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Abstract:

In the current environmentally constrained context, deploying effective environmental regulations (ERs) to promote greener technologies is necessary. Green technology innovation efficiency (GTIE) reflects the efficiency of an industry’s use of resources in the green technology innovation process. However, previous research has considered innovation as a black box regarding the potential contribution and diversity of ERs. In order to analyze the differential impacts of ERs on GTIE, this study classifies ERs into command-and-control, market-based and voluntary. By adopting China's 2000–2017 construction industry as a case study, this study analyzes GTIE evolution based on a network Epsilon Based Measure (EBM) model and analyze the impacts of ERs by Tobit Regression. Findings suggest that: (1) There is a significant disconnection between the Research & Development (R&D) and commercial application stages of green technology in construction industry. The construction industry is able to turn most R&D achievements into profits at the commercialization stage, but a large amount of R&D investment does not produce R&D achievements. (2) Different types of ERs have different impacts on GTIE, but their intended outcomes can only be achieved by a suitable combination of them.

Keywords: Green technology innovation; Environment regulations; Sustainable development; Network DEA model; Tobit regression model.

1 Introduction

Sustaining economic growth while protecting the environment is one of the major obstacles for further development of the global economy (Wu et al. 2018). Indeed, the traditional economic development approach at the expense of the environment no longer meets the needs of society (Hölscher et al. 2018). As a result, many governments have started to encourage various industries to implement green technological innovation as well as reduce energy consumption and pollutant emissions in the production process (Gente and Pattanaro 2019; Yin and Li 2018). However, when industrial companies have to bear most of the innovation costs, they may not be overly motivated to conduct all the required changes (Silajdžić et al. 2015). In this scenario, environmental regulations have become an effective means for governments to stimulate the industry to adopt such measures.

Environmental regulations (ERs) provide external incentives for industry to adjust its production methods observing some environmental constraints that are placed on companies by governments (He et al. 2020; Li et al. 2018a). Nevertheless, researchers have pointed out the limitations of environmental regulations. For example, Pan et al. (2019) considered that although environmental regulations effectively promote green technology innovation in industry, such innovation will undoubtedly lead to an increase in innovation costs and correspondingly reduce industry's willingness to innovate. Feng et al. (2018) viewed the issue from the perspective of foreign enterprises, highlighting that strict environmental regulations increase the environmental costs of innovation, which directly affects the willingness of international investors to enter the domestic market. However, most studies (e.g. Li et al. 2018a; Wang and Shen 2016) suggest that to mitigate this limitation, the government needs to adopt appropriate ERs to improve the green technology innovation efficiency (GTIE) in the industry.

Green technology innovation efficiency (GTIE) reflects the efficiency of the industry's use of resources in the green technology innovation process (Lin et al. 2018a). It is usually expressed as the ratio between the resources input and benefits output. The improvement of innovation efficiency means that industry can reasonably allocate resources, obtain more benefits with less investment and reducing innovation costs (Du and Li 2019). Although previous studies have shown that ERs can stimulate the industry to carry out more innovation activities (e.g. Lee 2010), the relationship between ERs and GTIE needs to be further analyzed. At the same time, ERs have a diversity of characteristics, and different types of ERs have different effects in practice (Ren et al. 2018).

The purpose of this research study is to analyze the impact of different types of ERs on GTIE. This study selects the 2000-2017 Chinese construction industry as a representative case study. In order to evaluate the GTIE, this study divides the green technology innovation (GTI) process into two stages: Research & Development (R&D) stage and commercialization stage. It also divides ERs into three types: command-and-control (CER), market-based (MER), and voluntary (VER). Then, Data envelopment analysis (DEA) is performed through a network Epsilon Based Measure (EBM) model. Energy consumption and unanticipated output are also incorporated in the efficiency measurement framework, and the network EBM model is used to measure the efficiency of GTI at each stage (R&D and commercialization). Finally, a Tobit regression model is used to analyze the relationship between different types of ERs and GTIE. Hence, the contributions of this study are: (1) this study proposes a more reasonable and accurate evaluation method of the GTIE by dividing green technology

R&D into several stages, (2) this study breaks down the impacts of different types of ERs on GTIE. Based on the results of the study, policy makers will be able to pass and combine ERs that are more effective at promoting GTIE. This by improving the industry's resources allocation efficiency to more easily achieve the sustainable development goals of resource conservation and environmental protection.

There are some reasons for choosing the Chinese construction industry as a representative case study. China's construction industry is one of the largest contributors to China's carbon emissions, accounting for *ca*. 40% of the country's total annual emissions. The environmental problems caused by carbon dioxide as the main representative pollutant are the main obstacle to the further development of this industry. Additionally, the construction industry has historically been rendered a "high consumption and high pollution" industry. However, the Chinese government has started to actively encourage the construction industry to initiate GTI activities, reduce pollutant emissions in the production process, and reduce the consumption of resources. In this process, the Chinese government has passed a series of ERs whose effectiveness is yet to be analyzed. Therefore, this study adopts the Chinese construction industry as the research object as we expect it to be representative on the impacts that different types of ERs can have on GTIE.

The remainder of the article is organized as follows. Section 2 reviews the literature on GTIE in the construction industry and ERs. Section 3 presents the datasets, indicators and variables, and Section 4 describes the data analysis procedure. Section 5 includes the GTIE analysis and regression results. The implications of these results are discussed in Section 6. Finally, Section 7 presents the Conclusions along with some research limitations and continuations.

2 Literature review

Improving the GTIE can improve the efficiency of resource utilization and reduce environmental pollution. ERs are also effective tools for governments to deal with environmental problems. However, ERs can either inhibit or promote GTIE. This section will review the most relevant studies on GTIE first. Then, it will review the relationship between ERs and GTIE, and, finally, on current measurement models of innovation efficiency.

2.1 Green technology innovation efficiency

Improving GTIE in the industry has become a significant area of research (Lai et al. 2017). In the industry context, green technology innovation mainly refers to the technology innovation behavior that follows ecological principles and ecological economic laws (European Commission 2011). With this perspective, GTIE represents the ability of the industry to take advantage of innovation resources. It is used to evaluate whether an industry can maximize its benefits for a given level of investment (Schiederig et al. 2012).

To promote the sustainable development of industry, though, finding new ways to improve the GTIE is necessary (Miao et al. 2017). So far, researchers have established some indicator-based systems to evaluate GTIE. Tseng et al. (2013), for example, focused on the practical process of GTI, and constructed an indicator-based system including management innovation, process innovation, product innovation, and technological innovation. Du et al. (2019) discussed the environmental factors of GTI in China and proposed a system considering non-expected outputs (for example CO_2, SO_2, etc.).

Previous studies have also focused on the factors that influence GTIE. Li et al. (2018b) established an SFA (Stochastic Frontier Analysis) model to analyze GTIE in the high-end manufacturing industry. Their results indicated that the level of government funding, company scale, market maturity and industrial agglomeration had a significant impact on GTIE. Gao et al. (2018) also pointed out the influence of the institutional environment on the reverse technology spillover effects on GTIE.

However, when analyzing previous literature on GTIE, it is evident that researchers have not fully taken account of the staggered nature of GTI. GTI is usually deemed as a single stage process. This simplification can produce unreliable efficiency estimates. Instead, GTI is a multi-stage process that transforms technology innovation resources into technology R&D achievements. Then, those technology R&D achievements can produce economic benefits (Bi et al. 2016). Therefore, it is necessary to divide green technology innovation into multiple stages to representatively evaluate GTIE.

2.2 Environmental regulation and green technology innovation efficiency

Environmental pollution is a worldwide problem that constrains industrial development and economic growth (Wang and Shen 2016). In order to promote sustainable economic development, national governments have formulated a series of policy instruments, which are commonly known as ERs (Schreck and Wagner 2017).

Environmental regulations (ERs) refer to all laws addressing environmental issues. Frondel et al. (2007) pointed out that the ERs are also a major driving force for green innovation. Specifically, ERs are an effective means to address pollution problems arising from industry (Wang et al. 2019). For example, ERs can limit pollutant emissions by compulsory means, such as through charging environmental taxes to industries. In order to not incur the additional tax caused by environmental pollution, enterprises will voluntarily reduce the level of pollutant emissions (Hájek et al. 2019).

ERs can also improve or prevent the GTIE of industry (Wang and Zou 2018). On one hand, industry will normally assume most of the cost of the innovation process, but in many cases, it will not necessarily secure the corresponding innovation benefits (Esmaeilpoorarabi et al. 2020). This phenomenon is known as the positive externality of innovation. In order to avoid the negative impact of positive externalities on GTI, governments often attempt to stimulate industry through subsides and other means (Liu and Feng 2019). On the other hand, in order to reduce the high cost of innovation, the industry needs to constantly improve its GTIE and maximize the innovation benefits (Miao et al. 2017).

Limited research has verified the influence of ERs on GTIE, though. Kesidou and Demirel (2012) analyzed the UK and suggested that ERs only under some conditions could effectively improve GTIE in the industry. Guo et al. (2018) pointed out that the effect of ERs on GTIE is not a simple linear relationship. The study by Guo et al. (2018) also identified that ERs initially inhibit GTIE, but there can be an inflection point, after which the intensity of ERs becomes greater. Overall, previous research has not found a clear explanation as to which there seem to be some contradictory findings.

However, ERs can be characterized through a diversity of mechanisms. Indeed, different types of ERs have different effects on industry (Aldieri et al. 2019). Specifically, ERs can be divided into command-and-control environmental regulations (CER), market-based environmental regulations (MER) and voluntary environmental regulations (VER) (Ren et al. 2018; Shen et al. 2019). Hence, in order to effectively evaluate the impact of ERs on GTIE, it seems necessary to analyze the effects of each type of ER separately.

