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Sustainable Impact of Green Building on the Eco-Economic Efficiency of the Construction Industry: Evidence from China

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Abstract: Addressing the global warming challenge, the carbon emissions reduction potential of green building (GB) is garnering increasing attention. However, the extent to which GB can impact the eco-economic efficiency (EE) of the construction industry remains unclear. To fill this gap, based on panel data for 30 regions of China from 2003 to 2018, in this study, a comprehensive analysis of the EE and sustainable impact of GB is conducted using a super slacks-based measure (SBM-DEA), panel vector autoregression (PVAR) and threshold models. The findings reflect that only about 10% of provinces have achieved EE effectiveness, with pure technical effectiveness being a significant driving force behind this. The average comprehensive, pure technical, and scale EE show a 62.23%, 46.42%, and 31.91% improvement potential regarding the efficiency frontier. The EE in the Eastern Region is relatively high, while the Western Region surpassed the Central Region in regards to EE in the areas of scale and pure technical efficiency. EE is significantly reduced in the current period (year) when it is subject to the positive impact of a standard deviation from the existing economic level. This impact was the strongest in period 1, then gradually disappeared until period 6, aligning with the Kuznets curve's theoretical assumption. GB awareness negatively impacted the current period, but is expected to gradually show a positive effect after period 2. The urbanization, green building awareness, and green building coverage make a very small contribution to the EE, accounting for 8.6%, 1.6%, and 9%, respectively, with early EE and economic level identified as the primary variables affecting the current EE. The impact of GB on EE exhibits a threshold effect, with the ecological effect of GB significant only in cities with economic levels higher than 11.063. This research contributes to the existing knowledge of the eco-economic mechanism of GB and provides insights for government policies, promoting the sustainable development of the GB market.

Keywords: green building; eco-economic efficiency; SBM-DEA; PVAR; threshold model

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1. Introduction

Architecture is essential for human survival, as it transforms the natural environment and provides material and spiritual satisfaction. However, modern construction industry development is not sustainable. Donella Meadows' perspective in "The Limits of Growth" highlights the formation of "reinforced concrete forests" due to increasing urbanization, leading to heat island effects and severe environmental pollution, including construction waste, dust, and carbon emissions [1,2]. The IPCC report indicates that the construction industry consumes roughly 40% of global energy and is associated with 36% of global carbon emissions, figures which are expected to grow, according to the International Energy Agency [3]. Green building (GB), which integrates architecture and ecology, aims to revolutionize architectural concepts across the areas of technology, society, economy, culture, and ecology, striving for a harmonious coexistence between people, architecture, and nature throughout the life cycle [4]. Over the past few decades, GB's rapid development has given rise to new concepts regarding energy conservation, water conservation, land conservation, innovation, and low-carbon development.

However, as an innovative eco-economic development model, GB still has obvious limitations relative to large-scale promotion. The primary concern is that the market mechanism diminishes the significance of ecological capital, the progression of ecological compensation is slow-moving, the eco-economic benefits fail to meet expectations, and the payment habits of beneficiaries are difficult to develop [5,6]. This indicates that the industrial transformation of the eco-economic innovation model faces numerous challenges. The GB market is influenced by intricate policy, technology, economic, and market factors. To overcome these limitations, it is vital to understand the advantages of policy support, enhance the development and application of ecological innovation technology, create external conditions to improve green performance, and maximize the sustainable impact of GB. These topics warrant further in-depth exploration.

Thus, the primary aim of this study is to explore the sustainable impact of GB on the eco-economic efficiency (EE) of the construction industry. Firstly, environmental indicators are introduced to build an assessment system, with the SBM-DEA model then applied to evaluate the EE of various provinces in China. Subsequently, a panel vector autoregressive (PVAR) analysis model is used to identify the impact of GB on EE under the effects of various control variables. The variance decomposition model is employed to predict future influencing trends. Finally, a threshold model is used to analyze the impact mechanism of regional GB on EE under different scenarios. This research could provide both theoretical and practical support for the development of an institutional system that promotes GB innovation, as well as the advancement of an eco-economic model.

2. Literature Review

2.1. Eco-Economic Benefits of GB

The ecological environment and economic development experienced an early stage of opposition and struggle, and gradually embraced a sustainable process of seeking integration. In this context, GB emerged with the purpose of alleviating the pressure on the environment and resources.

Currently, the eco-economic benefits of GB have been explored by multiple researchers. Ries et al. (2006) found that after implementing GB, equipment productivity rose by 25%, energy consumption fell by 30%, and significant cost savings were achieved [7]. Consistent with this view, He (2020) concurred that GB's core value lies in enhancing resource utilization and minimizing environmental pollution [8]. Additionally, Eichholtz et al. (2013) demonstrated that the improvement of energy efficiency in GBs can be converted into rental and asset value, generating substantial economic returns [9]. Similarly, Cajias and Piazolo (2013) discovered that green residential buildings in Germany yield a 3.15% higher rate of return than conventional buildings, rental prices increase by 0.76/m^2, and energy savings of 1% lead to a 0.08% increase in rental prices and a 0.45% rise in market values [10]. Furthermore, GBs also have a positive impact on public health [11]. Newsham et al. (2018) suggested that improving indoor environmental quality in GBs can help reduce absenteeism and working time affected by asthma, respiratory allergies, depression, and stress, enhancing work efficiency [12]. Wuni et al. (2019) also found that GBs adopting eco-friendly innovative designs from a life-cycle perspective can decrease energy consumption, the amount of building materials, and natural resources, while enhancing environmental performance for a healthy lifestyle [13].

2.2. Challenges Faced by Development of GB Innovative Eco-Economic Model

Despite the innovative eco-economic model for GBs' potential, several challenges persist in its development. Research reveals that stakeholder resistance to change and the initial cost premium are significant obstacles to the implementation of GB technology [14,15]. Chau et al. (2010) highlight the influence of users' willingness to pay and their individual preferences on green building performance [16]. Environmentalists and conventional citizens prioritize energy conservation over indoor air quality improvement, noise reduction, landscape expansion, and water conservation. This preference is often driven by a lack of understanding regarding the productivity and health benefits of green buildings, as well as the effective methods to quantify them. As a result, enhancing the knowledge transfer system of green buildings is crucial. This enables various stakeholders to comprehend the cost premium, long-term cost-effectiveness, health, and productivity benefits of green buildings [17]. For the cost of GB, Bartlett and Howard (2000) revealed that most practitioners believe that more energy-efficient and environmentally-friendly buildings would cost 5–15% more from the beginning [18]. However, the rapid advancements in green materials, management systems, technological innovation, and manufacturing have made green buildings more accessible, eliminating excuses for governments, enterprises, and users to evade environmental and economic sustainability, paving the way for the development of green buildings [19].

Institutional obstacles are widely recognized as some of the most significant challenges in promoting green building (GB) projects [20]. Similarly, Darko et al. (2017) found that the absence of national standards and regulations is the most frequently cited obstacle in studies [21]. Aktas and Ozorhon (2015) proposed that during the implementation of green building projects, unapproved materials, poor building design, and difficulties in document preparation will also reduce the efficiency of the entire green project [22]. Chan et al. (2017) further proposed four key strategies to promote the development of GB, including one focused on mandatory government policies and regulations [23].

In addition, the returns of GB remain unstable. A study by Refahi and Talkhabi (2015) reveals a payback period of 25–57 years for green roofs [24]. Additionally, GBs possess marginal effects. A London-based community study found that the marginal effects of GB in the leasing and trading markets decrease by 2% and 5% for each additional GB [25]. This indicates that the economic performance of GBs should consider complex policy factors and the supply curve of the market. For such dilemmas, the most effective way to reconstruct the market mechanism and promote the transformation of green technology is give the government the leading role and carry out effective policy promotion [26]. By formulating policies regarding industry norms, technological innovation, and financial support, the government can meaningfully intervene, guide, and cultivate the green market, thereby fostering the sustainable transformation of social development [27].

3. Data and Methods

3.1. SBM-DEA

3.1.1. Variable Selection and Data Sources

This paper introduces undesired output to construct an EE index system. The panel data is based on the input-output analysis of the construction industry in 30 regions of China from 2003 to 2018. The data is gathered from the China Energy Statistical Yearbook, the China Construction Industry Statistical Yearbook, the China Statistical Yearbook, and the official website of the National Bureau of Statistics. The specific index system is presented in Table 1.

Table 1. Index system of EE.

Index	Category	Name	Means
Input	Resource	Technical level	Technical equipment rate (CNY/person)
		Capital investment	Fixed assets (CNY 100 million)
		Human resources	Number of employees (ten thousand people)
Undesirable output	Environment	Carbon emissions	CO_2 emissions (ten thousand tons)
Desirable output	Economic	Output value	Output value of construction industry (CNY 100 million)

As shown in Table 1, the indicator system is constructed from the three aspects of resources, environment, and economy, including the input indicators, undesirable output and desirable output.

Input indicators: Capital investments play a vital role as input resources and are a fundamental condition for the operation of construction enterprises. Fixed assets are used to evaluate capital investments [28]. Given the labor-intensive nature of the construction industry, the number of employees is used as a measure of human resources [29]. The industry's technical level can be assessed, to some extent, through its machinery and equipment. Thus, the proportion of technical equipment is chosen to measure the technical level [30].

Desirable output indicator: The most direct indicators for measuring output are products and output value. The study uses the total output value of the construction industry from the Industry Statistical Yearbook as the output value [29].

Undesirable output indicator: The undesired output of the construction industry usually includes wastewater, exhaust gas, and solid waste. The most significant environmental impact of the construction industry is the emission of greenhouse gases, which is also one of the most important advantages of GBs. Therefore, the undesired output in this study is quantified by CO_2 emissions [28,30].

