can be established as

$$\theta^* = \min \frac{1 - 1/i \sum_{z=1}^i s_z^- / x_{zm}}{1 + 1/u + v(\sum_{p=1}^u s_p^+ / y_{pm} + \sum_{q=1}^v s_q^{b-} / b_{qm})},$$

$$s.t. \ x_{zm} \geq \sum_{\substack{j=1 \\ j \neq m}}^n x_{zj} \lambda_j - s_z^-, \quad z = 1, \dots, i;$$

$$y_{pm} \leq \sum_{\substack{j=1 \\ j \neq m}}^n y_{pj} \lambda_j + s_p^+, \quad p = 1, \dots, u,$$

$$b_{qm} \geq \sum_{\substack{j=1 \\ j \neq m}}^n b_{qj} \lambda_j - s_q^{b-}, \quad q = 1, \dots, v; \lambda \geq 0, s_z^-, s_p^+, s_q^{b-} \geq 0,$$
(1)

where  $\theta^*$  is the CIEE;  $x_{zm}$ ,  $y_{pm}$ , and  $b_{qm}$  are the  $z$ -th input,  $p$ -th wanted output, and  $b$ -th unwanted output of  $DMU_m$ , respectively;  $s_z^-$ ,  $s_p^+$ , and  $s_q^{b-}$  are the slack terms of the  $z$ -th input,  $p$ -th wanted output, and  $b$ -th unwanted output, respectively;  $j$  is the serial number of the  $j$ -th DMU; and  $\lambda_j$  is the weight of the  $j$ -th DMU.

If any of  $s_z^-$ ,  $s_p^+$ , and  $s_q^{b-}$  is nonzero, the efficiency of  $DMU_m$  is smaller than 1 and the DMU is invalid. In this case, the slack terms should be eliminated to turn the invalid DMU into a valid DMU. If and only if  $s_z^- = s_p^+ = s_q^{b-} = 0$ , the efficiency of  $DMU_m$  is greater than 1, and the DMU is valid.

**3.2. Index System.** The study aims to discuss the CIEE under the constraint of carbon dioxide emissions. The so-called energy efficiency reflects the ratio of optimal energy consumption to actual energy consumed in the construction industry. Huo et al. [23] conceptualized the TF energy efficiency of the CI but did not include carbon dioxide emissions as an unwanted output. Inspired by Huo et al. [23], the study defines CIEE as the maximum financial output and minimum carbon dioxide emissions of the CI, under fixed labor, capital, and energy inputs. The CIEE in this research is a TF efficiency of the CI under the constraint of environmental factors. Under the above definition, the study establishes the input and output indices of CIEE, which are comprehensive, scientific, feasible, and concise. The index system contains three inputs, as well as wanted and unwanted outputs. The three inputs are labor, capital, and energy. The wanted output is the overall output level of the industry, and unwanted outputs are carbon emissions of the construction industry. The connotations of each index are detailed as follows.

**Labor.** The history of China's CI indicates that construction is a typical labor-intensive industry. Labor is the key to the growth of the CI. In general, labor input can be characterized by two key indices: labor quantity and labor quality. The latter index is difficult to quantify and not mentioned in relevant

statistical yearbooks. Considering data availability and comprehensiveness, the study quantifies labor by the number of employees in CI.

**Capital.** The CI growth needs to be supported by a huge sum of capital. The capital input can be characterized well by the capital stock of the CI. However, it is impossible to compute the capital stock of the industry because the capital of the industry has a complex composition, and the fixed asset depreciation rate is not specified in relevant documents. Thus, the CI was selected as the capital input. The total assets of the CI can accurately measure the capital input of the industry in each part.

**Energy.** Energy is the core input of our index system, for the research aims to measure CIEE. In fact, energy is an indispensable factor for the CI growth. This industry consumes many types of energy. If each kind of energy is substituted for the DEA, the assessment accuracy will be undermined by the sheer number of input indices. According to the conversion coefficients specified in GB/T 2589-2020, which convert various types of energy into 10,000 TCE, the physical quantity of each kind of energy was transformed into a standard quantity, and the standard quantities of all types of energy were added up to measure the energy input. Specifically, this study selects primary energy such as raw coal, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, natural gas, heating power, and electricity. The consumption of each primary energy was multiplied by the corresponding conversion coefficient, and the results were added up to obtain the total energy consumption in the construction industry.