2.3 DEA in efficiency evaluation

Green technology innovation (GTI) is seen as key for sustainable development (Kuo and Smith 2018). It is then of prime importance to evaluate GTIE. This work is not only conducive to the practitioners of the industry to understand the current use of technology R&D resources. It can also to provide an objective reference point for governments to formulate policies that improve GTI benefits.

In the recent decade, many evaluation methods for the GTIE have been proposed. Among them, Data Envelopment Analysis (DEA) has attracted extensive attention. As a non-parametric method, DEA has outstanding advantages in avoiding subjective factors, simplifying algorithms and dealing with multi-input and multi-output problems. This is why DEA is widely used in efficiency evaluation and ranking of decision making units (DMUs).

To cite some examples, Song et al. (2015) constructed a DEA-Malmquist model to measure the impact of foreign direct investment and technology spillover effects on GTIE. Lin et al. (2018b) also used a DEA-Malmquist model to measure the technological innovation efficiency of the tourist equipment manufacturing industry.

However, previous studies used DEA to measure innovation efficiency on the basis of radial measure. They also assumed that all input-output factors increased or decreased in the same proportion, which led to inaccurate efficiency values.

Tone and Tsutsui (2010) constructed an EBM (Epsilon Based Measure) model combining radial and non-radial characteristics to Measure the efficiency value. This EBM model not only solves the slack problem of input/output variables, it also solves the problem of unexpected output generated in the process of innovation. Zeng et al. (2019) used another EBM model to estimate the CO_2 emissions efficiency of various regions in China and assessed potentials regional energy conservation and emissions reduction. Finally, Wu et al. (2019) also adopted an EBM model to incorporate undesired output (CO2) into the efficiency measurement framework and analyzed the production efficiency of coal mining enterprises.

It should be noted, though, that most previous studies have also ignored the multi-stage characteristics of innovation activities and regarded innovation activities as a "black box". However, network EBM models can handle multi-stage processes (Tavana et al. 2013), which makes them a good tool for the purpose of this study.

3 Data and variable description

This section describes the process of data collection (section 3.1) and variable selection (section 3.2) in detail. Then, the regression model for analyzing the potential impacts of ERs on GTIE is presented (in section 3.3).

3.1 Data Sources

The Chinese construction industry is used to provide a case reference for countries to formulate their own sustainable development policies. The data spans the 2000-2017 period. The industrial structure and GTI data of the construction industry are from China's statistical yearbooks (2001-2018, http://www.stats.gov.cn/tjsj/ndsj/) and China's statistical yearbooks of the construction industry (2001-2018, https://www.yearbookchina.com/navibooklist-n3018111232-1.html). Energy consumption and other data are from China's energy statistical yearbooks (2001-2018, https://www.yearbookchina.com/navibooklist-n3019090603-1.html). Environmental regulation data are from China's environmental yearbooks (2001-2018, https://www.yearbookchina.com/navibook-YZGHW.html) and China's environmental statistics yearbook (2001-2018, https://www.yearbookchina.com/navibooklist-n3019041927-1.html). Some data is also published by the National Bureau of Statistics (http://data.stats.gov.cn/).

3.2 GTIE indicator selection

Based on the theoretical framework of innovation value chain by (Hansen and Birkinshaw 2007), GTI is divided into two main stages: the R&D stage and commercialization stage (see Figure 1) as follows.

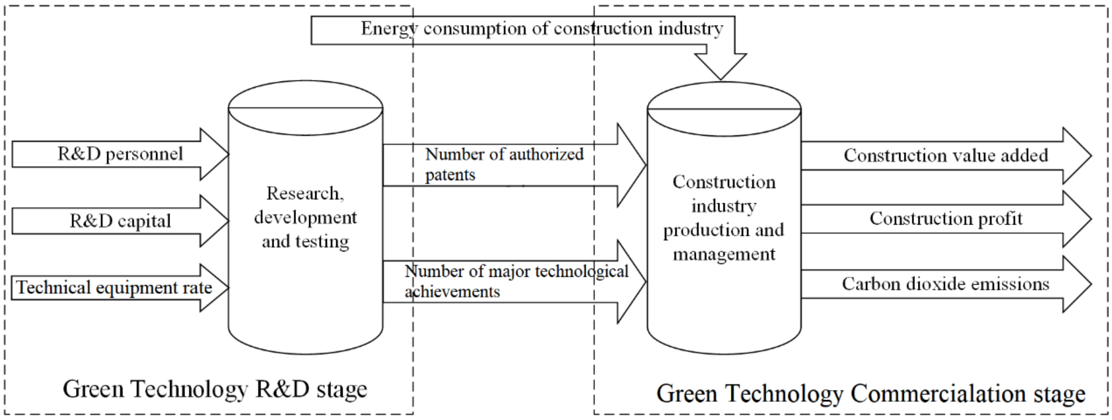

Figure 1. Green technology innovation process of the construction industry

(1) Green technology R&D stage (stage 1)

GTI is a process in which some resources are invested and economic benefits are obtained. This resource investment process mainly encompasses human resources, material resources and financial resources (Halme and Korpela 2014). Human resource input here is represented by the indicator of technical R&D personnel (Yang et al. 2020). GTI in the construction industry is extremely dependent on knowledge and technology. Hence, a high-level R&D team is critical for the implementation of GTI (Gonzalez-Moreno et al. 2018). Considering the access to representative information, the number of construction professionals in state-owned enterprises and institutions is used to represent the Human resources input. These personnel are engaged in specialized GTI activities in the construction industry, including the whole process of design, research and development, management and commercialization of innovation activities.

The input of Material resources usually refers to the input of R&D equipment (Frank et al. 2016; Trigkas et al. 2012). At the R&D stage, equipment is needed to develop or improve an original technology or product. The technical equipment rate of construction enterprises as the R&D equipment index is used to measure the Materials input (Wen et al. 2020).

Finally, due to the characteristics of GTI, R&D costs are usually high, i.e., they usually need substantial Financial support (Xiang et al. 2019). Referring to the previous research (Sirin 2011; Voutsinas et al. 2018), R&D expenditure is taken as the index to measure the investment on GTI. Due to the lack of specific data and statistics on GTI, it is assumed that this is calculated as the proportion of construction industry R&D expenditure vs the total national R&D expenditure (2.33%). On the other hand, the output sof the green technology R&D stage are usually some technical achievements. In the construction industry, R&D achievements include new products, but also non-material achievements such as new technologies. This is the reason why Popp (2005) and Wang and Huang (2007) proposed that in the absence of more robust indicators, the number of patents can be used as an effective measurement indicator for the R&D stage. This view was also supported by Thomas et al. (2011) and Zhong et al. (2011), who also used it as an output index of the green technology R&D stage. Consequently, the number of major technological achievements and the number of authorized patents is adopted as the output indicators at this stage.

(2) Green technology commercialization stage (stage 2)

This stage reflects how industrial enterprises and other innovative entities are putting their green technological achievements into the market in order to increase the economic benefits of commercial activities (Walsh 2012). In the green technology commercialization stage, the number of authorized patents and the number of major technological achievements from the previous stage are taken as an input index. In addition, the commercialization process of GTI usually consumes large amounts of energy. Accordingly, energy consumption is used as the resource input to calculate the efficiency of green technology commercialization stage (Mohmand et al. 2017).

Furthermore, the purpose of this stage is to produce economic benefits, and the value added of construction and gross profits are important indices to measure economic benefits (Chancellor and Lu 2016). However, due to the production processes involved, there will also be some concomitant pollution emissions and environmental problems (Marzouk et al. 2017). Therefore, besides the expected output such as economic benefits, it is necessary to include other non-expected outputs such as CO_2 emissions.

Table 1. Descriptive statistics of variables used in green technology innovation

	Indicators	**Units**	**Mean**	**S.D.**	**Min.**	**Max.**
Input	R&D personnel	10 Thousand People	96.03	33.99	34.90	146.00
	R&D expenditure	100 Million Yuan	161.30	129.74	20.86	410.01
	Technical equipment rate	Yuan / People	10151.11	1877.29	6304.00	13458.00
Intermediate input/output	Number of authorized patents	Item	34970.56	32438.65	5848.00	98381.00
	Number of major technological achievements	Item	1444.61	278.60	1031.00	1908.00
	Energy consumption	10 Thousand Ton	4906.06	2136.23	2179.00	8390.00
Output	Construction Value Added	100 Million Yuan	17997.95	13430.48	3341.09	39765.33
	Construction profit	100 Million Yuan	3107.89	2596.36	192.06	7491.78
	Carbon dioxide emissions	10 Thousand Ton	3452.17	990.34	2078.16	4952.91

3.3 Tobit Regression model variable description

The types of environmental regulations are divided into command-and-control environmental regulations (CER), market-based environmental regulations (MER) and voluntary environmental regulations (VER) as follows (Liu et al. 2018).

(1) Command-and-control environmental regulations (CER)

CER refer to the mandatory regulations implemented by governmental departments or environmental protection agencies to protect the environment. CER are widely used tools for environmental regulation in China. For measuring the level of intensity of CER, previous scholars used the number of newly implemented regulations (e.g. Zheng and Shi 2017). However, Li and Ramanathan (2018) believe that in some cases, governments are not always able to implement effectively their new enacted laws and regulations. Therefore, Li and Ramanathan (2018) recommendation is adopted, and selected the number of environmental administrative penalty cases by the government each year used as the indicator to measure the CER intensity.