In this study, the carbon accounting method proposed by the United Nations Intergovernmental Panel on Climate Change (IPCC) is adopted to estimate CO_2 emissions, utilizing energy consumption data from the China Energy Statistical Yearbook. The computation formula is presented below.

$$CO_2 = \sum_j C_j * CF_j * LCV_j * O_j * \frac{44}{12} \quad (1)$$

where CO_2 represents the overall carbon dioxide emissions, C_j represents the consumption of the j energy (t), CF_j represents the carbon emission factor of the j energy (kgC/GJ), LCV_j represents the average low calorific value of the j energy (GJ/t), and O_j represents the oxidation rate of the j energy. The detailed coefficients are shown in Table 2 below.

Table 2. Carbon emission coefficient.

Type of Energy	Carbon Emission Factor$_i$ (kgC/GJ) [a]	Average Low Calorific Value$_i$ (GJ/t) [b]	Oxidation Rate$_i$
Raw Coal	25.8	20.908	0.899
Cleaned Coal	25.8	26.344	0.899
Other Washed Coal [d]	25.8	12.545	0.899
Briquette	25.8	16.800	0.899
Coke	29.2	28.435	0.970
Coke Oven Gas [d]	12.1	17.981 (GJ/10^3 m^3)	0.990
Other Gas	12.1	8.429 (GJ/10^3 m^3)	0.990
Crude Oil	20.0	41.816	0.980
Gasoline	18.9	43.070	0.980
Kerosene	19.6	43.070	0.980
Diesel oil	20.2	42.652	0.980
Fuel Oil	21.1	41.816	0.980
Liquefied Petroleum	17.2	50.179	0.990
Natural Gas	15.3	38.931 (GJ/10^3 m^3)	0.990
Other Petroleum Products	20.0	40.190	0.980
Other Coking Products	29.2	Zhang.435	0.970
Heat [a]		0.03412 kgce/10^6 J	
Electricity [a]		0.1229 kgce/kWh	
Other energy [c]		10^4 tce	

Notes: ([a]) IPCC (2006); ([b]) China Energy Statistical Yearbook (2017); ([c]) calculated according to the standard coal coefficient (0.9714 kgtce/kg) IPCC (2006); ([d]) coke oven gas according to the maximum value (16.726~17.981) and other washed coal (8.363~12.545).

The raw energy material consumption data for the construction industry in China is derived from the regional energy balance scale in the China Energy Statistical Yearbook for the years 2003 to 2018. The results are presented in Figure 1.

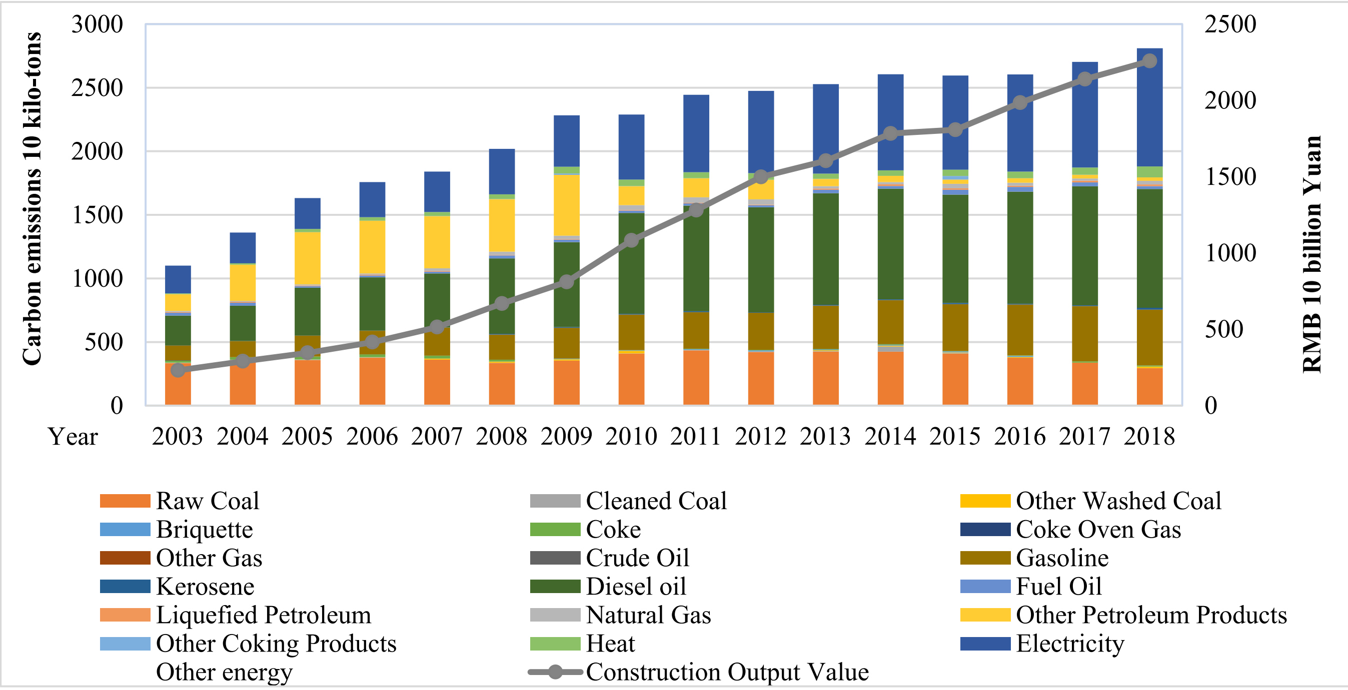


Figure 1. Proportion of carbon emissions from various energy sources and the output value of construction.

As illustrated in Figure 1, the primary CO_2 emission sources include coal utilization, gasoline consumption, diesel consumption, other petroleum products, and electricity usage. During the research period, gasoline, diesel, and electricity have progressively emerged as the dominant energy types. Notably, diesel and electricity have successfully disrupted the traditional reliance on raw coal, significantly contributing to CO_2 emissions in the modern construction industry.

3.1.2. Super-SBM Model

Tone (2001) proposed a slacks-based measure (SBM) model that introduces non-radial and undesired values of slack variables [31]. This model often leads to many decision-making units with an efficiency value of 1, hindering effective comparison. However, Tone (2002) introduced slack variables into the objective function, establishing a non-angle, non-radial super-SBM model [32]. This updated model not only addresses the problem of slack variables but also distinguishes effective decision-making units. Consequently, the super-SBM model is employed in this paper to analyze the EE via super-efficient, non-radial, and undesired output calculations. The specific modeling process is detailed below.

Assume there are n decision-making units (DMU), and each DMU $i \in n$. X is the m input of the i DMU, and the input matrix is $X = (x_{ij}) \in R^{m\times n}$. Y is the s output of the i DMU, and the output matrix is $Y = (y_{ij}) \in R^{s\times n}$. λ is the weight of the i DMU. Then, the production possibility set P can be expressed as:

$$P = \{(x, y)\,|x \geq \lambda X, y \leq \lambda Y, \lambda \geq 0\} \tag{2}$$

Assume S_1 is the desirable output, and S_2 is the undesirable output. Then, the matrixes are $X = (x_{ij}) \in R^{m\times n}$, $Y^d = (y_{ij}) \in R^{s1\times n}$, and $Y^u = (y_{ij}) \in R^{s2\times n}$, which represent the matrixes of input, desirable output, and undesirable output, respectively. For a decision-making unit DMU_0, its efficiency value can be expressed as:

$$\rho* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^d}{y_{r0}^d} + \sum_{r=1}^{s_2}\frac{s_r^u}{y_{r0}^u}\right)} \tag{3}$$

$$\text{s.t.} = \begin{cases} x_0 = \lambda X + s^- \\ y_0 = \lambda y^d + s^d \\ y_0 = \lambda y^u + s^u \\ \sum_{i=1}^{n}\lambda_i = 1 \\ s^-, s^d, s^u, \lambda \geq 0 \end{cases} \tag{4}$$

Among them, s^-, s^d, and s^u are the slack variables of input, desirable output, and undesirable output. x_0, y_0^d, and y_0^u are the input, desirable output, and undesirable output of the DMU. λ is the weight, and the value of the objective function ρ* of the DMU's efficiency value is between 0 and 1. When *uprho** is 1, and the corresponding slack variables s^-, s^d, and s^u are all 0, this indicates that the DMU does not show input redundancy or output shortage, and the DMU is SBM effective. If ρ* is less than 1, or at least one of the slack variables s^-, s^d, and s^u is not 0, it means that the efficiency of the DMU is at a low level. In such cases, companies can respond by reducing the input or increasing the output to improve the efficiency of the DMU.

To solve the problem that the traditional SBM model cannot effectively distinguish the decision unit equal to 1, the improved super-efficient SBM model is as follows:

$$\rho* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{\overline{x_i}}{x_{i0}}}{1 + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^d}{y_{r0}^d} + \sum_{r=1}^{s_2}\frac{s_r^u}{y_{r0}^u}\right)} \tag{5}$$

$$\text{s.t.} = \begin{cases} \overline{x} \geq \sum\limits_{j=1,\neq 0}^{n}\lambda_j x_i \\ \overline{y^d} \leq \sum\limits_{j=1,\neq 0}^{n}\lambda_j {y^d}_i \\ \overline{y^u} \geq \sum\limits_{j=1,\neq 0}^{n}\lambda_j {y^u}_i \\ \sum\limits_{j=1,\neq 0}^{n}\lambda_i = 1 \\ \overline{y^d}, \overline{y^u}, \lambda \geq 0 \\ \overline{y^d} \leq y_0^d, \overline{y^u} \geq y_0^u, \overline{x} \geq x_0 \end{cases} \tag{6}$$

3.2. Panel Vector Autoregressive Analysis

3.2.1. Variable Selection and Data Sources

The panel vector autoregressive analysis examines the effectiveness of GBs in China, utilizing panel data from 30 provinces. The GB data is extracted from the Green Building Comprehensive Information Management Platform, constructed by the Ministry of Housing and Urban-Rural Development. Due to the project statistics ending in September 2016, the panel data for the period 2011–2015 is selected, encompassing aspects like urbanization, green building awareness, economic level, GB coverage, and EE. The data sources include the Green Building Comprehensive Information Management Platform, the China Statistical

Yearbook, the Construction Industry Statistical Yearbook, and the National Bureau of Statistics. The specific statistical analyses of the variables are presented in Table 3.