**Wanted Output.** The CI contains multiple sectors that output diverse products. Thus, it is improper to measure the wanted output with the physical quantity. In the existing studies, the CI output level is characterized by such indices as the total industrial output, the construction industry added value, the construction area, and the total taxes and profits. Among them, the total construction industry output better demonstrates the financial value created by the production projects of the CI in an accounting year. This index can accurately measure the overall output level of the industry from the monetary angle. Hence, the study chooses the total CI output to measure the wanted output.

**Unwanted Output.** As an energy-intensive industry, the CI produces various environmental pollutants during the production. Carbon dioxide is a typical representative of these environmental pollutants. Most scholars advocate controlling the emissions of this gas during the energy utilization of the CI. However, the direct carbon dioxide emissions of the industry are not available in the relevant statistical yearbooks. Thus, the study adopts the IPCC's carbon emission calculation method. Ten primary energies and two secondary energies were selected; each of them was converted into standard quantity, multiplied with the corresponding carbon emission coefficient, and then added up to obtain the carbon dioxide emissions of the CI.

**3.3. Impactors.** The study tries to disclose the impactors of China's CIEE. The CI is the pillar of the national economy and a typical energy intensity industry. The CI development

has much to do with economy, technology, institution, and policies. The previous literature suggests that energy efficiency is greatly affected by technical level [13], energy price [14], energy consumption structure [15], marketization level [16], geographical location [17], and environmental regulation [18]. On this basis, the study chooses 7 main impactors of CIEE. The impact mechanism of each factor on the CIEE is as follows.

*Economic Growth (EG).* EG was illustrated with the natural log of GDP per capita. As a mainstay of the national economy, the CI is inevitably influenced by EG. On the one hand, EG promotes the growth of per capita income, which stimulates the consumption demand for CI. As a result, the CI will expand, consume more energy, and suppress CIEE. On the other hand, parts with a fast EG tend to invest more in construction and environmental technologies. These technologies promote the CIEE by saving energy and reducing emissions in the CI. Overall, the influence of EG on CIEE is uncertain.

*Enterprise Scale (ES).* ES was illustrated with the total output of the CI as a percentage of the number of construction enterprises. The CI ES is closely associated with the production efficiency. Compared with small construction enterprises, large enterprises concentrate lots of manpower, capital, and materials and boost advanced large production equipment. The resulting scale effect boosts the production efficiency and favors the energy conservation and emission reduction of construction enterprises.

*Property Right Structure (PRS).* PRS was illustrated with the output of state-owned construction enterprises as a percentage of the total regional CI output. It reflects the proportional relationship between state-owned enterprises (SOEs) and non-SOEs. In general, the said proportion has a negative correlation with the marketization degree of the CI. Fan et al. [30] confirmed that the improvement of marketization greatly improves the efficiency of energy use. If the CI is highly marketized, the enterprises will be more likely to engage in benign competition, the resources will be allocated more reasonably, and the productivity of the industry will be improved. These obviously enhance the CIEE.

*Production Level (PL).* PL was illustrated with the natural log of the labor productivity calculated based on the total CI output. It comprehensively reflects the production technology level, the enthusiasm and skillfulness of workers, and the management level of regional CI. Generally speaking, if regional CI has high labor productivity, the industry tends to be good at energy use.

*Technical Level (TL).* TL was illustrated with the natural log of the technical equipment (TM) rate of the CI. Garbaccio et al. [31] demonstrated that energy efficiency is primarily improved by technical progress. The TM rate of the CI refers to how much the industry is mechanized. The higher the degree of mechanization, the more advanced the mechanical equipment. High mechanization enables the CI to optimize and upgrade the production process, reduce the energy consumption during construction, and promote the CIEE.

*Environmental Regulation (ER).* ER was illustrated with the ratio of regional pollution control investment to regional

GDP. It reflects the constraint of the government on pollutant-emitting enterprises. In general, the government limits the pollutant emissions by enterprises through investing in pollution control and charging the pollution discharge fee. The stricter the regional ER, the higher the environmental cost of enterprise production. To reach the environmental standard, enterprises must invest more in the research and development of clean techniques. The results will elevate energy efficiency by enhancing energy conservation and emission reduction abilities.

*Urbanization Level (UL).* UL was illustrated with the ratio of the urban population to the regional population. Studies have shown the tight bound between UL and CI growth. China is experiencing the largest urban construction in human history [32]. With the continuous improvement of urbanization, more and more people move to cities and towns, and the population agglomeration effect is increasingly prominent. This calls for the construction of better urban buildings. Thus, the CI is propelled to transform and upgrade itself into a cleaner industry.