(2) Market-based environmental regulations (MER)

The implication of MER is that governmental departments and environmental protection agencies use market means to control industrial pollution. For the measurement of MER, previous scholars used the pollutant discharge fees to measure the strength of MER (e.g. Li and Ramanathan 2018; Shen et al. 2019). Indeed, since 2003, the pollutant discharge fees system in China has been widely implemented across different regions of the country and has been thoroughly reported in statistical yearbooks. Therefore, pollutant discharge fees in the various regions of China are used as an indicator of MER.

(3) Voluntary environmental regulations (VER)

The implication of VER is that the public is urged to participate in the environmental protection process spontaneously, and thereby supervise the production behavior of industry. In this regard, Xie et al. (2017) and Ren et al. (2018) used the number of complaint letters on pollution and environmental related problems as an indicator to measure the strength of VER. This because the public is more sensitive to changes in their immediate surrounding environment. Therefore, the number of written letters from the petition office of the Ministry of Ecology and Environment (China) is used as an indicator to measure the strength of VER.

Additionally, the following control variables are used to ensure the correctness of the regression results: (1) economic development level (GDP): expressed by regional GDP; (2) industrial development level (IDP): total output value of construction industry as a percentage of GDP; and (3) technology innovation level (STI): technology market turnover.

Table 2 summarizes of the descriptive statistics of each variable.

Table 2. Variable selection and descriptive statistics

Category	Indicators	Unit	Mean	S.D.	Min	Max
Dependent variable	GTIE	\	0.863	0.105	0.674	1.000
Independent variable	CER	Item	100117.10	20810.54	55209.00	139059.00
	MER	10 thousand yuan	1488473.00	547938.20	579607.00	2199000.00
	VER	Number	3369.89	1350.14	1632.00	7038.00
Control variable	GDP	100 million	383134.80	239153.90	100280.10	820754.30
	IDP	%	0.211	0.048	0.125	0.276
	STI	100 million	4547.65	4024.48	651.00	13424.22

4 Research methods

A network EBM model is used to evaluate the multi-stage nature of GTI. This model allows measuring both the inputs and (desired and undesired) outputs of the multiple stages in the innovation process. The model is described in section 4.1. Additionally, on calculating the GTIE of the Chinese construction industry, the overall efficiency distribution state and its evolution over time are further explored by means of a kernel density estimation diagram. This technique is described in section 4.2. Finally, Tobit regression is used when analyzing the relationship between ERs and GTIE. The Tobit regression models are detailed in section 4.3.

4.1 Network EBM model

Tavana et al. (2013) network EBM model is used, as its efficiency calculation results are more realistic and reliable than other approaches. The model is

$$\gamma^* = \min \theta - \varepsilon_x \sum_{i=1}^{m} \frac{w_i s_i}{x_{i0}}$$

$$\text{s.t.}\,\theta x_{i0} - \sum_{j=1}^{n} \lambda_i x_{ij} - s_i = 0, i = 1, \dots, m$$

$$\sum_{j=1}^{n} \lambda_i y_{rj} \geq y_{r0}, r = 1, \dots, s \tag{1}$$

$$\lambda_i \geq 0$$

$$s_i \geq 0$$

where γ^* represents the optimal efficiency value, satisfying $0 \leq \gamma^* \leq 1$, w_i is the input element, the weight of i satisfies $\sum_{i=1}^{m} w_i = 1 (w_i \geq 0, \forall i)$, θ represents the radial efficiency value, s_i is the slack variable corresponding to the *i*-th input element, and ε_x is a parameter that combines radial θ and non-radial slack variables, λ represents the relative importance of the reference decision unit.

Following Tavana et al. (2013), it is assumed that there are *n* decision making units (DMU) to be evaluated, and each decision making unit DMU_j (j=1..., n) contains K nodes. x_{ij}^h and y_{ij}^h respectively represent input *i* of node h of DMU_j (i =1..., m_h) and output r (r=1..., sh), m_h and r_h are the input and output quantities of the h node, respectively. The link from the *k*-th node to the *h*-th node is defined as (k, h), and all the links constitute a set L. $z_{f_{(h,h')}j}^{(h,h')}$ ［j=1， …， n；（h，h'）∈L］ represents the intermediate output from the *h*-th node to the h' node. The comprehensive efficiency can be obtained by solving

$$\gamma^* = \min \sum_{h=1}^{K} W_h(\theta_h - \varepsilon_x^h \sum_{i=1}^{m_h} \frac{w_i^h s_i^h}{x_{i0}^h})$$

$$\text{s.t.} \sum_{j=1}^{n} x_{ij}^h \lambda_j^h + s_i^h = \theta_h x_{i0}^h, \mathrm{i} = 1, \dots, m_h, h = 1, \dots, K$$

$$\sum_{j=1}^{n} y_{rj}^h \lambda_j^h \geq y_{r0}^h, \mathrm{r} = 1, \dots, s_h, h = 1, \dots, K \tag{2}$$

$$\sum_{j=1}^{n} z_{f_{(h,h')}j}^{(h,h'')} \lambda_i^h = \sum_{j=1}^{n} z_{f_{(h,h')}j}^{(h,h''')} \lambda_i^{h''}, f_{(h,h')} = 1, F_{(h,h')}, \forall (h,h')$$

$$\theta_h \leq 1, h = 1, \dots, K$$

$$\lambda_j^h \geq 0, \mathrm{j} = 1, \dots, n, h = 1, \dots, K$$

$$s_i^h \geq 0, \mathrm{i} = 1, \dots, m_h, h = 1, \dots, K$$

where: w_i^h represents the weight of the *i*-th input of the *h*-th node, and satisfies$\sum_{i=1}^{m_h} w_i^h = 1$; s_i^h represents the slack of the *i*-th input of the *h*-th node; θ_h

and ε_i^h are the planning parameters of the radial part; W_h represents the decision-making by the decision maker The importance of the h-th node: According to Tavana et al. (2013) definition, the efficiency of each stage can be solved by

$$\gamma_{NEBM}^h = \theta_h - \varepsilon_x^h \sum_{i=1}^{m_h} \frac{w_i^h s_i^h}{x_{i0}^h}) \tag{3}$$

4.2 Kernel density estimation

The network EBM model from the previous subsection allowed calculating the GTIE as well as its phased efficiency in the Chinese construction industry. Now, the overall distribution state of GTIE and its trend of convergence (or divergence) are further explored by kernel density estimation. We choose kernel density estimation as other similar methods (such as the conditional β convergence, absolute β convergence and other efficiency convergence methods) are limited when reflecting the changes in efficiency gaps. Namely, For datasets$(x_1, x_2, \ldots, x_n)$, the kernel density estimation function is

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} k(\frac{x - X_i}{h})$$

where n is the number of observations; $k(x)$ is the kernel function, $k \geq 0$, $k(x) = k(-x)$ and $\int k(x)dx = 1$; h is the bandwidth, h is a constant value for all $x \in R$. In the kernel density function, the most important estimates of $k(x)$ include Gaussian nucleus, Epanechnikov nucleus, triangular nucleus and quadratic nucleus. The basis of selection comes from the intensity of packet data (Okabe et al. 2009). In general, the fewer packet data are selected, the more likely there is a need to select a Gaussian kernel (Kim and Scott 2012). Bandwidth is critical in kernel density estimation. If the bandwidth is too small, the estimation result may be rough; if the bandwidth is too large, the estimation result will be too smooth (Silverman 1986). The Gaussian kernel function and Stata15.1 software is used to estimate the nuclear density curve of the GTIE of the construction industry and its overall distribution.

4.3 Tobit regression model

National data from 2000 to 2017 are used for empirical analysis and to establish the Tobit model to study the impact of three types of ERs on GTIE. The logarithmic transformation is used of most variables to avoid multi-collinearity between variables, and to consider the heteroscedasticity of random error terms in the overall regression function.

Four Tobit models are used, which include both linear terms (Model 1) and nonlinear terms (Model 2). Considering that the policy effects sometimes have a certain delay, a regression model of ER with 1 phase lag (Model 3 and Model 4) is also established. Model 1 is first established to study the linear relationship between the three types of ERs and the construction industry GTIE, with

$$GTIE_t = \alpha_0 + \sum_{i=1}^{3} \beta_i ER_{i,t} + \beta_4 GDP_t + \beta_5 IDP_t + \beta_6 STI_t + \varepsilon_t \qquad \text{Model 1}$$

Among them, $GTIE_t$ represents the GTIE, t represents the year, where its specific value has been calculated by the network EBM model. ERi represents different types of environmental regulations. *i*=1,2,3, it represents CER, MER, and VER environmental regulations. GDP, IDP and STI represent the level of economic development, ownership structure, industrial development and technological innovation. α_0 is a constant term and ε_t is a perturbation term.

To study the possible nonlinear relationships between the three types of ER and GTIE, the quadratic term of the environmental regulation tool is introduced based on model 1, and proposes model 2:

$$GTIE_t = \alpha_0 + \sum_{i=1}^{3} \beta_i ER_{i,t} + \sum_{i=1}^{3} \beta_{i+3} ER_{i,t}^2 + \beta_7 GDP_t + \beta_8 IDP_t + \beta_9 STI_t + \varepsilon_t \quad \text{Model 2}$$

Models 1 and 2 are focused on investigating the impact of current ERs on GTIE. However, an effective consideration of the impact of ERs on GTIE may take some time to be appreciated (and measured). Therefore, linear and nonlinear models and lags the control variable by one year are established to avoid the two-way causal relationship with productivity (Rubashkina et al. 2015). This produces models 3 and 4, as the lagged counterparts of models 1 and 2

$$GTIE_t = \alpha_0 + \sum_{i=1}^{3} \beta_i ER_{i,t-1} + \beta_4 GDP_{t-1} + \beta_5 IDP_{t-1} + \beta_6 STI_{t-1} + \varepsilon_t \qquad \text{Model 3}$$

$$GTIE_t = \alpha_0 + \sum_{i=1}^{3} \beta_i ER_{i,t-1} + \sum_{i=1}^{3} \beta_{i+3} ER_{i,t-1}^2 + \beta_7 GDP_{t-1} + \beta_8 IDP_{t-1} + \beta_9 STI_{t-1} + \varepsilon_t \qquad \text{Model 4}$$

5 Results

In this section we present and interpret the major results of the network EBM model, the Kernel density estimation and the Tobit regression.