Table 3. EE indexes of green building.

Variable	Mean	S.D.	Minimum	p25	p50	p75	Maximum
urb	55.446	12.777	34.967	46.649	52.66	60.921	89.607
gdpp	4.70×10^4	2.10×10^4	1.60×10^4	3.30×10^4	3.90×10^4	5.90×10^4	1.10×10^5
green	3.262	4.015	0.021	0.932	1.96	3.938	24.351
baidu	63.914	36.416	1.1	40	57	86	161
eco	0.377	0.467	0.041	0.099	0.186	0.397	2.164

Note: P25, p50, and p75 are quartiles.

Urbanization (urb): Urbanization divides cities into spaces for populations, technology, and capital, significantly impacting the construction industry's technology, quality, and environmental efficiency. This paper uses the proportion of urban population to the total annual population as a metric for urbanization. Economic level (gdpp): Economic development determines the extent of investment in technology and capital within the construction industry. The per capita GDP of each region is used to measure the economic level. Green building coverage (green): The coverage of GB is an important prerequisite for achieving eco-economic benefits. This paper measures the coverage of green buildings by calculating the ratio of annual green building area to total building area. Green building awareness (Baidu): As the most widely used search engine in China, the Baidu index can effectively indicate people's cognitive trends. Therefore, this paper uses the Baidu index of green buildings to measure green building awareness. Eco-economic efficiency (eco): The comprehensive EE value of each region in China is selected to study the eco-economic impact of GBs.

3.2.2. PVAR Model

Vector autoregression (VAR), proposed by Sims (1980), winner of the Nobel Prize in Economics, is an econometric model of dynamic simultaneous equations for joint endogenous variables [33]. It constructs a regression function by integrating endogenous variables in the system and their lagged terms from other endogenous variables. This model expands the traditional univariate model into the vector autoregressive model for multivariate time series. By orthogonalizing impulse response functions, the impact of changes between variables is examined, and numerous target economic indicators are analyzed and predicted. Further, Holtz-Eakin et al. (1988) expanded VAR to the panel vector autoregression (PVAR) model by introducing the pulse impact of individual effects and time point effect variables on individual differences and different cross sections [34]. The PVAR model has the advantages of loose endogenous variable conditions and panel data processing. Moreover, the GMM employed in the PVAR model has loose requirements for data distribution characteristics, thereby enhancing the model's robustness. Consequently, the PVAR model is extensively used in research related to various economic issues.

This study faces the problem of endogeneity. Due to the limitation of the database, the length of the panel data is relatively short. The PVAR model offers advantages in regards to the analysis of endogenous variables. The estimation condition is satisfied when $T \geq Lag + 3$, and the stable lag parameter estimation requires only $T \geq 2Lag + 2$ (T is the length of the time series; Lag is the variable lag order). Consequently, the application of the PVAR model is scientifically valid and reasonable. Moreover, to meet the PVAR model's demand for data stability, some of the original data is logarithmized (This is because the percentage data in the regression is usually not processed; thus, only the non-percentage data is processed accordingly.). The regression model for the impact of GB on EE is presented below.

The first-order PAVR equation, based on provincial panel data, can be expressed as:

$$Y_{it} = \alpha j + \sum_{\mathrm{j}=1}^{p} Yi(\mathrm{t}-\mathrm{j}) + \varepsilon_{it},\ \mathrm{i} = 1, 30, \mathrm{t} = 2011\text{–}2015,\ \varepsilon_{it} \sim N\left(0,\ \sigma_{it}^{2}\right) \tag{7}$$

Among these, $\mathrm{Y_{it}}$ is the vector function of the area research variable in a specific time, α_{j} is the parameter, i is the area, t is the specific time, and $\varepsilon_{\mathrm{it}}$ is the residual vector.

The vector matrix function can be specifically expressed as:

$$\begin{aligned} \mathrm{lneco}_{it} = \alpha 1 + \sum_{\mathrm{j}=1}^{p} \gamma_{1j}\, \mathrm{urb}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \beta_{1j}\, \mathrm{green}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \chi_{1j}\, \mathrm{lngdpp}_{i(\mathrm{t}-\mathrm{j})} + \\ \sum_{\mathrm{j}=1}^{p} \eta_{1j}\, \mathrm{lnbaidu}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \lambda_{1j}\, \mathrm{lneco}_{i(\mathrm{t}-\mathrm{j})} + \varepsilon_{it}, \varepsilon_{it} \sim N\left(0, \sigma_{it}^{2}\right) \end{aligned} \tag{8}$$

$$\begin{aligned} \mathrm{urb}_{it} = \alpha 1 + \sum_{\mathrm{j}=1}^{p} \gamma_{1j}\, \mathrm{urb}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \beta_{1j}\, \mathrm{green}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \chi_{1j}\, \mathrm{lngdpp}_{i(\mathrm{t}-\mathrm{j})} + \\ \sum_{\mathrm{j}=1}^{p} \eta_{1j}\, \mathrm{lnbaidu}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \lambda_{1j}\, \mathrm{lneco}_{i(\mathrm{t}-\mathrm{j})} + \varepsilon_{it}, \varepsilon_{it} \sim N\left(0, \sigma_{it}^{2}\right) \end{aligned} \tag{9}$$

$$\begin{aligned} \mathrm{green}_{it} = \alpha 1 + \sum_{\mathrm{j}=1}^{p} \gamma_{1j} \mathrm{urb}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \beta_{1j} \mathrm{green}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \chi_{1j} \mathrm{lngdpp}_{i(\mathrm{t}-\mathrm{j})} + \\ \sum_{\mathrm{j}=1}^{p} \eta_{1j} \mathrm{lnbaidu}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \lambda_{1j} \mathrm{lneco}_{i(\mathrm{t}-\mathrm{j})} + \varepsilon_{it},\ \varepsilon_{it} \sim N\left(0,\ \sigma_{it}^{2}\right) \end{aligned} \tag{10}$$

$$\begin{aligned} \mathrm{lngdpp}_{it} = \alpha 1 + \sum_{\mathrm{j}=1}^{p} \gamma_{1j} \mathrm{urb}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \beta_{1j} \mathrm{green}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \chi_{1j} \mathrm{lngdpp}_{i(\mathrm{t}-\mathrm{j})} + \\ \sum_{\mathrm{j}=1}^{p} \eta_{1j} \mathrm{lnbaidu}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \lambda_{1j} \mathrm{lneco}_{i(\mathrm{t}-\mathrm{j})} + \varepsilon_{it},\ \varepsilon_{it} \sim N\left(0,\ \sigma_{it}^{2}\right) \end{aligned} \tag{11}$$

$$\begin{aligned} \mathrm{lnbaidu}_{it} = \alpha 1 + \sum_{\mathrm{j}=1}^{p} \gamma_{1j} \mathrm{urb}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \beta_{1j} \mathrm{green}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \chi_{1j} \mathrm{lngdpp}_{i(\mathrm{t}-\mathrm{j})} + \\ \sum_{\mathrm{j}=1}^{p} \eta_{1j} \mathrm{lnbaidu}_{i(\mathrm{t}-\mathrm{j})} + \sum_{\mathrm{j}=1}^{p} \lambda_{1j} \mathrm{lneco}_{i(\mathrm{t}-\mathrm{j})} + \varepsilon_{it},\ \varepsilon_{it} \sim N\left(0,\ \sigma_{it}^{2}\right) \end{aligned} \tag{12}$$

The Helmert transformation method is adopted in the PVAR model to manage the fixed effects of each variable to ensure that the transformed variables are orthogonal to the lagging explanatory variables. Therefore, lagging explanatory variables can be used as instrumental variables in the generalized matrix method GMM estimation equation.

3.3. Threshold Analysis

The majority of existing research on the EE of the construction industry employs simple linear regression, neglecting the potential non-linear relationship. Nonlinearities can be detected through the threshold analysis method, which captures the structural mutation non-linear threshold in the regression model, enabling the identification of the threshold function. Consequently, this study uses Hansen's nonlinear panel threshold regression model for the empirical examination [35]. By utilizing economic level as the threshold variable and urbanization rate and green building awareness as the adjustment parameters, a single-threshold panel model is developed. The specific formula is provided below:

$$\mathrm{eco}_{it} = \lambda + \alpha_1 \mathrm{urb_{it}} + \alpha_2 \mathrm{baidu_{it}} + \beta_1 \mathrm{green_{it}} I(gdpp_{\mathrm{it}} \le \gamma) + \beta_2 \mathrm{green_{it}} I(gdpp_{\mathrm{it}} > \gamma) + \eta_j + \kappa_t + \varepsilon_{it} \tag{13}$$

In Formula (13), i denotes the province, t denotes the year, and $\mathrm{eco_{it}}$, $\mathrm{urb_{it}}$, $\mathrm{baidu_{it}}$, and $\mathrm{green_{it}}$ represent the EE level, urbanization rate, green building awareness, and green building coverage rate of the construction industry of i province in t year. I (•) represents the indicator function, $\mathrm{gdpp_{it}}$ is the threshold variable, γ is the variable threshold value, η_{j} is the individual specific effect, κ_{t} is the time specific effect, and ε_{it} is the random interference term.

Multi-threshold panel model (The double-threshold model was used as an example in this paper.):

$$\begin{aligned} \mathrm{eco}_{it} = \lambda + \alpha_1 \mathrm{urb_{it}} + \alpha_2 \mathrm{baidu_{it}} + \beta_1 \mathrm{green_{it}} I(gdpp_{\mathrm{it}} \le \gamma_1) \\ + \beta_2 \mathrm{green_{it}} I(\gamma_1 < gdpp_{\mathrm{it}} \le \gamma_2) + \beta_3 \mathrm{green_{it}} I(gdpp_{\mathrm{it}} > \gamma_2) + \eta_j + \kappa_t + \varepsilon_{it} \end{aligned} \tag{14}$$

Threshold model estimation process: The threshold estimation is based on Hansen's multi-threshold processing method for panel data. First, H0: the null hypothesis of no threshold, is established for a single threshold. Then, the least squares regression analysis is implemented. Last, the bootstrap method, recommended by Hansen for the significance test of the minimum threshold value and the corresponding parameters of the residual sum of squares, is conducted. If the significance P value test is passed, the null hypothesis is rejected, and the threshold value is achieved.