Considering the impact mechanisms above, the authors constructed a panel data model:

$$\begin{aligned} \text{CIEE}_{it} = & \alpha_{it} + \beta_{1it} \text{EG}_{it} + \beta_{2it} \text{ES}_{it} + \beta_{3it} \text{PRS}_{it} + \beta_{4it} \text{PL}_{it} \\ & + \beta_{5it} \text{TL}_{it} + \beta_{6it} \text{ER}_{it} + \beta_{7it} \text{UL}_{it} + \mu_{it}, \end{aligned} \quad (2)$$

where  $i$  is the symbol of each PAR;  $t$  is the symbol of each year;  $\text{CIEE}_{it}$  is the CIEE of PAR  $i$  in year  $t$ ;  $\text{EG}_{it}$ ,  $\text{ES}_{it}$ ,  $\text{PRS}_{it}$ ,  $\text{PL}_{it}$ ,  $\text{TL}_{it}$ ,  $\text{ER}_{it}$ , and  $\text{UL}_{it}$  are seven explanatory variables, respectively; the EG, ES, PRS, PL, TL, ER, and UL of PAR  $i$  in year  $t$ ;  $\beta_1$ - $\beta_7$  are the coefficients of the EG, ES, PRS, PL, TL, ER, and UL, respectively;  $\mu_{it}$  is a random disturbance; and  $\mu_{it}$  is the influence of stochastic factors other than explanatory and explained variables on the explained variable (it is variability that cannot be explained by the linear relationship between explanatory and explained variables). The value of each coefficient represents the degree of influence of the corresponding factor on the CIEE.

**3.4. Data Description.** Thirty Chinese provincial administrative regions (PARs) were covered in the research scope. The study period lasts from 2005 to 2018. Four PARs were excluded, including Taiwan, Hong Kong, Macau, and Tibet, because the data on some variables in these parts are missing for several consecutive years. The original data were extracted from the relevant statistical yearbooks released in the study period. The few individual missing data were completed through interpolation.

## 4. Results Analysis

**4.1. CIEE Results.** Under our index system, the data on inputs and outputs were processed in maxDEA, and the CIEE of every PAR in the study period was measured. For intuitiveness, the average CIEE of each PAR in each year is presented in Figure 1.

Figure 1 shows a large provincial difference in China's CIEE. From 2005 to 2018, Beijing, Heilongjiang, Zhejiang,

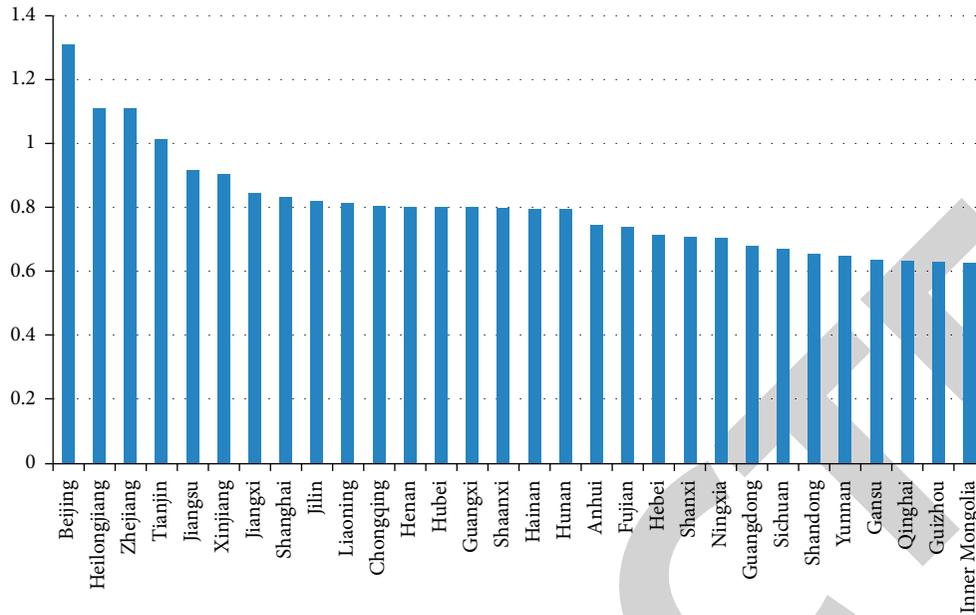


FIGURE 1: Average CIEE of each PAR.

and Tianjin were the only PARs with an average CIEE surpassing one. In these four PARs, the CI energy utilization reached the optimal level. In fact, these PARs constitute the efficient frontier. None of the other PARs reached that frontier, leaving room for improvement. Except Heilongjiang, Beijing, Zhejiang, and Tianjin all belong to the oriental part. The good performance of these PARs originates from the high development level of their CI, as evidenced by sufficient funds, abundant talents, and high economic benefits.