5.1 Green technology innovation efficiency (GTIE) of the construction industry

There is a requirement to test whether the staged input and output indicators meet the monotonic hypothesis, that is, as the input quantity increases, the output cannot be reduced. Therefore, the annual input and output are tested by Pearson correlation, and the test results are shown in Table 3. The results show that each input indicator and output indicator are positively correlated at a significant level of 1%, thereby satisfying the monotonic hypothesis. Among them, FI1-3 represents R&D personnel, R&D expenditure, and the technical equipment rate; FO1/SI1 represents the number of authorized patents, FO1/SI1 represents the number of major technological achievements; SI3 represents energy consumption; SO1-3 represents construction value added, construction profit, and carbon dioxide emissions.

Table 3. Correlation test of input and output indicators of GTIE

	FI1	FI2	FI3	FO1/SI1	FO2/SI2	SI3	SO1	SO2	SO3
FI1	1								
FI2	0.9489*	1							
FI3	0.7296*	0.6498*	1						
FO1/SI1	0.9050*	0.9879*	0.5807**	1					
FO2/SI2	0.8922*	0.9488*	0.6648*	0.9377*	1				
SI3	0.9723*	0.9892*	0.7017*	0.9643*	0.9433*	1			
SO1	0.9525*	0.9939*	0.6954*	0.9764*	0.9486*	0.9918*	1		
SO2	0.9585*	0.9962*	0.6885*	0.9758*	0.9467*	0.9932*	0.9982*	1	
SO3	0.9781*	0.9676*	0.7033*	0.9340*	0.9282*	0.9921*	0.9722*	0.9746*	1

Note: ** and * indicate the level of significance of 5% and 1%.

According to the network EBM model, MaxDEA7.0 software was used to calculate the efficiency of the stages (namely the green technology R&D stage and the green technology commercialization stage) and the overall efficiency of green technology innovation (GTIE) in the construction industry. The calculation results are shown in Table 4, and the construction industry's GTIE changes in each year are shown in Figure 2.

Table 4. Chinese construction industry GTIE in 2000-2017

Year	GTRD stage efficiency	GTC stage efficiency	Overall efficiency (GTIE)
2000	1.000	0.907	0.907
2001	1.000	1.000	1.000
2002	0.722	0.729	0.674
2003	0.768	0.794	0.743
2004	0.695	0.912	0.788
2005	0.739	1.000	0.869
2006	0.748	0.877	0.789
2007	0.669	0.770	0.680
2008	0.673	1.000	0.836
2009	0.636	1.000	0.818
2010	0.759	0.908	0.815
2011	0.713	1.000	0.857
2012	0.821	1.000	0.910
2013	0.848	1.000	0.924
2014	0.839	1.000	0.919
2015	1.000	1.000	1.000
2016	1.000	1.000	1.000
2017	1.000	1.000	1.000
Average	0.813	0.939	0.863

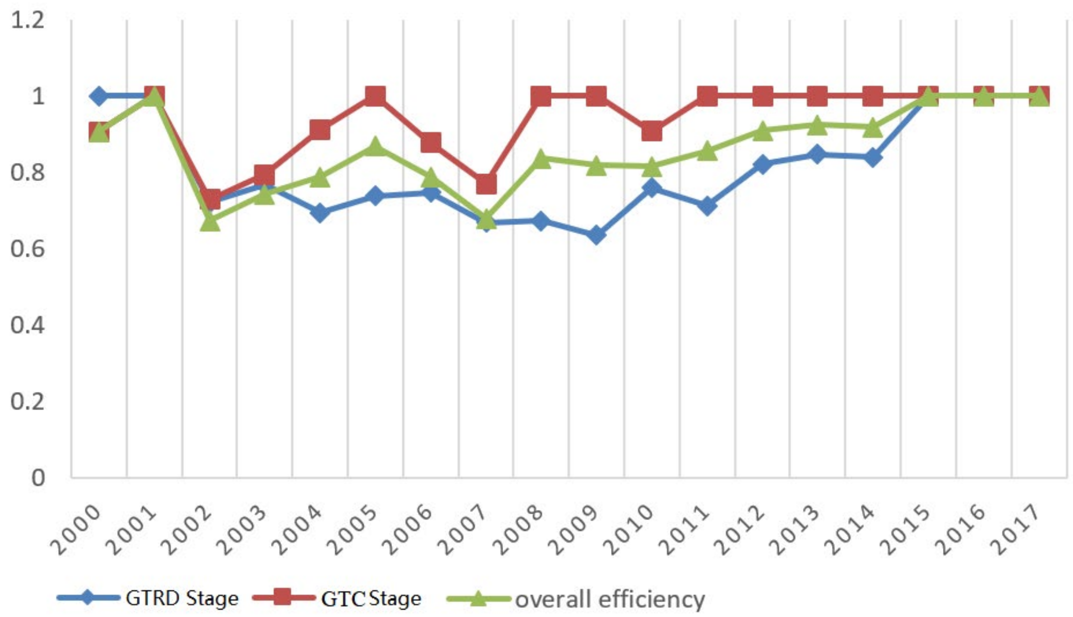

Figure 2. Changes in the GTIE of the Chinese construction industry from 2000-2017

As can be derived from Figure 2, the average value of the construction industry's GTIE in 2000-2017 is 0.863. This indicates that the GTIE of the construction industry is at a medium-to-high level. It is also apparent that the industry has achieved certain results in the green technology R&D (GTRD) stage and the green technology commercialization (GTC) stage, and the resource utilization efficiency is relatively high. Furthermore, the GTIE declined in 2002, to 0.674, mainly due to the decline in the GTRD stage efficiency and GTC stage efficiency in the same period. Since 2003, though, the GTIE has shown an upward trend, reaching 0.869 in 2005, reflecting the fluctuation of innovation efficiency in the construction industry. In 2006, the GTIE value declined, and in 2007, there was an inflection point, showing a trend of M-type change. In the last ten years of development, the overall GTIE level began to slowly pick up, and has reached the value of 1 since 2015.

The average efficiency of the GTRD stage is 0.813, which is lower than the overall GTIE and GTC stage, and has gone through transitions from high to low and then from low to high. This indicates that the resource utilization rate in the GTRD stage of the construction industry was low, which led to a waste of invested resources, reflecting that the growth of GTIE was mainly limited to the GTRD stage. Furthermore, a large amount of investment in R&D did not appear to bring corresponding returns, and there was excessive redundancy of resource input in the system. At the same time, this data reflects the growth of GTIE, which is mainly limited by the GTRD stage. Also, the efficiency of the GTRD stage is low and this could be due to a number of factors, such as neglecting the need for improved technology development efficiency as well as poor resource management in the construction sector (Donghun 2017).

The average efficiency of the GTC stage is 0.939, which is higher than the overall GTIE and the efficiency of the GTRD stage. This indicates that the resources utilization rate in the GTC stage is higher, and the technology achievements in the previous stage can be converted into corresponding economic profits. At the same time, the GTIE overall efficiency and GTC stage efficiency indicate that the growth of the construction industry's GTIE is mainly due to the influence of the GTC stage. This further explains that technology achievement can play an important role in improving the economic benefits of the construction industry, and GTI is indeed an appropriate development pathway to promote a greener development of the construction industry (Brochner 2010).

In Figure 3, it can be found that the GTIE and its phased efficiency in the Chinese construction industry also have certain differences in its variation trend. The overall efficiency value (named *kdensity gtie*) shows a single peak distribution. However, the height and width of the crest are low and large. This indicates that the overall efficiency value of technological innovation varies greatly every year. The efficiency of green technology R&D stage also presents a single peak distribution (named *kdensity gtie 1*), with the peak to the left. This indicates that the efficiency of green technology R&D stage is concentrated at a lower level. The efficiency of green technology commercialization stage, on the other hand, shows a multi-peak distribution (see *kdensity gtie 2*), with the highest peak appearing at the efficiency value of 1. This indicates that the efficiency of green technology commercialization stage is concentrated at a higher level.