The multiple threshold estimation process is used to fix the first threshold and continue to search for significant thresholds. Then, the new threshold is used to re-verify the first threshold to ensure its stability. Next, the process listed above is repeated until the results show inconsistencies. Last, the "non-rejection domain" is constructed using the likelihood ratio statistics to obtain the effective confidence interval of the threshold value, which serves as a reference for threshold selection.

4. Results

4.1. The EE of the Provincial Construction Industry

In empirical analysis, super-SBM CRS and super-SBM VRS models are employed to measure the comprehensive EE and pure technical EE using DEA Solver 5.1 software. Additionally, the formula "comprehensive EE = pure technical EE × scale EE" is used to measure scale EE. In order to ensure the effectiveness of the data display, only specific relatively effective results are selected for display.

4.1.1. Provincial EE

The comprehensive, pure technical, and scale EE of China's provinces are examined, yielding the results depicted in Figures 2–4. EE is classified into five levels: DEA effective ($\geq$1.0), high level (0.8–1.0), medium-high level (0.6–0.8), medium level (0.4–0.6), and low level (0–0.4).

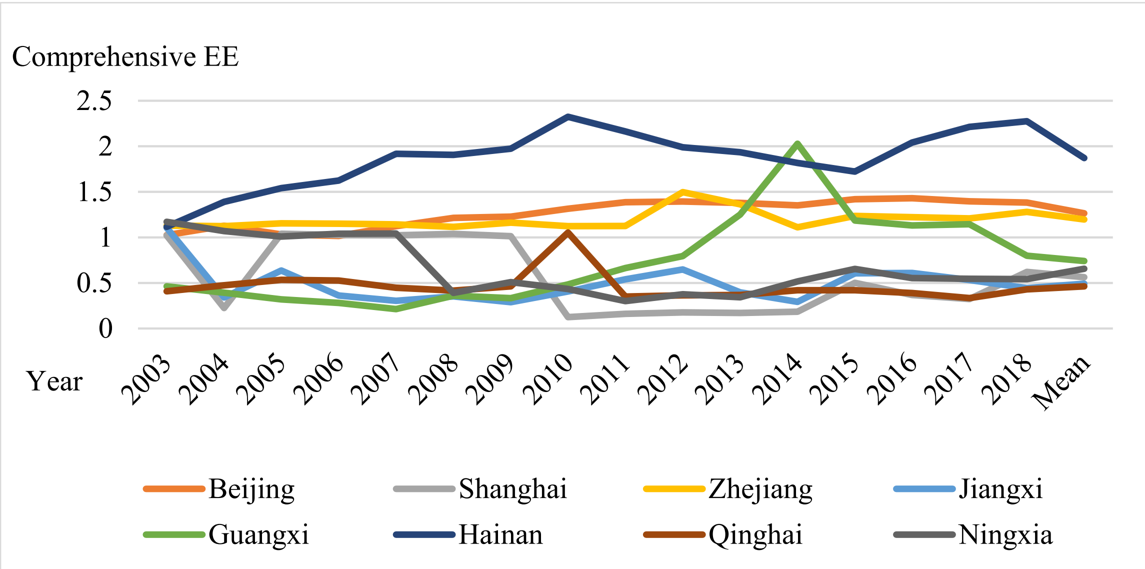


Figure 2. Comprehensive EE of China's provincial construction industry.

As depicted in Figure 2, the EE exhibits a fluctuating upward trend across most regions of China. During the study period, only three regions—Beijing, Hainan, and Zhejiang—reached an effective level (DEA $\geq$ 1.0). The EE of Shanghai, Ningxia, Guangxi, and Jiangxi is effective in some years. Specifically, Guangxi's EE improved from 2013 to 2016, reaching a relatively effective level. However, the EE in the other three regions initially showed higher values, but gradually decreased to a lower level.

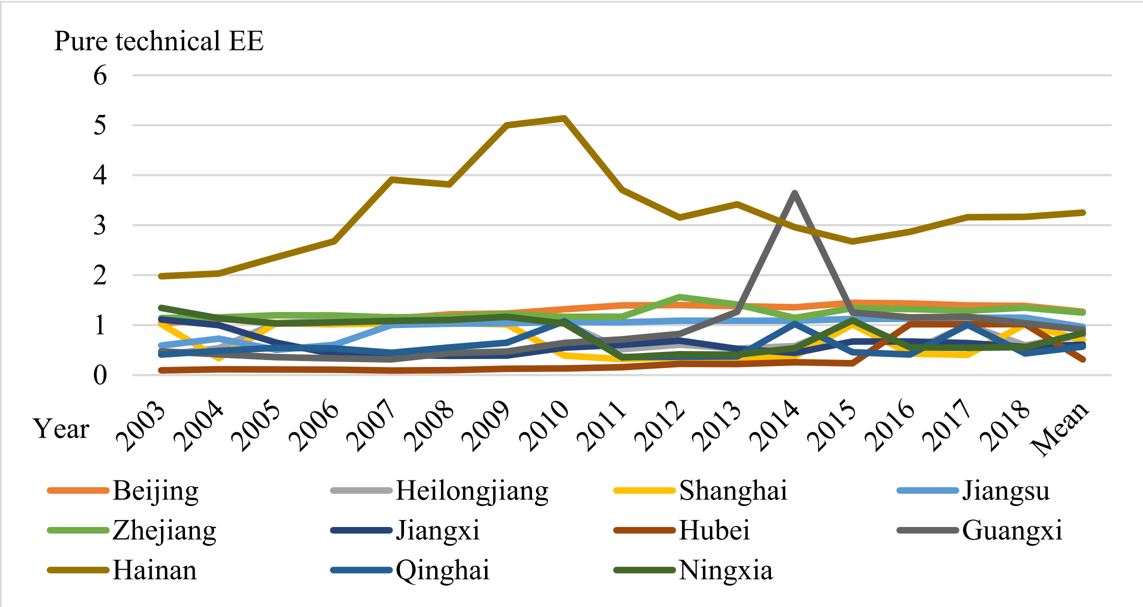


Figure 3. Pure technical EE of China's provincial construction industry.

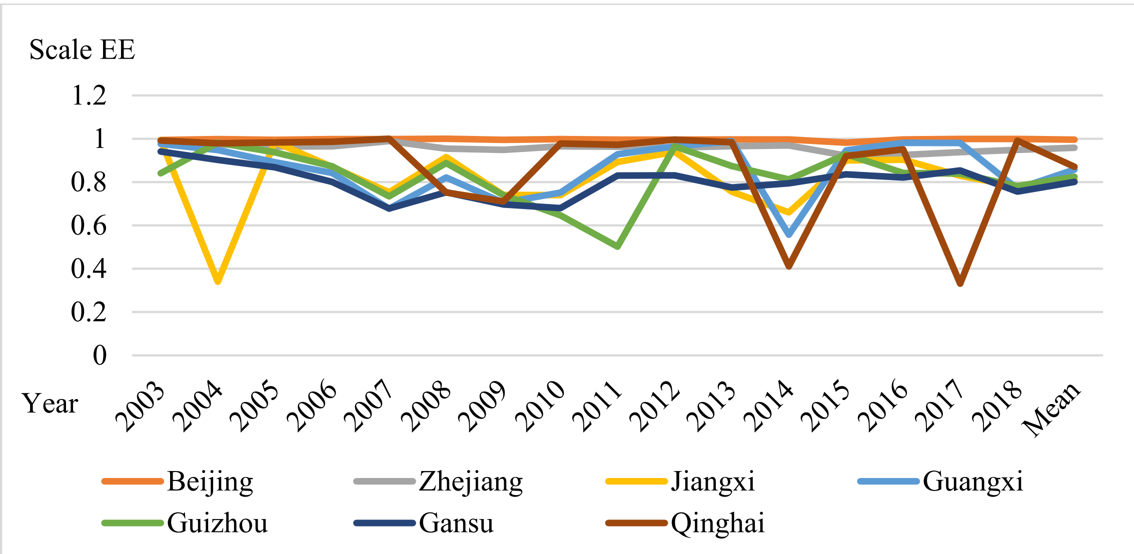


Figure 4. Scale EE of China's provincial construction industry.

Furthermore, a comparison of the average comprehensive EE in various regions indicates that Hainan, Beijing, and Zhejiang rank among the top three regions, with all achieving an effective level. The average comprehensive EE in Guangxi and Ningxia reaches a medium-high level (0.6–0.8), while Shanghai, Jiangxi, and Qinghai are at a medium level (0.4–0.6). In contrast, the average comprehensive EE in other regions is relatively low (0–0.4). The average comprehensive EE of China's provinces is generally at a relatively low level. Regions accounting for over 70% of the total exhibit a significant distance from the frontier of the average comprehensive EE levels.

As depicted in Figure 3, the pure technical EE exhibits a volatile upward trend across most regions of China. Only the pure technical EE of Hainan, Beijing, and Zhejiang has achieved the effective level. In Shanghai, Ningxia, Guangxi, Jiangsu, Hubei, and Jiangxi, the effective level was reached in some years. Among these regions, the pure technical EE of Guangxi and Jiangsu has reached a relatively effective level in recent years, showing a significant improvement. In Ningxia and Shanghai, the pure technology EE was initially high but declined in the intermediate stage before being improved in 2015 and reaching the effective level. However, Jiangxi's pure technical EE displayed a relatively high trend in the early stage, and although the EE continued to improve year after year, it never reached the effective level. Hubei's pure technology EE has experienced a significant improvement in 2016, finally achieving the effective level.