From 2005 to 2018, the average CIEEs of Jiangsu, Xinjiang, Jiangxi, Shanghai, Jilin, Liaoning, Chongqing, and Henan fell between 0.8 and 1. These PARs were close to the efficient frontier and achieved relatively good performance. However, the CI developed fast recently in these PARs. Some labor and energy were wasted during utilization; that is, the inputs were redundant. That is why these PARs failed to optimize their CIEEs.

The average CIEEs of Hubei, Guangxi, Shaanxi, Hainan, Hunan, Anhui, Fujian, Hebei, Shanxi, and Ningxia fell within 0.7–0.8. These PARs belong to the middle level of CIEE in the country and have a certain potential for improvement. Most of them belong to the middle and occidental parts, and only a few belong to the oriental part.

The average CIEEs of Guangdong, Sichuan, Shandong, Yunnan, Gansu, Qinghai, Guizhou, and Inner Mongolia were below 0.7, trailing the other PARs in China. These PARs have an immense potential for CIEE improvement. The undesirable CIEE is closely associated with the redundancy of inputs and insufficiency of wanted output.

Overall, the Chinese PARs differed significantly in CIEE. The CIEEs of Chinese PARs are closely correlated with the level of economic development. The economically developed PARs tend to have a high CIEE, while the economically backward PARs tend to have a low CIEE. Only a few PARs (e.g., Beijing, Heilongjiang, Zhejiang, and Tianjin) realized

the optimal CIEEs, and most PARs ended up with invalid CIEEs. Hence, China’s CI has huge potential in terms of saving energy and reducing emissions.

By geography, economic development, and resource endowment, China was further divided into three parts: oriental part, middle part, and occidental part. Specifically, the oriental part includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the middle part includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; the occidental part includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. Figure 2 shows the CIEE trends of China and the three parts. The CIEEs of the country and the three parts all followed a trend like an inverted U in the study period: their CIEEs first increased and then decreased with the elapse of time. In addition, there were significant differences in CIEE between the three parts. During 2005–2018, the average CIEEs of oriental, middle, and occidental parts were 0.8699, 0.8266, and 0.7134, respectively. The oriental part realized the greatest CIEE, the middle part achieved the second-highest CIEE, and the occidental part ended up with the lowest CIEE. Therefore, China should focus more on the middle and occidental parts during the green construction of the CI.

**4.2. Regression Results.** The CIEE impactors were regressed by the panel data model (2) on Stata 12.0. Table 1 reports the coefficient, *t*-value, and *p* value of each explanatory coefficient. For convenience, the estimations of both fixed- and random-effects models were presented. The Hausman test result was 24.69 at 1% of significance, suggesting that the model has significant fixed effects. Hence, the selected variables can be better explained by the results of the fixed-effects model. As a result, the study chooses to interpret the

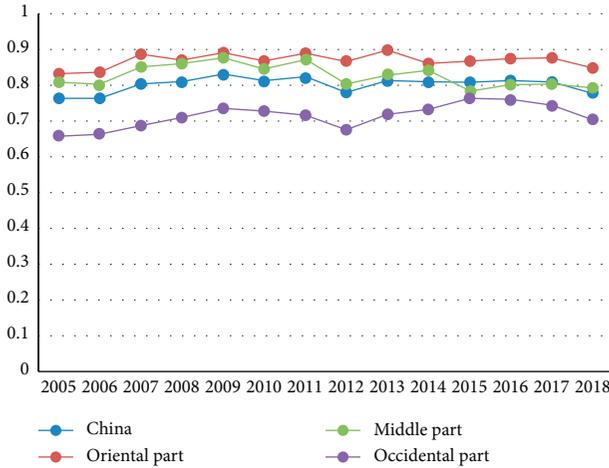


FIGURE 2: CIEEs of China and oriental, middle, and occidental parts.

TABLE 1: Regression results.