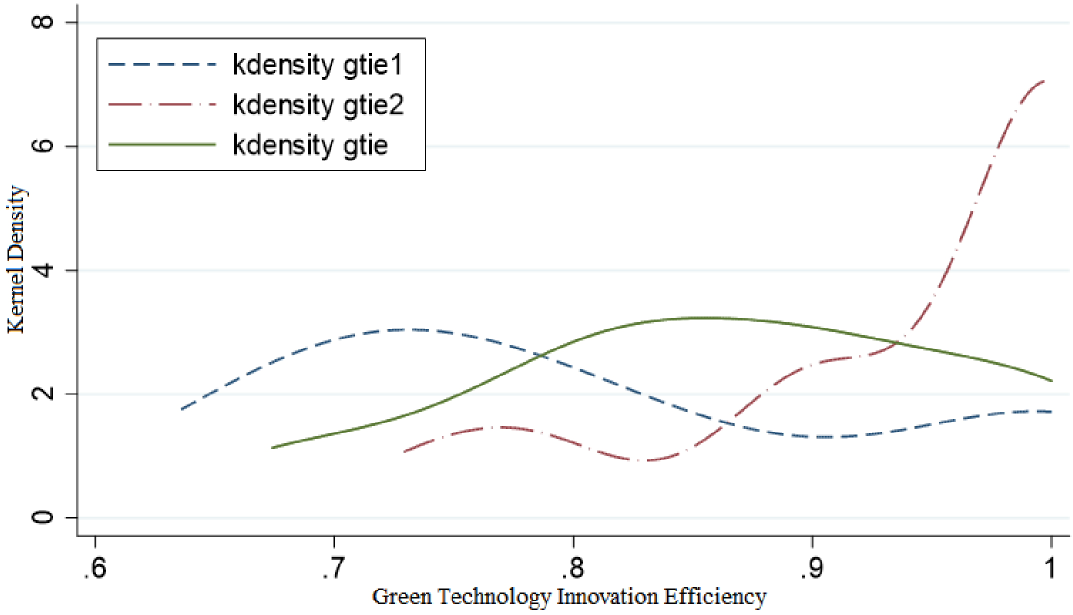

Figure 3. 2000-2017 Construction Industry GTIE Kernel Density Map

According to the overall results of the GTIE measurement and kernel density estimation, the GTIE of the Chinese construction industry is relatively high from 2000-2017, the GTRD efficiency is greatly improved, and the GTC efficiency is also good.

The fluctuation of GTIE indicates that the industrial structure of the Chinese construction industry is constantly adjusting and is gradually optimized, which demonstrates that it is affected to a certain extent by the application of ERs (Du et al. 2019; Guo et al. 2018). Since 2005, China's economic development mode has gradually shifted to one of environmentally-oriented sustainable development. In this context, the construction industry, which originally had a low energy efficiency, began to focus on green technology innovation activities (Xing and Cao 2019). In order to improve the GTIE, the construction industry must first improve the GTRD efficiency, which involves a number of supporting activities. This includes controlling the scale of inputs, reducing any redundancy of resources, improving the quality of output, and developing further technological innovation resources across the industrial base and with greater technical efficiency (Bin Ibrahim et al. 2010). At the same time and according to the results of this study, there is a need to improve the GTC efficiency. When applying the technology achievement to the industrial production process, we need to take into account the impact of production activities on the environment, accelerate the green transformation of the construction industry, and more broadly promote green development of the society (Yang and Huang 2016).

5.2 Regression analysis

5.2.1 Unit root and co-integration test

In order to test the validity of the estimated results and avoid pseudo-regression problems as much as possible, the stationarity test of the data is required. In this study, ADF is adopted for the unit root test, and the test results are shown in Table 5. Under the condition of first difference, the unit root test results of GTIE, CER and STI are significant at 1% confidence level, that is, there is no unit root. MER, VER, GDP and IDP have unit roots in the first difference, but they are significant at 1% after the second difference, that is, the null hypothesis is rejected. It can be observed that the difference of all the sequences in the model are stationary, and the second-order difference test does not contain a unit root, so it has good level of stationarity.

Table 5. Unit root test result

	ADF	p	Conclusion
GTIE	-2.527	0.1090	non-stationary
ΔGTIE	-5.266***	0.0000	stationary
Δ^2GTIE	-6.619***	0.0000	stationary
CER	-2.853	0.0511	non-stationary
ΔCER	-4.676***	0.0001	stationary
Δ^2CER	-6.050***	0.0000	stationary
MER	-1.098	0.7158	non-stationary
ΔMER	-2.442	0.1302	non-stationary
Δ^2MER	-4.546***	0.0002	stationary
VER	0.280	0.9764	non-stationary
ΔVER	-2.536	0.1071	non-stationary
Δ^2VER	-3.764***	0.0033	stationary
GDP	4.366	1.0000	non-stationary
ΔGDP	-2.082	0.2518	non-stationary
Δ^2GDP	-4.151***	0.0008	stationary
IDP	-2.090	0.2486	non-stationary
ΔIDP	-2.255	0.1870	non-stationary
Δ^2IDP	-4.004***	0.0014	stationary
STI	8.934	1.0000	non-stationary
ΔSTI	-3.776***	0.0032	stationary
Δ^2STI	-6.682***	0.0000	stationary

Note: *** indicates that the test value is significant at the level of 1%; Δ said first order difference, Δ^2 said second order difference.

The result of the unit root test highlights that the sequence of variables in the model is second-order single integration, so it is necessary to conduct the co-integration test on the data to determine whether there is a co-integration relationship between each variable. In this study, the EG-ADF test and the Johansen test are used for the co-integration test.

The results of the EG-ADF test are shown in Table 6. The results show that the ADF statistic for the residual sequence is significant at the 1% confidence level, indicating a significant co-integration relationship for each variable of the data.

Table 6. EG-ADF test result

Variable	statistic	1% threshold	5% threshold	10% threshold
e	-3.593	-2.66	-1.95	-1.6

When performing the Johansen test, firstly, according to the information criterion, the lag order of the variable is determined to be 1, and this allows the co-integration rank to be calculated. The analysis results are shown in Table 7. When the maximum rank is 2, the trace statistic is 64.1703, which is less than 5% threshold, indicating that there are two co-integration relations for each variable.

Table 7. Johansen test result

Co-integration rank (Max)	Eigenvalue	Trace Statistics	5% Threshold
0	-	145.1792	124.24
1	0.93898	100.4337	94.15
2	0.89632	64.1703*	68.52
3	0.84787	34.0416	47.21
4	0.66182	16.6949	29.68
5	0.36077	9.5351	15.41
6	0.34276	2.8197	3.76
7	0.16158	-	-

The results of the EG-ADF test and the Johansen test indicate that the data passed the co-integration test, and therefore it can be concluded that there is a significant co-integration relationship among the variables.

5.2.2 Regression result

The GTIE of the construction industry each year was adopted as the dependent variable, the three different types of ERs as the independent variable, and the level of economic development, industrial development, scientific and technological innovation as control variables. Finally, the Tobit regression model was used to verify the relationship between three types of ERs and the GTIE in construction industry from 2000 to 2017. The statistical analysis software used in this study is Stata15.1, and the regression results are shown in Table 8. As can be seen, LRχ2 values of all models were significant at 99% confidence, indicating that the models met the overall significance test (Otero et al. 2012).

Table 8. Results of regression analysis

Variable	No lag		One-year lag	
	Model 1	Model 2	Model 3	Model 4
CER	-0.1149 -0.83	-6.2007 -0.53	0.0432 0.37	-25.9323** -2.92
CER^2		0.2482 0.49		1.1468** 2.94
MER	0.4197* 1.87	-23.568** -2.88	-0.1852 -0.91	24.4617*** 3.65
MER^2		0.8731** 2.92		-0.9080*** -3.68
VER	-0.3411** -2.74	4.0505 1.65	-0.0645 -0.60	1.6986 0.42
VER^2		-0.2729 -1.80		-0.1007 -0.40
GDP	-1.6917*** -3.09	-2.3753*** -4.52	-0.2368 -0.47	1.0390* 2.01
IDP	-8.4622*** -3.65	-8.3404*** -3.89	-7.8126*** -3.73	-10.0197*** -5.21
STI	1.4759*** 3.65	1.8164*** 5.31	0.5931 1.62	0.0081* 0.03
C	10.3702*** 3.51	200.2607** 4.232.96	3.4061 1.33	-35.0291 -0.86
LR χ^2	25.64***	35.01***	24.32***	34.04***
Log likelihood	17.6686	22.3561	18.9457	23.8059

Note: ***, ** and * represent significant levels of 10%, 5% and 1%.

(1) Results of the current regression model (Model 1 and Model 2)

It can be observed from the regression model of the current period that the linear relationship between CER and GTIE is negative, but not significant; the coefficient of the first term is negative and the coefficient of the second term is positive, which is not significant, indicating that CER of the current period hardly affects GTIE of the construction industry.

The linear relationship between MER and GTIE in the current period was positive and significant at 90% confidence; the coefficient of the first term is negative and the coefficient of the second term is positive, both of which are significant under 95% confidence. This indicates that there is a non-linear relationship between MER and GTIE in the current period, and the relationship is U-shaped.

The linear relationship between current VER and GTIE was negative and significant with 95% confidence, the coefficient of the first term is positive and the coefficient of the second term is negative, but they are not significant. This indicates that there is a linear relationship between current VER and GTIE of the construction industry.

(2) Results of regression model with lag (Model 3 and Model 4)

It can be observed from the regression model of the lag phase that the linear relationship between the CER of the lag phase and the GTIE of the construction industry is positive but not significant. The coefficient of the primary term of the nonlinear relationship is negative, the coefficient of the quadratic term is positive, and at 95%, confidence is significant. The regression model further shows that the CER of the lag phase has a significant nonlinear relationship with the construction industry GTIE, and it is U-shaped.

The linear relationship between the MER of the lag phase and the GTIE of the construction industry is negative, but not significant; the coefficient of the primary term of the nonlinear relationship is positive, the coefficient of the quadratic term is negative, and significant at 99% confidence. It shows that the MER of the lag phase has a significant nonlinear relationship with the construction industry GTIE, and it is inverted U-shaped.

The linear relationship between the VER and the construction industry GTIE is negative, but not significant. The coefficient of the primary term of the nonlinear relationship is positive, and the coefficient of the quadratic term is negative, but they are not significant, indicating that the VER of the lag phase has little effect on the GTIE of the construction industry.