Analyzing the average pure technical EE across various regions reveals that Hainan, Beijing, and Zhejiang maintain their positions among the top three, at an effective level. Jiangsu, Guangxi, and Ningxia have reached a high level, while Heilongjiang, Shanghai, and Jiangxi have achieved a medium-high level. Qinghai stands at a medium level, and most other regions fall into the low level category. In regards to the comprehensive EE, there are more regions exhibiting a medium to high level. Nonetheless, approximately 67% of the regions are still far from the frontier of pure technical EE, indicating substantial room for improvement in regards to China's pure technical EE.

As illustrated in Figure 4, there is an upward trend in the scale EE across most regions of China. The average scale EE of each province in China is at a medium or above level. In comparison to comprehensive EE and pure technology EE, there is a considerable difference. Only the average scale EE (0.996) of Beijing is close to DEA effectiveness, and there are no areas at the effective level in general. Provinces such as Beijing, Zhejiang, Qinghai, Guangxi, Guizhou, Jiangxi, and Gansu have reached a high level. Ningxia, Chongqing, Fujian, Shanghai, Xinjiang, Sichuan, Anhui, Jilin, Yunnan, Inner Mongolia, and Hunan are at the medium-high level. Other regions are at a medium level. Although the scale EE of each region is relatively high, there is still room for improvement.

4.1.2. Average Annual EE

In this section, the average annual EE is further analyzed. The results are shown in Figure 5.

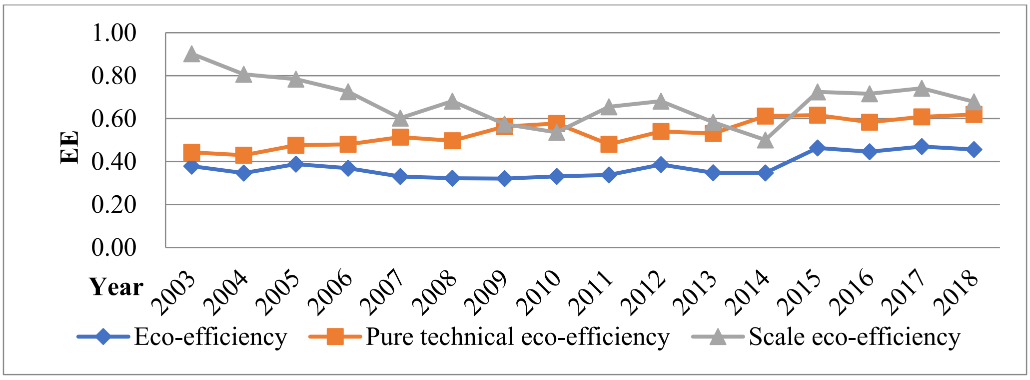


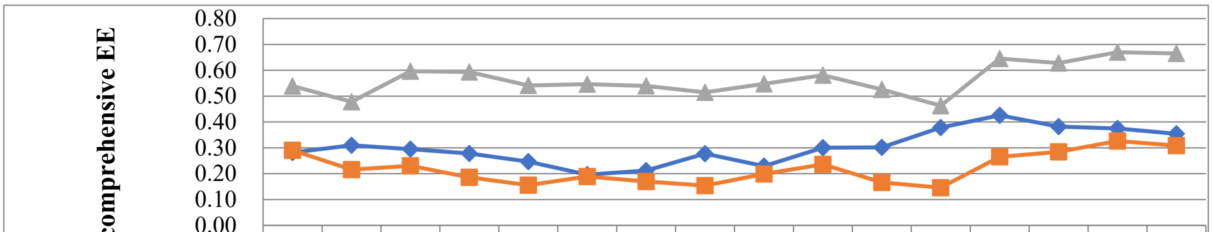
Figure 5. Annual average EE of construction industry.

As shown in Figure 5, the average annual EE is generally lower than 0.5. The average comprehensive EE, pure technical EE, and scale EE are 0.3777, 0.5358, and 0.6809 respectively. Compared with the efficiency frontier, each efficiency value has a 62.23%, 46.42%, and 31.91% improvement potential.

The comprehensive EE value exhibits small fluctuations and increases, driven by the interplay of pure technical EE and scale EE. From 2003 to 2007, the comprehensive EE decreased as the scale EE declined rapidly. Although the pure technical EE improved, this increase was not enough to drive the comprehensive EE. From 2007 to 2012, the EE steadily improved but did not exceed the 0.4 level. During this period, the pure technical EE further increased, while the scale EE showed a rebounding upward trend. Their synergistic effects were optimal for ensuring the steady growth of EE. Then, from 2012 to 2014, small fluctuations occurred due to the decline in the scale EE and the slow improvement of the pure technical EE. Since 2014, the pure technical EE has steadily increased to 0.6, and the scale efficiency has rebounded to 0.7. Consequently, the comprehensive EE has broken through the 0.45 level, reaching 0.47 in 2017, and remained above 0.45 at the end of the study period. This indicates that although progress has been made in recent years, the overall level of EE still exhibits significant potential for improvement.

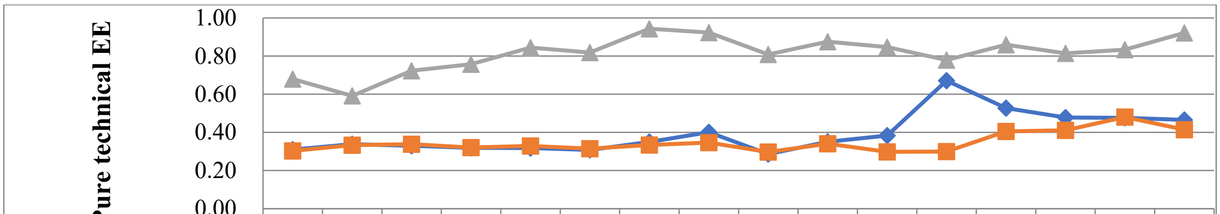
4.1.3. EE in the Three Major Regions

Regional analysis typically relies on economic characteristics to distinguish the Western, Central, and Eastern regions. The Western cluster includes Chongqing, Guizhou, Sichuan, Yunnan, Shaanxi, Qinghai, Guangxi, Inner Mongolia, Ningxia, Xinjiang, and Gansu; the Central Region encompasses Shanxi, Jiangxi, Hubei, Hunan, Jilin, Heilongjiang, Anhui, and Henan; and the Eastern Region includes Beijing, Tianjin, Jiangsu, Liaoning, Zhejiang, Hebei, Shandong, Shanghai, Fujian, Guangdong, and Hainan. This article provides valuable insights into the formulation and implementation of regional policies by comparing and analyzing the EE in three regions. The details are presented in Figures 6–8.



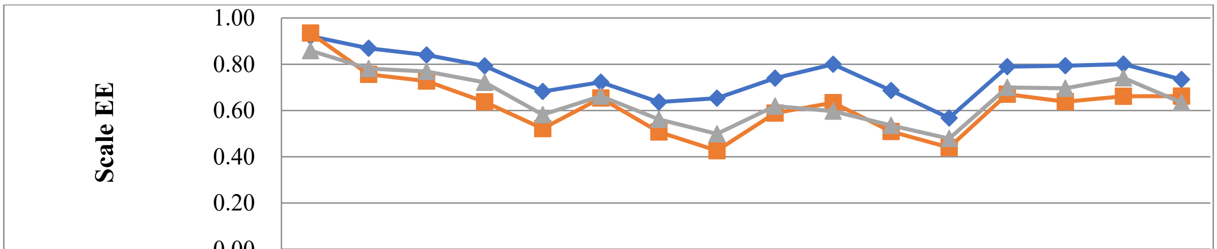
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Western Region	0.282	0.309	0.294	0.278	0.246	0.196	0.211	0.277	0.229	0.300	0.301	0.378	0.425	0.382	0.374	0.354
Central Region	0.290	0.215	0.230	0.186	0.155	0.189	0.170	0.153	0.199	0.236	0.166	0.146	0.265	0.284	0.326	0.308
Eastern Region	0.539	0.477	0.596	0.593	0.541	0.546	0.539	0.514	0.547	0.580	0.526	0.463	0.645	0.628	0.669	0.665

Figure 6. EE of China's regional construction industry.



	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Western Region	0.309	0.338	0.329	0.319	0.317	0.308	0.349	0.400	0.286	0.350	0.383	0.671	0.527	0.478	0.476	0.465
Central Region	0.303	0.333	0.338	0.320	0.329	0.315	0.333	0.346	0.296	0.340	0.297	0.299	0.404	0.410	0.480	0.414
Eastern Region	0.679	0.591	0.723	0.757	0.844	0.819	0.943	0.923	0.809	0.875	0.847	0.779	0.860	0.814	0.834	0.921

Figure 7. Pure technical EE of China's regional construction industry.



	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Western Region	0.921	0.869	0.839	0.792	0.681	0.722	0.636	0.653	0.739	0.799	0.686	0.567	0.789	0.793	0.800	0.734
Central Region	0.934	0.756	0.727	0.637	0.521	0.653	0.507	0.426	0.588	0.634	0.509	0.439	0.670	0.637	0.661	0.662
Eastern Region	0.858	0.780	0.768	0.721	0.581	0.661	0.561	0.498	0.619	0.596	0.535	0.478	0.699	0.695	0.741	0.634

Figure 8. Scale EE of China's regional construction industry.

As depicted in Figure 6, the regional comprehensive EE generally exhibits an upward trend of volatility. In 2014, both the Eastern and Central regions experienced the lowest comprehensive EE, while the Western Region's comprehensive EE was at its lowest in 2008. Recently, during the study period, the comprehensive EE in the Western, Central, and Eastern regions reached relatively high levels, indicating an improvement. The Eastern Region's EE is significantly higher than that of the other two regions, with the exception of a two-year low of 0.4779 in 2004 and 0.4630 in 2014, when the EE was above 0.5. There was a significant increase in 2015, exceeding 0.6 for the first time and remaining stable at a relatively high level until 2018. The Western Region's comprehensive EE has experienced long-term inefficiency fluctuations, with high episodes at the beginning and end of the study period. From 2003 to 2013, it fluctuated to the level of 0.3, reaching its lowest level of 0.1964 in 2008 and gradually recovering to around 0.3. In 2015, there was a significant improvement, exceeding 0.3 for the first time and reaching a high level of 0.42 in 2018. Despite these results, the comprehensive EE remains relatively inefficient and requires further improvement.