Variable	Fixed effects			Random effects		
	Coefficient	<i>t</i> -value	<i>P</i> value	Coefficient	<i>t</i> -value	<i>P</i> value
EG	-0.1417***	-3.54	0.001	-0.1582***	-4.06	0.001
ES	0.1098***	8.96	0.001	0.1017***	8.44	0.001
PRS	0.2208***	3.03	0.003	0.2012***	2.88	0.004
PL	0.0412	1.34	0.181	0.0076	0.25	0.800
TL	-0.0279*	-1.70	0.090	-0.0202	-1.25	0.210
ES	2.1667	2.34	0.020	2.2076**	2.38	0.017
UL	0.1082	0.49	0.621	0.6575***	3.78	0.001
AdjR <sup>2</sup>	0.2269			0.2085		
obs	420			420		

Note. \*Significance level of 10%, \*\*significance level of 5%, and \*\*\*significance level of 1%.

meaning of each explanatory variable with the estimations of the fixed-effects model.

EG had a negative impact on CIEE at 1% of significance, which implies that the growth of GDP per capita suppresses CIEE. The reason rests with the current economic growth model. At present, the economic growth of some parts in China still consumes lots of energy and emits a huge number of pollutants. The CI has not moved away from the extensive development model and still faces the prominent problem of low resource output rate. It is highly necessary to transform the extensive development of the CI to refined development.

As expected, ES significantly promotes CIEE. Zhang et al. [33] also discovered that the scale of construction enterprises has a positive correlation with the development level of regional CI. Big construction enterprises have a prominent scale effect, which promote the productivity of the CI.

The estimation coefficient of PRS was positive at the 1% of significance. The greater the output of construction enterprises as a proportion of regional CI output is, the more favorable it is to improve the CIEE. This result goes against our expectations. In China, the national economy is

dominated by the state-owned economy and underpinned by large SOEs. Compared with small and medium private enterprises, SOEs tend to be large in scale and highly sensitive to national policies on energy conservation and emission reduction. Therefore, a high proportion of SOEs in the CI benefits the implementation of national green policies and promotes the CIEE.

The estimation coefficient of PL failed to pass the significance test, indicating that the CI labor productivity does not significantly affect the CIEE. This is probably attributable to the low labor productivity of China's CI. Despite the recent fast growth, the labor productivity of China's CI remains relatively low, compared with that in developed countries or with that in other industries. Statistics show that China's total labor productivity in 2015 was merely 40% of the global average and 7.4% of that in the United States.

Unlike what was expected, TL significantly inhibited CIEE. Admittedly, improving the TM rate of the CI favors effective energy utilization and reduces energy intensity. Nonetheless, China's CI is still severely imbalanced across parts. In some backward parts, the equipment of construction enterprises is of low technical content, seriously aged, energy-inefficient, and poor in productivity.

As expected, ER has a significant positive correlation with CIEE. This result demonstrates that, as the Chinese government attaches more importance to the environment, ER plays a greater role in limiting pollutant emissions by enterprises. Besides, strict ER raises the threshold for polluting enterprises to enter the market, forcing the sub-standard construction enterprises to exit the market. Suffice it to say that ER drives the paradigm shift of the CI and accelerates the high-quality green reform of the industry.

UL did not significantly affect CIEE. The possible cause is that urbanization stimulates the scale expansion of the CI, which boosts the demand for inputs. With the expansion of the CI, some PARs face irrational allocation of labor and energy in the industry, and the local construction enterprises overlook management improvement. As a result, lots of resources are wasted.

## 5. Conclusions

Taking carbon dioxide emissions of the CI as the unwanted output, the study sets up a CIEE index system under the constraint of carbon dioxide emissions and measures the provincial CIEEs of China in 2005–2018. After disclosing the regional variation of CIEE, the authors discussed the influencing factors of CIEE with the panel data model. The following are the main findings.

On the provincial level, there were significant differences between Chinese PARs in CIEE. During the study period, only a few PARs (e.g., Beijing, Heilongjiang, Zhejiang, and Tianjin) realized the optimal CIEEs, and most PARs failed to optimize their CIEEs, leaving room for improvement. The failure is closely related to the input redundancy and insufficiency of the wanted output.

On the regional level, the CIEEs of oriental, middle, and occidental parts followed a trend like an inverted U in the study period, and the three parts diverged in the CIEE trend.

The oriental part had a much higher CIEE than the middle and occidental parts. Compared with the oriental part, the middle and occidental parts have an immense potential for saving energy and reducing emissions in the CI.

According to the results of the panel data model on CIEE factors, the CIEE is significantly promoted by ES, PRS, and ER and greatly suppressed by EG and TL. In addition, CIEE is not greatly affected by PL and UL.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The author declares no conflicts of interest.

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