5.3 Robustness check

In order to test the robustness of the above Tobit model estimation results, this study uses the regression model to test the robustness of the estimation results. If the core variables in the test results are still significant, then the results are robust. If the core variables in the test results become insignificant, then the results would not be robust. In our analysis, the Tobit model was replaced by the GLM model for regression analysis, and the standard deviation was estimated using the clustering robust standard error method. The test results are shown in Table 9. It can be observed that after regression with the GLM model, the core variable coefficient and significance remain basically unchanged, which indicates that the analysis results of the model are robust

.

Table 9. Robustness test

Variable	No lag		One-year lag	
	Model 1	Model 2	Model 3	Model 4
CER	-0.0063	13.672*	0..1145	-22.0650**
	-0.06	1.74	1.30	-4.96
CER^2		-0.6049*		0.9794**
		-1.74		4.99
MER	0.3815**	-13.8858**	-0.1745	23.7052***
	1.99	-1.69	-0.87	4.92
MER^2		0.5246**		-0.8798***
		1.71		-4.92
VER	-0.2341**	1.9566	-0.0295	2.8240
	-2.54	0.95	-0.32	1.47
VER^2		-0.1414		-0.1711
		-1.11		-1.44
GDP	-1.5150***	--2.2468***	-0.2141	0.9794**
	-3.37	-3.24	-0.45	2.00
IDP	-5.8266***	--5.9354***	-6.6206***	-9.8934***
	-3.84	-2.70	-3.68	-7.63
STI	1.2160***	1.6336***	0.5046	0.0327
	3.68	3.90	1.56	0.11
C	8.0751***	25.0280	2.3129	-56.2718
	4.79	0.95	1.14	-3.15
LR χ^2	-2.3017	-2.3202	-2.4040	-2.7939
Log likelihood	-31.7456	-25.9753	-28.2927	-19.8137

6 Discussion

According to the aforementioned research results, the command-and-control environmental regulations (CER) with the lag phase and the green technology innovation efficiency (GTIE) of the construction industry show a significant U-shaped relationship. CER show significant temporal lag, since the enforcement of government administrative rights requires a certain amount of time to have an effect (Li and Ramanathan 2018). It can be observed that there is an obvious inflection point in the influence of CER on GTIE in the Chinese construction industry. With the gradual increase of CER implementation intensity, GTIE appears to exhibit a trend of first declining and thereafter rising. Therefore, it is recommended that the Chinese government continue to promote the implementation of CER, introduce more effective environmental protection laws and regulations, increase environmental administrative penalties, and promote the improvement of GTIE in the construction industry.

There is a significant inverted U-shaped relationship between market-based environmental regulations (MER) of the lag phase and the construction industry's GTIE. Due to the openness and dynamic nature of the market, the market-based environmental regulations (MER) of the lag phase are more significant than in the current period. It can be seen that MER are the dominant ERs at present, which have the most far-reaching impact on the GTIE of the construction industry. With the increase of MER implementation intensity, the GTIE of the construction industry shows a trend of first increasing and then decreasing. According to research by Porter (1991), moderate implementation intensity of MER is conducive to improving the GTIE in the construction industry. Furthermore, moderate market incentive MER intensity can help improve the GTIE in the construction industry (Wang et al. 2019). In order to avoid high environmental protection costs and remain competitive , the construction industry will actively undertake green technology innovation (Alpay et al. 2002). However, high-intensity MER will potentially lead to a situation where the construction industry has to increase the cost of environmental pollution control and capital input, which may result in crowding out investment in other aspects of the industry and result in negative impact on the operation of the construction industry (Jaffe et al. 2002).

The voluntary environmental regulations (VER) of the current period have a significant negative relationship with the GTIE in the construction industry. VER mainly involves a series of environmental protection actions by different stakeholders including residents, the construction industry and non-governmental organizations to support the implementation of environmental policies. However, VER has a negative impact on the efficiency of GTI in the construction industry, which is different from the position found in previous studies (Korhonen et al. 2015). This highlights that VER have a crowding out effect on GTI, and excessive VER strength will likely hinder future improvements of GTIE in the construction industry.

Hence, to summarize the findings from this research study, it can be observed that the three types of environmental regulations have different levels of impact on the GTIE of the Chinese construction industry. However, the combination of different types of environmental regulations can promote a greener development of this industry (Iraldo et al. 2011). More precisely, among the three types of environmental regulations, it is evident that MER has the most far-reaching impact. Therefore, to promote the green development of the construction industry, it is necessary to improve MER performance, that is, promote the wider implementation of the emissions trading system, and strengthen the use of the market mechanisms to solve externality problems. Additionally, it is also recommended that the government comprehensively implement CER and MER to further strengthen the green technical innovation of the construction industry.

7 Conclusions

This study has divided the construction industry innovation activities in two stages: the green technology R&D (GTRD) stage and the commercialization (GTC) stage. A network EBM model has been used to measure the staged efficiency and overall efficiency of the green technology innovation of the Chinese construction industry. Then, a Tobit regression model has been proposed to analyze the impact of three different types of environmental regulations (ERs) on green technology innovation efficiency (GTIE). This study has the following two main conclusions:

(1) There is a disconnection between R&D and the commercial use in the green technology innovation activities of the construction industry. It has been found that, except for the year 2000, the green technology commercialization efficiency in the construction industry from 2001 to 2017 was always higher than the green technology R&D efficiency. This indicates that the construction industry is capable of applying technologies to the market and turn them into economic benefits. However, there is redundancy of resource investment in the green technology R&D stage, and a large amount of R&D investment does not eventually deliver any R&D achievements. Therefore, the key to improve the GTIE is to improve the efficiency of green technology at the R&D stage, so that the invested resources of R&D can be fully taken advantage of and more R&D achievements can be delivered.

(2) Different types of environmental regulations have different effects on the green technology innovation efficiency. The combined application of the three types of environmental regulations can effectively improve the GTIE. More precisely, first, command-and-control environmental regulations has a U-shaped relationship with the GTIE, and there is an obvious lag. This means that the government's command-and-control environmental regulations will initially inhibit the industry's green innovation behavior and reduce the GTIE. Then, when the "inflection point" is crossed, command-and-control environmental regulations can have a positive impact on GTIE. Of course, it should also be noted that command-and-control environmental regulations will not be effective immediately after promulgation. Instead, they will have an impact after a period of implementation. Second, there is an inverted U-shaped relationship between market environmental regulations and GTIE. This shows that although market

environmental regulations can improve GTIE at the beginning, after the inflection point, market environmental regulations will inhibit GTIE. Finally, there is a negative linear relationship between voluntary environmental regulations and GTIE, but it is only effective in the current period. This is mainly because the current development of voluntary environmental regulation is not perfect and cannot have a positive effect on improving the green technology innovation activities. Therefore, the government needs to improve the public's awareness of environmental supervision and strengthen the role of voluntary environmental regulations. In general, it has been found that there is no type of environmental regulation that has the most effective effect on GTIE. Then, to improve GTIE, the three types of environmental regulations should be combined.

In general, this study contributes to the body of knowledge on green technology innovation efficiency on two fronts. Firstly, the study has proposed a different and more effective evaluation method of green technology innovation efficiency in the construction industry. So far, the green technology innovation process had been regarded as a black box. However, upon dividing the process into two stages (i.e. the green technology R&D stage and green technology commercialization stage) we have been able to discriminate between the different effects the process can have on industrial companies from the construction sector. Furthermore, this complements previous theoretical research on green technology innovation efficiency. Secondly, this study provides clearer guidance for governments to formulate more effective environmental regulations. As demonstrated, different types of environmental regulations have differential impacts on the innovation efficiency of green technology. They also affect green technology innovation during different time periods. Therefore, governments should consider these differential effects and time lags when issuing a combination of environmental regulations designed for the construction industry.

This study also has some limitations. Firstly, the study analyzes the impact of environmental regulations on GTIE, mainly because the market mechanism has a certain degree of limitations. More often, it is necessary to encourage industry to improve innovation efficiency from the perspective of the government. However, this does not mean that the market mechanism is not important. Future research will need to incorporate market mechanisms into the research scope and analyze the driving mechanisms of GTIE under the dual role of government policies and market mechanisms. Secondly, this study adopts the Chinese construction industry as the research object and provides a case study for other countries to use environmental regulations to improve their GTIE. Although this research study can be extrapolated to other contexts, the implementation process also needs to take into account the other countries' conditions. These aspects remain to be further explored.

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References

Aldieri, L., Ioppolo, G., Vinci, C. P., and Yigitcanlar, T. (2019). Waste recycling patents and environmental innovations: An economic analysis of policy instruments in the USA, Japan and Europe. *Waste Management*, 95, 612-619. https://doi.org/https://doi.org/10.1016/j.wasman.2019.06.045

Alpay, E., Kerkvliet, J., and Buccola, S. (2002). Productivity Growth and Environmental Regulation in Mexican and U.S. Food Manufacturing. *American Journal of Agricultural Economics*, 84(4), 887-901.