In comparison, the Central Region's comprehensive EE is at the lowest level and has experienced inefficiency fluctuations. The most efficient periods occur at the beginning and end of the study period, with EEs of around 0.3 in 2003, 2017, and 2018. The rest of the period showed a low-efficiency decline and rise, with small fluctuations. From 2007 to 2014, the comprehensive EE was in its lowest efficiency period, around 0.15. After 2014, there was an upward trend, reaching a high level of 0.3084 in 2018. In general, the Eastern Region's comprehensive EE has always been above 0.5 and has exceeded 0.6 in recent years, showcasing a relatively high efficiency. The Central and Western regions' comprehensive EE has shown an increasing trend in recent years, but it still remains at a low level of around 0.3 and 0.4.

As shown in Figure 7, the regional pure technical EE generally exhibits an upward trend relative to volatility. In 2004, the pure technical EE in the Eastern Region reached its lowest level at 0.5914. Subsequently, it attained the highest efficiency level of 0.9438 in 2009, maintaining this high level until 2018, at an average of 0.9219. In contrast, the pure technical EE in the Central and Western regions generally followed the same development trend before 2012, with a maximum efficiency difference of only about 0.05. However, the pure technical EE in the Central Region began to decline after 2012, reaching a stable level of approximately 0.4 by 2015. The pure technical EE in the Western Region experienced rapid growth, peaking at 0.6715 in 2014 before decreasing to 0.4651 in 2018. In summary, the highest levels of pure technical EE are reported for Eastern China, followed by the Western and Central regions. In particular, the pure technical EE in the Eastern Region has been above 0.8 over the past two years, which is relatively high. Conversely, the pure technical EE of the Central and Western regions has been below 0.5 in recent years.

As illustrated in Figure 8, there is a downward trend for the regional scale EE. The scale in the Western Region surpasses that of the Eastern and Central regions. A significant difference of 0.09 is observed in the Central and Eastern regions' scale EE in 2006. In contrast, the scale EE in the Western Region experiences significant fluctuations, reaching its highest level in 2003, at 0.9216, and its lowest level in 2014, at 0.5676. In the past two years, there has been an improvement in the scale EE, which has been maintained at a relatively high level of around 0.8. However, the Central and Eastern regions experienced a low period in terms of scale EE from 2007 to 2014, displaying a fluctuating downward trend. The scale efficiency decreased from 0.9246 and 0.8589 in 2003 to 0.662 and 0.6343 in 2018, respectively. Despite being at a relatively high level compared to the comprehensive EE and pure technical EE, the scale EE of the three major regions has not yet reached the effective level.

4.2. Sustainable Impact of GB

4.2.1. Panel Unit Root Test

To ensure the stability of the variables, this study employs the panel data unit root test method proposed by Maddala and Wu (1999) [36]. Specifically, this paper utilizes the unit root LLC inspection for homogeneous panels and the unit root IPS inspection for heterogeneous panels, along with distinct parameter configurations. The test results are presented in Table 4.

Table 4. Variable stationarity test.

Test \ Variables	lneco	urb	lnbaidu	green	lngdpp
LLC Adjusted t *	-2.10×10^{13} 0.00	-4.3×10^{9} 0.000	-7.0×10^{12} 0.000	-5.0×10^{13} 0.000	-2.0×10^{12} 0.000
IPS W-t-bar	−2.44 0.007	−0.744 0.023	−1.565 0.044	−5.610 0.000	−3.090 0.049
Stationarity	***	**	**	***	**

Note: *, **, and *** denote a significance of 10%, 5%, and 1%, respectively.

The results presented in Table 4 suggest that all variables significantly reject the null hypothesis of panel unit roots, indicating data stability during the study period, thus allowing for the implementation of PVAR analysis.

4.2.2. Optimal Lag Order Selection

Lag order is an important concept in time series analysis, which reflects the degree to which the historical state of time series data affects the current state. In practical applications, selecting the optimal lag order is one of the key issues in time series prediction. To estimate the PVAR system, this study adopted the AIC (Akaike information criterion), BIC (Bayesian information criterion), and HQIC (Hannan–Quinn Information Criterion) screening criteria to identify the optimal lag period [33,34]. These three indicators all add a penalty term (number of parameters) on the basis of the error term. The more complex the model, the larger the indicator will become. But overall, the information loss criterion indicator is required to be as small as possible. The guiding principle involves selecting the minimal amount of information as the optimal lag period for the model. The results are summarized in Table 5.

Table 5. Selection of optimal lag order of PVAR model.

Lag Order	AIC	BIC	HQIC
1	7.436	12.296 *	9.396 *
2	7.161 *	14.142	9.892
3	50.154	60.663	53.516

Note: * denotes the significance of the optimal lag period.

As depicted in Table 5, the optimal lag order for the BIC and HQIC criteria is 1, whereas for the AIC criteria, it is 2. Considering the short research period and the minimal difference between the second-order and first-order parameters of the AIC criterion, this paper selects one lag order as the optimal choice for further analysis.

4.2.3. GMM Estimate

When employing the PVAR model, it is typically necessary to manage the fixed effects existing within the sample data. The mean difference method is used to eliminate the fixed effects of each variable, while ensuring an orthogonal transformation between the transformation variable and the lag regression coefficient to minimize the influence of the error term. In this study, the GMM (generalized method of moment) is applied to estimate the parameters of EE, urbanization rate, green building coverage, economic level, and green building awareness. The results are presented in Table 6.

Table 6. Parameter estimation results of the PVAR model.

h_dlneco	Coef.	Std. Err.	z	p > ∣z∣	[95% Conf.	Interval]
h_dlngdpp L1.	−9.578	3.178	−3.010	0.003 ***	−15.806	−3.350
h_durb L1.	0.331	0.496	0.670	0.505	−0.641	1.302
h_dlnbaidu L1.	0.139	0.145	0.960	0.338	−0.146	0.424
h_dgreen L1.	0.051	0.021	2.380	0.017 **	0.009	0.093
h_dlneco L1.	0.246	0.094	2.630	0.009 ***	0.063	0.429

Note: Coef. is the coefficient of the independent variable in the regression equation; Std. Err. is the standard deviation of each regression coefficient; z represents the z-test statistics for each regression coefficient; p > ∣z∣ is the *p*-value of each regression coefficient; 95% Conf. Interval is the 95% confidence interval for each regression coefficient. *, **, and *** denote a significance of 10%, 5%, and 1%, respectively.

As depicted in Table 6, the lag phase variables of economic level (lngdpp), green building coverage (green), and energy efficiency (EE) significantly affect EE. The economic level exhibits a substantial negative impact, while green building coverage and EE show a positive effect. The results imply that the previous year's economic growth significantly reduced EE, which is consistent with the inverted U-shaped curve of the Kuznets curve theory. Therefore, in regions with developed economies, it is essential to allocate resources wisely, promote green technology development, and implement strict building environment regulations. Additionally, green buildings have played a crucial role in enhancing the EE of the construction industry. EE has demonstrated a certain degree of persistence, with early EE potentially accelerating future improvements. It should be noted that lagging urbanization (urb) and green building awareness (lnbaidu) have minimal effects on EE. This could be due to the presence of numerous variable lags in the PVAR model, although this does not affect the predictive analysis.

4.2.4. Impulse Response Analysis

The orthogonal impulse response model used in this research guarantees that the impulse response of other variables remains unaffected, enabling the extraction of the orthogonal impulse between variables. This method is scientifically robust. In this paper, the base period economic level (lngdpp), green building coverage (green), urbanization (urb), green building awareness (lnbaidu), and energy efficiency (EE (lneco) are established as the impulse function of one unit. To validate the model, 1000 Monte Carlo simulations were performed within a 5% confidence interval, with an exploratory period of 10 years. Subsequently, the influence of variables through the dynamic response of various variables to shocks is analyzed, as depicted in Figure 9.

As shown in Figure 9, the impulse response is delineated, with an emphasis on the EE in the fifth row of the chart in response to influences from other variables. The dashed line represents the baseline. The curves represent the impulse response curve and confidence interval curve. The ensuing results can be attained from these data.

(1) Facing the impact of the orthogonalization of the economic level, the EE demonstrates a pronounced negative response. This result indicates that the EE experiences a substantial reduction in the current period when exposed to a positive impact derived from the economic level's standard deviation. The response is the most prominent in the first period, gradually attenuating over the years, and disappearing in the sixth period. This suggests that due to the prioritization of economic growth, the EE of the construction industry has been insufficiently acknowledged. In recent years, despite the ongoing promotion of GB technologies and strategic plans created by the state and local governments, the focus on economic development has remained unchanged. Corresponding incentive policies and environmental regulations have not effectively addressed the Kuznets curve for environmental pollution after the economic level has reached an inflection point, hindering

the increasing trend of EE. Consequently, targeted strategies and policy implementation are required to enhance the EE of the construction industry.

(2) EE improvement is noted when subjected to a one-standard-deviation positive urbanization impact. This impact is the most significant in the second period, preceding a gradual decline until the sixth period. This suggests a current urbanization-promoting effect on the EE of the construction industry.

(3) Initially, there is a negative response to green building awareness, which is followed by a positive impact. This suggests that the current EE decreases when positively influenced by the standard deviation of green building awareness. After the first period, the EE improves and reaches its peak in the second period, before gradually weakening until the sixth period. This indicates that while green building awareness negatively affects the current period, it will enhance the improvement of EE over time.

(4) The orthogonal effect of green building coverage demonstrates a substantial positive response, suggesting that the EE is significantly enhanced in the current period upon exposure to a standard deviation of green building coverage. This effect is the most pronounced in the first period, gradually weakening until it disappears in the fourth period. This indicates that the current advancement of green buildings plays a crucial role in improving EE. However, the duration of its effects is relatively short, and to achieve long-term efficiency improvement, the promotion of green buildings is required.