Bi, K., Huang, P., and Wang, X. (2016). Innovation performance and influencing factors of low-carbon technological innovation under the global value chain: A case of Chinese manufacturing industry. *Technological Forecasting and Social Change*, 111, 275-284. https://doi.org/https://doi.org/10.1016/j.techfore.2016.07.024

Bin Ibrahim, A. R., Roy, M. H., Ahmed, Z., and Imtiaz, G. (2010). An investigation of the status of the Malaysian construction industry. *Benchmarking: An International Journal*, 17(2), 294-308. https://doi.org/10.1108/14635771011036357

Brochner, J. (2010). Construction contractors as service innovators. *Building Research and Information*, 38(3), 235-246. https://doi.org/10.1080/09613211003616706

Chancellor, W., and Lu, W. S. (2016). A Regional and Provincial Productivity Analysis of the Chinese Construction Industry: 1995 to 2012. *Journal of Construction Engineering and Management*, 142(11), 9. https://doi.org/10.1061/(asce)co.1943-7862.0001177

Donghun, Y. (2017). The regional-innovation cluster policy for R&D efficiency and the creative economy: with focus on Daedeok Innopolis. *Journal of Science and Technology Policy Management*, 8(2), 206-226. https://doi.org/10.1108/jstpm-09-2016-0025

Du, J. L., Liu, Y., and Diao, W. X. (2019). Assessing Regional Differences in Green Innovation Efficiency of Industrial Enterprises in China. *International Journal Of Environmental Research And Public Health*, 16(6), 23. https://doi.org/10.3390/ijerph16060940

Du, K., and Li, J. (2019). Towards a green world: How do green technology innovations affect total-factor carbon productivity. *Energy Policy*, 131, 240-250. https://doi.org/https://doi.org/10.1016/j.enpol.2019.04.033

Esmaeilpoorarabi, N., Yigitcanlar, T., Kamruzzaman, M., and Guaralda, M. (2020). How does the public engage with innovation districts? Societal impact assessment of Australian innovation districts. *Sustainable Cities and Society*, 52, 101813. https://doi.org/https://doi.org/10.1016/j.scs.2019.101813

Feng, Z., Zeng, B., and Qian, M. (2018). Environmental Regulation, Two-Way Foreign Direct Investment, and Green Innovation Efficiency in China's Manufacturing Industry. *International Journal of Environmental Research and Public Health*, 15(10). https://doi.org/10.3390/ijerph15102292

Frank, A. G., Nogueira Cortimiglia, M., Duarte Ribeiro, J. L., and Subtil De Oliveira, L. (2016). The effect of innovation activities on innovation outputs in the Brazilian industry: market-orientation vs. technology-acquisition strategies. *Research Policy*, 45(3), 577-592. https://doi.org/10.1016/j.respol.2015.11.011

Frondel, M., Horbach, J., and Rennings, K. (2007). End-of-pipe or cleaner production? An empirical comparison of environmental innovation decisions across OECD countries. *Business Strategy and the Environment*, 16(8), 571-584. https://doi.org/10.1002/bse.496

Gao, Y., Tsai, S.-B., Xue, X., Ren, T., Du, X., Chen, Q., and Wang, J. (2018). An Empirical Study on Green Innovation Efficiency in the Green Institutional Environment. *Sustainability*, 10(3), 13. https://doi.org/10.3390/su10030724

Gente, V., and Pattanaro, G. (2019). The place of eco-innovation in the current sustainability debate.

Waste Management, 88, 96-101. https://doi.org/https://doi.org/10.1016/j.wasman.2019.03.026

Gonzalez-Moreno, A., Diaz-Garcia, C., and Saez-Martinez, F. J. (2018). R&D team composition and product innovation: gender diversity makes a difference. *European Journal of International Management*, 12(4), 423-446. https://doi.org/10.1504/ejim.2018.10012421

Guo, Y. Y., Xia, X. N., Zhang, S., and Zhang, D. P. (2018). Environmental Regulation, Government R&D Funding and Green Technology Innovation: Evidence from China Provincial Data. *Sustainability*, 10(4), 21. https://doi.org/10.3390/su10040940

Hájek, M., Zimmermannová, J., Helman, K., and Rozenský, L. (2019). Analysis of carbon tax efficiency in energy industries of selected EU countries. *Energy Policy*, 134, 110955. https://doi.org/https://doi.org/10.1016/j.enpol.2019.110955

Halme, M., and Korpela, M. (2014). Responsible Innovation Toward Sustainable Development in Small and Medium-Sized Enterprises: a Resource Perspective. *Business Strategy and the Environment*, 23(8), 547-566. https://doi.org/10.1002/bse.1801

Hansen, M. T., and Birkinshaw, J. (2007). The Innovation Value Chain. *Harvard Business Review Home*, 85(6), 121-130.

He, Q., Wang, Z., Wang, G., Zuo, J., Wu, G., and Liu, B. (2020). To be green or not to be: How environmental regulations shape contractor greenwashing behaviors in construction projects. *Sustainable Cities and Society*, 63, 102462. https://doi.org/https://doi.org/10.1016/j.scs.2020.102462

Hölscher, K., Wittmayer, J. M., and Loorbach, D. (2018). Transition versus transformation: What's the difference? *Environmental Innovation and Societal Transitions*, 27, 1-3. https://doi.org/https://doi.org/10.1016/j.eist.2017.10.007

Iraldo, F., Testa, F., Melis, M., and Frey, M. (2011). A Literature Review on the Links between Environmental Regulation and Competitiveness. *Environmental Policy and Governance*, 21(3), 210-222. https://doi.org/10.1002/eet.568

Jaffe, A. B., Newell, R. G., and Stavins, R. N. (2002). Environmental Policy and Technological Change. *Environmental & Resource Economics*, 22(1-2), 41-70.

Kesidou, E., and Demirel, P. (2012). On the drivers of eco-innovations: Empirical evidence from the UK. *Research Policy*, 41(5), 862-870. https://doi.org/https://doi.org/10.1016/j.respol.2012.01.005

Kim, J., and Scott, C. D. (2012). Robust Kernel Density Estimation. *Journal of Machine Learning Research*, 13, 2529-2565.

Korhonen, J., Patari, S., Toppinen, A., and Tuppura, A. (2015). The role of environmental regulation in the future competitiveness of the pulp and paper industry: the case of the sulfur emissions directive in Northern Europe. *Journal Of Cleaner Production*, 108, 864-872. https://doi.org/10.1016/j.jclepro.2015.06.003

Kuo, T.-C., and Smith, S. (2018). A systematic review of technologies involving eco-innovation for enterprises moving towards sustainability. *Journal of Cleaner Production*, 192, 207-220. https://doi.org/10.1016/j.jclepro.2018.04.212

Lai, X., Liu, J., Shi, Q., Georgiev, G., and Wu, G. (2017). Driving forces for low carbon technology innovation in the building industry: A critical review. *Renewable and Sustainable Energy Reviews*, 74, 299-315. https://doi.org/https://doi.org/10.1016/j.rser.2017.02.044

Lee, C.-W. (2010). The effect of environmental regulation on green technology innovation through supply chain integration. *International Journal of Sustainable Economy*, 2(1), 92-112. https://doi.org/10.1504/IJSE.2010.029943

Li, H., Zhang, J., Wang, C., Wang, Y., and Coffey, V. (2018a). An evaluation of the impact of environmental regulation on the efficiency of technology innovation using the combined DEA model: A case study of Xi'an, China. *Sustainable Cities and Society*, 42, 355-369. https://doi.org/https://doi.org/10.1016/j.scs.2018.07.001

Li, L., Su, F., Zhang, W., and Mao, J.-Y. (2018b). Digital transformation by SME entrepreneurs: A capability perspective. *Information Systems Journal*, 28(6), 1129-1157. https://doi.org/10.1111/isj.12153

Li, R., and Ramanathan, R. (2018). Exploring the relationships between different types of environmental regulations and environmental performance: Evidence from China. *Journal Of Cleaner Production*, 196, 1329-1340. https://doi.org/https://doi.org/10.1016/j.jclepro.2018.06.132

Lin, S., Sun, J., Marinova, D., and Zhao, D. (2018a). Evaluation of the green technology innovation efficiency of China's manufacturing industries: DEA window analysis with ideal window width. *Technology Analysis & Strategic Management*, 30(10), 1166-1181. https://doi.org/10.1080/09537325.2018.1457784

Lin, Y., Deng, N., and Gao, H. (2018b). Research on Technological Innovation Efficiency of Tourist Equipment Manufacturing Enterprises. *Sustainability*, 10(12), 17. https://doi.org/10.3390/su10124826

Liu, Y., and Feng, C. (2019). What drives the fluctuations of "green" productivity in China's agricultural sector? A weighted Russell directional distance approach. *Resources, Conservation and Recycling*, 147, 201-213. https://doi.org/https://doi.org/10.1016/j.resconrec.2019.04.013

Liu, Y., Li, Z., and Yin, X. (2018). The effects of three types of environmental regulation on energy consumption—evidence from China. *Environmental Science & Pollution Research*, 1-18.

Marzouk, M., El-zayat, M., and Aboushady, A. (2017). Assessing Environmental Impact Indicators in Road Construction Projects in Developing Countries. *Sustainability*, 9(5), 21. https://doi.org/10.3390/su9050843

Miao, C., Fang, D., Sun, L., and Luo, Q. (2017). Natural resources utilization efficiency under the influence of green technological innovation. *Resources, Conservation and Recycling*, 126, 153-161. https://doi.org/https://doi.org/10.1016/j.resconrec.2017.07.019

Mohmand, Y. T., Wang, A. H., and Saeed, A. (2017). The impact of transportation infrastructure on economic growth: empirical evidence from Pakistan. *Transportation Letters-the International Journal of Transportation Research*, 9(2), 63-69. https://doi.org/10.1080/19427867.2016.1165463

Okabe, A., Satoh, T., and Sugihara, K. (2009). A kernel density estimation method for networks, its computational method and a GIS-based tool. *International Journal of Geographical*

Information Science, 23(1), 7-32. https://doi.org/10.1080/13658810802475491

Otero, L. D., Centeno, G., Otero, C. E., and Reeves, K. (2012). A DEA-Tobit Analysis to Understand the Role of Experience and Task Factors in the Efficiency of Software Engineers. *Ieee Transactions On Engineering Management*, 59(3), 391-400. https://doi.org/10.1109/tem.2010.2101078

Pan, X. F., Ai, B. W., Li, C. Y., Pan, X. Y., and Yan, Y. B. (2019). Dynamic relationship among environmental regulation, technological innovation and energy efficiency based on large scale provincial panel data in China. *Technological Forecasting and Social Change*, 144, 428-435. https://doi.org/10.1016/j.techfore.2017.12.012

Popp, D. (2005). Lessons from patents: Using patents to measure technological change in environmental models. *Ecological Economics*, 54(2), 209-226. https://doi.org/https://doi.org/10.1016/j.ecolecon.2005.01.001

Porter, M. E. (1991). America's Green Strategy. *Scientific American*, 264(4), 168-170.