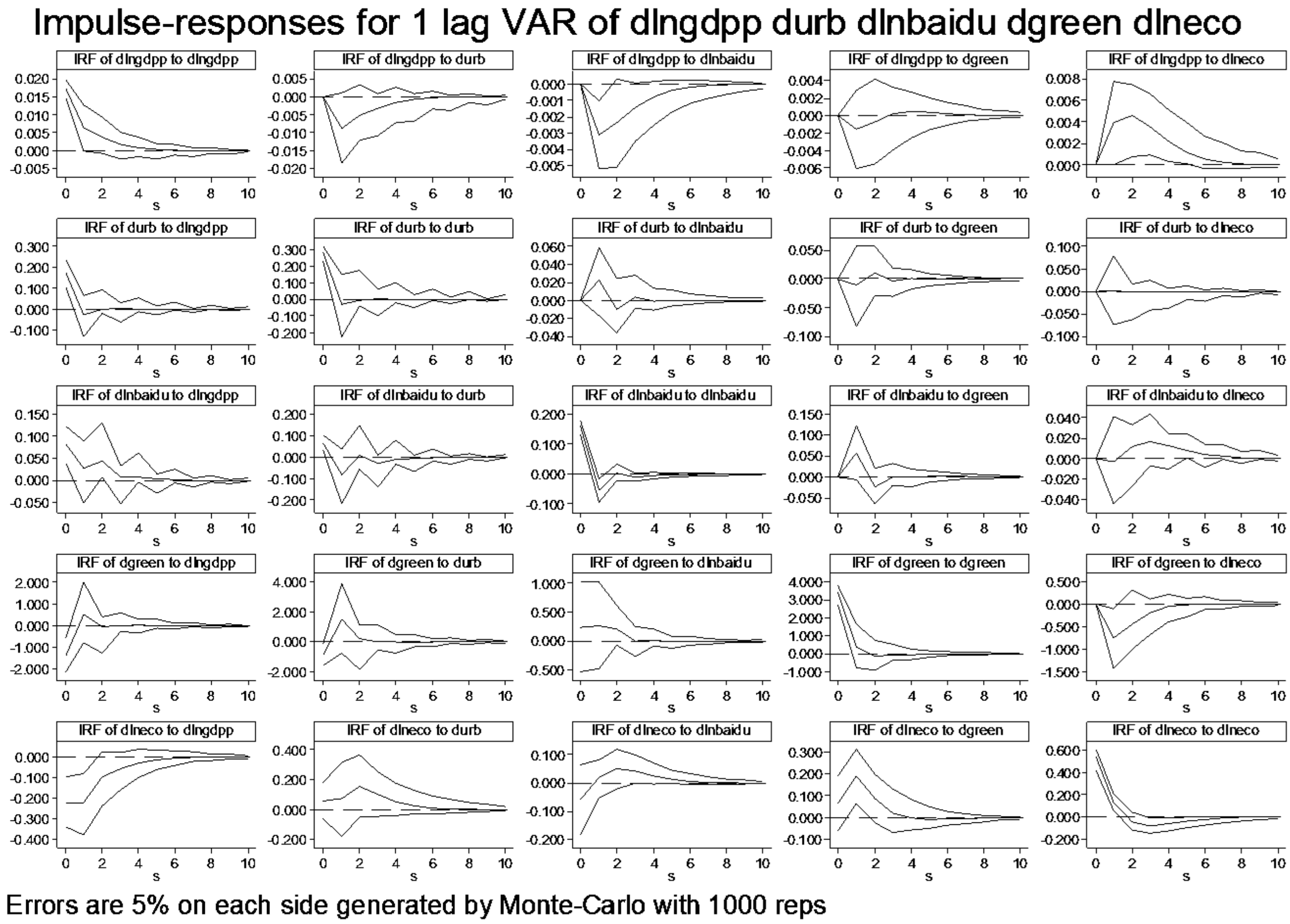


Figure 9. Impulse response diagram of ecological efficiency research using PVAR.

In addition, the impact response diagram in the fourth row of Figure 9 reveals that the economic status, urbanization, and EE have a substantial negative impact on GBs. This indicates that China's GB market is facing significant obstacles in its development. The conflict between ecological and economic benefits, coupled with the unique characteristics of GBs, including increased initial costs and a long capital return cycle, has led governments and enterprises to prioritize economic growth over the promotion of GBs. These entities aim to mitigate all negative environmental impacts through economic development. Nonetheless, the improvement of EE solely focuses on economic benefits, neglecting potential environmental gains. This approach is inherently unsustainable. Therefore, urgent measures are required to comprehensively enhance the EE.

4.2.5. Variance Decomposition

The variance decomposition function is constructed by decomposing endogenous variables into the impacts on the components of the PVAR model. It is used to measure the influence of endogenous variables on themselves. Additionally, this function provides insights into and predicts the degree of interaction among different variables. The specific results of the variance decomposition can be found in Table 7.

Table 7. Equation decomposition of prediction error of endogenous variables in the PVAR model.

Explained Variable	Period	dlngdpp	durb	dlnbaidu	dgreen	dlneco
dlneco	1	0.139	0.01	0.01	0.012	0.829
dlneco	2	0.212	0.019	0.008	0.087	0.673
dlneco	3	0.211	0.066	0.012	0.094	0.617
dlneco	4	0.208	0.081	0.015	0.091	0.604
dlneco	5	0.207	0.085	0.016	0.09	0.602
dlneco	6	0.206	0.086	0.016	0.09	0.602
dlneco	7	0.206	0.086	0.016	0.09	0.602
dlneco	8	0.206	0.086	0.016	0.09	0.602
dlneco	9	0.206	0.086	0.016	0.09	0.602
dlneco	10	0.206	0.086	0.016	0.09	0.602

As shown in Table 7, each variable's contribution to EE shows an increasing trend, which stabilizes in the sixth period. First, the early EE has a greater impact on the follow-up efficiency, stabilizing at 60.2%, indicating that the EE has a certain continuity. Second, the economic level makes the largest contribution to the EE, accounting for a stable level of 20.6%. This implies that realizing the improvement of the EE under the economic premise is the most practical solution at present. Therefore, the research and promotion of the realization of the economic benefits of GBs is the most important topic for the government, enterprises, and related practitioners. Moreover, the urbanization, green building awareness, and green building coverage make a relatively small contribution to the EE, accounting for 8.6%, 1.6%, and 9%, respectively. This shows that GBs cannot play a significant role in such a very low coverage ratio. In addition, under the background of a serious lack of awareness of GBs and the rapid development of the construction industry, driven by urbanization, the demand for GB has not been activated. The pulling effect of GB is weak, and thus, it is not an effective method for improving EE. Meanwhile, its effect period is too long, and the effect is too small, which leads to the dislocation of the ecological economy market, as well as development difficulties.

Based on the above research, it is concluded that: (1) The lagging economic level has a significant negative effect on the EE of the construction industry. Its influence period is longer, which is consistent with the assumption of the Kuznets curve theory of environmental pollution. (2) The coverage of green buildings has a significant positive impact on the EE, but the effect period is relatively short. (3) Economic level, urbanization, and EE have a certain negative impact on the development of green buildings, restricting the development of the green building market. (4) The cognition of green buildings has a certain positive impact on the development of green buildings. (5) From the perspective of variance decomposition, EE and economic level are the main contributing variables that affect the current ecological economic efficiency of the construction industry. Green building awareness and green building coverage make a small contribution to EE, and the effect is not obvious. The growth of the construction market brought about by urbanization has not improved the comprehensive EE of the construction industry. These results can provide a solid theoretical basis for the government to formulate macro-control strategies for green transformation.

4.3. Threshold Impact of GB

This section of the paper examines the threshold regression of the EE GBs on the panel statistics for China's provinces from 2011 to 2015, using Stata 13.1 software [37]. The outcomes and threshold effects are displayed in Table 8.

Table 8. Threshold effect estimation and test results.

Single Threshold		Double Threshold		Triple Threshold	
lnbaidu	−0.458 ** (−2.52)	lnbaidu	−0.482 *** (−2.61)	lnbaidu	−0.485 *** (−2.62)
urb	0.118 *** (3.13)	urb	0.119 *** (3.16)	urb	0.118 *** (3.12)
green (lngdpp ≤ 11.063)	0.007 (0.58)	green (lngdpp ≤ 10.297)	0.060 (0.89)	green (lngdpp ≤ 11.063)	0.073 (1.05)
green (lngdpp > 11.063)	0.092 *** (3.64)	green (10.297 < lngdpp ≤ 11.063)	0.009 (0.72)	green (10.297 < lngdpp ≤ 11.063)	0.018 (1.07)
		green (lngdpp > 11.063)	0.095 *** (3.69)	green (10.297 < lngdpp ≤ 11.063)	0.003 (0.20)
				green (lngdpp > 11.063)	0.094 *** (3.65)
Constant	−6.359 *** (−4.03)	Constant	−6.359 *** (−4.02)	Constant	−6.296 *** (−3.97)

Note: *, **, and *** denote a significance of 10%, 5%, and 1%, respectively.

From Table 8, it can be observed that the single threshold test passed at the 1% significance level, 0.092 *** (3.64), when green was (lngdpp > 11.063). However, the double and triple threshold tests did not show significant results. A threshold effect was found in the disparity of economic levels between GB and EE.

In regions with economic levels below 11.063, GB has a minimal influence on EE. Conversely, in areas with economic levels higher than this threshold, GB significantly boosts EE. This implies that regions with higher economic development levels are more conducive to the ecological role of green buildings. The possible reason is that enhancing people's economic levels can encourage the consumption of and attention towards green products. To cater to people's demand for environmental protection, developers and enterprises are more willing to develop GB projects, thus improving EE. Moreover, the results of the control variables indicate that urbanization has a significant positive effect on EE, while green building awareness demonstrates a significant inverse effect. This may be due to the fact that urbanization generates a huge construction market, causing some developers and enterprises to adopt a GB strategy to emphasize enterprise characteristics. The lack of in-depth knowledge relating to GB may deter market participants due to its high cost premiums, long return periods, and intricate rating procedures. These factors affect the development of the GB market and hinder the improvement of EE.