Ren, S., Li, X., Yuan, B., Li, D., and Chen, X. (2018). The effects of three types of environmental regulation on eco-efficiency: A cross-region analysis in China. *Journal Of Cleaner Production*, 173, 245-255. https://doi.org/10.1016/j.jclepro.2016.08.113

Rubashkina, Y., Galeotti, M., and Verdolini, E. (2015). Environmental regulation and competitiveness: Empirical evidence on the Porter Hypothesis from European manufacturing sectors. *Energy Policy*, 83(35), 288-300.

Schiederig, T., Tietze, F., and Herstatt, C. (2012). Green innovation in technology and innovation management – an exploratory literature review. *R&D Management*, 42(2), 180-192. https://doi.org/10.1111/j.1467-9310.2011.00672.x

Schreck, M., and Wagner, J. (2017). Incentivizing secondary raw material markets for sustainable waste management. *Waste Management*, 67, 354-359. https://doi.org/https://doi.org/10.1016/j.wasman.2017.05.036

Shen, N., Liao, H., Deng, R., and Wang, Q. (2019). Different types of environmental regulations and the heterogeneous influence on the environmental total factor productivity: Empirical analysis of China's industry. *Journal Of Cleaner Production*, 211, 171-184. https://doi.org/https://doi.org/10.1016/j.jclepro.2018.11.170

Silajdžić, I., Kurtagić, S. M., and Vučijak, B. (2015). Green entrepreneurship in transition economies: a case study of Bosnia and Herzegovina. *Journal of Cleaner Production*, 88, 376-384. https://doi.org/https://doi.org/10.1016/j.jclepro.2014.07.004

Silverman, B. W. (1986). *Density Estimation for Statistics and Data Analysis*, London: :Chapman and Hall.

Sirin, S. M. (2011). Energy market reforms in Turkey and their impact on innovation and R&D expenditures. *Renewable & Sustainable Energy Reviews*, 15(9), 4579-4585. https://doi.org/10.1016/j.rser.2011.07.093

Song, M., Tao, J., and Wang, S. (2015). FDI, technology spillovers and green innovation in China: analysis based on Data Envelopment Analysis. *Annals of Operations Research*, 228(1), 47-64. https://doi.org/10.1007/s10479-013-1442-0

Tavana, M., Mirzagoltabar, H., Mirhedayatian, S. M., Saen, R. F., and Azadi, M. (2013). A new network epsilon-based DEA model for supply chain performance evaluation. *Computers & Industrial Engineering*, 66(2).

Thomas, V. J., Sharma, S., and Jain, S. K. (2011). Using patents and publications to assess R&D efficiency in the states of the USA. *World Patent Information*, 33(1), 4-10. https://doi.org/https://doi.org/10.1016/j.wpi.2010.01.005

Tone, K., and Tsutsui, M. (2010). An epsilon-based measure of efficiency in DEA – A third pole of technical efficiency. *European Journal of Operational Research*, 207(3), 1554-1563. https://doi.org/https://doi.org/10.1016/j.ejor.2010.07.014

Trigkas, M., Papadopoulos, I., and Karagouni, G. (2012). Economic efficiency of wood and furniture innovation system. *European Journal of Innovation Management*, 15(2), 150-176. https://doi.org/10.1108/14601061211220959

Tseng, M.-L., Wang, R., Chiu, A. S. F., Geng, Y., and Lin, Y. H. (2013). Improving performance of green innovation practices under uncertainty. *Journal of Cleaner Production*, 40, 71-82. https://doi.org/https://doi.org/10.1016/j.jclepro.2011.10.009

Voutsinas, I., Tsamadias, C., Carayannis, E., and Staikouras, C. (2018). Does research and development expenditure impact innovation? theory, policy and practice insights from the Greek experience. *Journal of Technology Transfer*, 43(1), 159-171. https://doi.org/10.1007/s10961-015-9454-3

Walsh, P. R. (2012). Innovation Nirvana or Innovation Wasteland? Identifying commercialization strategies for small and medium renewable energy enterprises. *Technovation*, 32(1), 32-42. https://doi.org/10.1016/j.technovation.2011.09.002

Wang, E. C., and Huang, W. (2007). Relative efficiency of R&D activities: A cross-country study accounting for environmental factors in the DEA approach. *Research Policy*, 36(2), 260-273. https://doi.org/https://doi.org/10.1016/j.respol.2006.11.004

Wang, X., and Zou, H. (2018). Study on the effect of wind power industry policy types on the innovation performance of different ownership enterprises: Evidence from China. *Energy Policy*, 122, 241-252. https://doi.org/https://doi.org/10.1016/j.enpol.2018.07.050

Wang, Y., and Shen, N. (2016). Environmental regulation and environmental productivity: The case of China. *Renewable and Sustainable Energy Reviews*, 62, 758-766. https://doi.org/https://doi.org/10.1016/j.rser.2016.05.048

Wang, Y., Sun, X., and Guo, X. (2019). Environmental regulation and green productivity growth: Empirical evidence on the Porter Hypothesis from OECD industrial sectors. *Energy Policy*, 132, 611-619. https://doi.org/https://doi.org/10.1016/j.enpol.2019.06.016

Wen, Q., Chen, Y., Hong, J. K., Chen, Y., Ni, D. F., and Shen, Q. P. (2020). Spillover effect of technological innovation on CO2 emissions in China's construction industry. *Building and Environment*, 171, 12. https://doi.org/10.1016/j.buildenv.2020.106653

Wu, P., Wang, Y. Q., Chiu, Y. H., Li, Y., and Lin, T. Y. (2019). Production efficiency and geographical location of Chinese coal enterprises - undesirable EBM DEA. *Resources Policy*, 64, 12. https://doi.org/10.1016/j.resourpol.2019.101527

Wu, Y., Ke, Y., Xu, C., Xiao, X., and Hu, Y. (2018). Eco-efficiency measurement of coal-fired power plants in China using super efficiency data envelopment analysis. *Sustainable Cities and Society*, 36, 157-168. https://doi.org/https://doi.org/10.1016/j.scs.2017.10.011

Xiang, D., Chen, J. K., Tripe, D., and Zhang, N. (2019). Family firms, sustainable innovation and financing cost: Evidence from Chinese hi-tech small and medium-sized enterprises. *Technological Forecasting and Social Change*, 144, 499-511. https://doi.org/10.1016/j.techfore.2018.02.021

Xie, R.-h., Yuan, Y.-j., and Huang, J.-j. (2017). Different Types of Environmental Regulations and Heterogeneous Influence on “Green” Productivity: Evidence from China. *Ecological Economics*, 132, 104-112. https://doi.org/https://doi.org/10.1016/j.ecolecon.2016.10.019

Xing, Z. Y., and Cao, X. (2019). Promoting Strategy of Chinese Green Building Industry: An Evolutionary Analysis Based on the Social Network Theory. *Ieee Access*, 7, 67213-67221. https://doi.org/10.1109/access.2019.2918028

Yang, L. R., and Huang, C. F. (2016). INFORMATION PLATFORM TO IMPROVE TECHNOLOGICAL INNOVATION CAPABILITIES: ROLE OF CLOUD PLATFORM. *Journal of Civil Engineering and Management*, 22(7), 936-943. https://doi.org/10.3846/13923730.2014.929023

Yang, Z. B., Shao, S., Li, C. Y., and Yang, L. L. (2020). Alleviating the misallocation of R&D inputs in China's manufacturing sector: From the perspectives of factor-biased technological innovation and substitution elasticity. *Technological Forecasting and Social Change*, 151, 13. https://doi.org/10.1016/j.techfore.2019.119878

Yin, S., and Li, B. (2018). Transferring green building technologies from academic research institutes to building enterprises in the development of urban green building: A stochastic differential game approach. *Sustainable Cities and Society*, 39, 631-638. https://doi.org/https://doi.org/10.1016/j.scs.2018.03.025

Zeng, L., Lu, H., Liu, Y., Zhou, Y., and Hu, H. (2019). Analysis of Regional Differences and Influencing Factors on China's Carbon Emission Efficiency in 2005-2015. *Energies*, 12(16), 21. https://doi.org/10.3390/en12163081

Zheng, D., and Shi, M. (2017). Multiple environmental policies and pollution haven hypothesis: Evidence from China's polluting industries. *Journal of Cleaner Production*, 141, 295-304. https://doi.org/https://doi.org/10.1016/j.jclepro.2016.09.091

Zhong, W., Yuan, W., Li, S. X., and Huang, Z. (2011). The performance evaluation of regional R&D investments in China: An application of DEA based on the first official China economic census data. *Omega*, 39(4), 447-455. https://doi.org/https://doi.org/10.1016/j.omega.2010.09.004