After the threshold effect is estimated and tested, the significance of the threshold is tested, and the results are shown in Table 9.

This research uses the economic status of the provinces as the threshold variable, with corresponding threshold values of 10.605, 10.297, and 11.063. The analysis indicates that only one threshold reaches the 5% significance level within the 95% confidence interval [11.056, 11.123], thus rejecting the null hypothesis. This result suggests the presence of a single threshold in China's GB EE threshold model.

Table 9. Threshold and parameter estimation.

Model	Threshold Value	95% Confidence Interval	F	p	Critical Value		
					1%	5%	10%
Single threshold	11.063	[11.056, 11.123]	13.970 **	0.013	14.570	7.574	6.224
Double threshold	10.297 11.063	[10.294, 10.759] [11.056, 11.123]	0.823	0.533	24.283	10.075	6.468
Triple threshold	10.605	[10.460, 10.762]	0.850	0.440	12.915	4.361	3.512

Note: F and p values are the results of bootstrap sampling, repeated 150 times; *, **, and *** denote a significance of 10%, 5%, and 1%, respectively.

Additionally, the authenticity of the threshold value has also been tested in this paper. The estimated value of a single threshold parameter is the corresponding value when the likelihood ratio test statistic LR is zero. The result is illustrated in Figure 10.

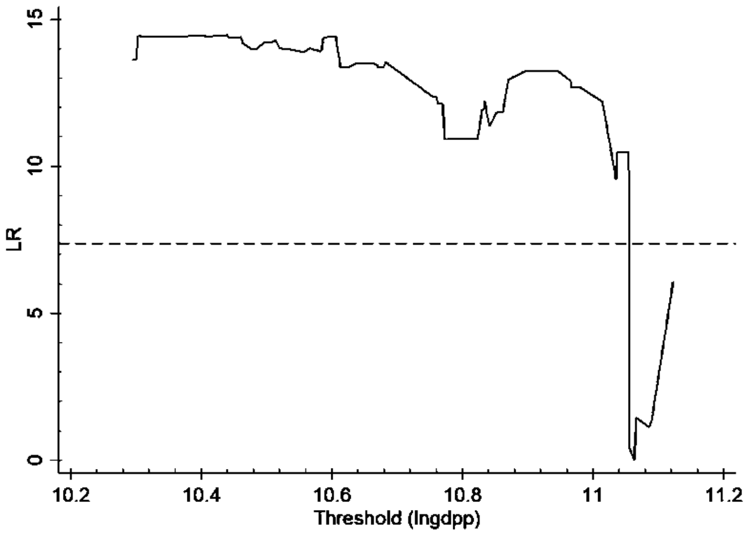


Figure 10. Threshold variable LR value graph (single threshold).

As shown in Figure 10, a dashed line denotes the corresponding critical value; the curve denotes the likelihood ratio test statistic LR value. The threshold estimate for 11.063 in the GB–EE threshold model lies within the 95% confidence interval. The LR value of this estimate is lower than the corresponding critical value at the 5% significance level. This observation indicates that the threshold value is within the acceptance domain, based on the original hypothesis, implying that the threshold value is equivalent to the true value. Additionally, the results presented in Figure 10 suggest that the effect of GB on EE exhibits a threshold effect.

The research further examined the provincial heterogeneity. A comprehensive map of the effective regional distribution of threshold values across China's provinces is presented in Table 10.

In Table 10, the effective threshold range was exceeded by only three regions in 2011: Beijing, Tianjin, and Shanghai. In 2012, Inner Mongolia and Jiangsu were added to the list, followed by Zhejiang in 2013 and Liaoning in 2014. By 2015, Fujian, Shandong, and Guangdong had reached this threshold, resulting in a total of ten effective provinces, representing one-third of the 30 research areas. This indicates a significant increase in the areas where GBs contribute to both ecological and economic efficiency. The initial ecological role of GBs has now been revealed.

Table 10. Threshold and provincial distribution.

	green → lneco	
	$\mathrm{lngdpp} \geq 11.063$	
Year	**Region**	**Count**
2011	Beijing, Tianjin, Shanghai	3
2012	Beijing, Tianjin, Inner Mongolia, Shanghai, Jiangsu	5
2013	Beijing, Tianjin, Inner Mongolia, Shanghai, Jiangsu, Zhejiang	6
2014	Beijing, Tianjin, Inner Mongolia, Liaoning, Shanghai, Jiangsu, Zhejiang	7
2015	Beijing, Tianjin, Inner Mongolia, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong	10

5. Discussion and Policy Implications

This paper subverts the conventional efficiency metrics in the construction industry through the integration of environmental indicators, ultimately creating a comprehensive analysis framework to evaluate the sustainable effects of GB. The results of this study are summarized in the subsequent conclusion.

5.1. Discussion

(1) The comprehensive EE of China's provinces displays relatively strong effectiveness in only a few regions. The pure technical EE reaches a higher level of development in the middle and advanced stages, but there is no effective region, with only Beijing approaching the level of DEA effectiveness. Throughout the majority of the research periods, the average annual pure technical EE has played a crucial role in enhancing the comprehensive efficiency. This indicates that although China's construction industry is developing rapidly, its performance is not good when measured with input-output models that take negative environmental effects into account. This is in line with the increasingly serious environmental pollution situation in China, and technology remains the optimal solution to address these issues at present.

(2) In the Eastern Region, despite having a relatively low scale, pure technical EE is higher due to talents, capital, and resources, significantly contributing to the overall EE. In contrast, the Western Region, influenced by its geographical location and diverse development factors, relies heavily on economies of scale to improve its comprehensive EE. The pure technical EE in the Western Region has significantly improved since 2011, and the subsequent research period mainly attributes the improvement in comprehensive EE to the enhancement of pure technical EE. This indicates that the Western Region is embracing green production methods and technological transformations. Concurrently, the Central Region's pure technical EE and scale EE enhancement is obscure, with both remaining at relatively low levels. Consequently, the EE in the Western Region has been gradually catching up and surpassing that of the Central Region, and there is an urgent need for targeted adjustments and improvements in the Central Region.

(3) The economic level has a long-term inhibitory effect on the EE of the construction industry. Historically, EE has been neglected and has become a victim of economic growth. Although the awareness of GB has a negative impact on the current period, it will promote the improvement of EE in the long run. In addition, the development of GB has a significant impact on EE. However, its impact is relatively short, and more effective promotion of GBs is required for long-term efficiency improvement. Early EE and economic level are the main contributing factors that affect the current EE. The construction market created by urbanization has not significantly improved the EE. The effect of urbanization on the ecological and economic performance of buildings is uncertain.

(4) The impact of GB on the EE of the construction industry presents a threshold effect. When the economic level develops to a certain point, GB can significantly promote the improvement of EE. For EE that considers both economic and environmental benefits, the current core driving factor is still economic benefits. The ecological role of GB only

has a significant impact on promoting the improvement of EE in select cities with high economic levels.

5.2. Policy Implications

Drawing upon the research findings above, several policy implications are proposed.

First, the development of regional heterogeneity strategies is of paramount importance. These strategies should be tailored to the unique mechanisms of EE in various regions. In response to the inefficiency of pure technology in the Central and Western regions, it is necessary to enhance policy promotion and incentives for science, technology, and green innovation. This will promote the accumulation of regional technological innovation elements, including talent, capital, and equipment. For the Eastern Region, with an advanced level of technology, the scale effect of GB projects can be expanded, and the resource optimization allocation mechanism can be further refined. Based on the region's characteristics and the built environment, scientific and rational GB development strategies can be designed.

Second, the successful implementation of fiscal and tax incentive policies is vital for achieving fairness and efficiency in resource allocation. The government should develop corresponding taxation and incentive strategies to achieve these objectives. Specifically, implementing a construction pollution tax and a fee system for polluters would be an effective approach. Moreover, the government should incentivize and provide subsidies for enterprises to bridge the gap between private and overall social costs in pursuing green building strategies. These policies can effectively stimulate the attainment of the optimal efficiency goal within the ecological mechanism.

Third, the development of an innovative system supportive of the ecological economy should be guided by the government. The concept of EE should be incorporated into the evaluation system for measuring development, encompassing both economic and ecological aspects. The system should also integrate additional environmental indicators, and an innovative method, like the quota system, can be employed to establish new control measures for resource consumption, emission rights transfer, carbon taxes, and emission rights trading.

Fourth, the public GB awareness should be cultivated. The government should deepen the mechanism for cultivating the public's awareness of green buildings. Environmental protection campaigns and targeted green building education and training could be conducted for the enterprises and the public by making full use of the media for energy-saving education activities. In addition, the intermediary agencies or consulting service organizations are encouraged to participate, thus promoting the improvement of the level of GB awareness.

6. Conclusions

The impact mechanism of GB on EE in the construction industry has been tested. The research results indicate that the EE is relatively low in most regions. Pure technical efficiency is the most important driving force. The EE in the Eastern Region is relatively high, while the results for the Western Region surpasses those for the Central Region due to its scale and pure technical efficiency. The economic level has a significant long-term negative impact on EE. GB awareness has a negative impact on the current period, but it is expected to gradually show a positive impact in the future. The coverage of GB has a significant positive impact on EE, but the impact period is relatively short. Economic level, urbanization, and EE have a negative impact on the development of GB. Early EE was identified as the main variable affecting current EE. The ecological effect of GB is only significant in cities reflecting high economic levels.

In terms of theoretical advancements, this study rebuilds the evaluation model of EE by incorporating eco-environmental indicators. The PVAR analysis framework is further introduced, along with regional threshold effect analysis. This research presents a novel scientific approach for exploring the ecological and economic mechanism of GB. Practical implications are also significant, as this article re-evaluates the efficiency of the construction industry using practical data, thereby addressing the absence of the environmental impact in traditional efficiency measurements. Furthermore, the study delves into the mechanism, influencing factors, and regional heterogeneity of GB. The research provides an effective reference for promoting GB practices.

There are limitations in regards to this paper. The restrictions on government and industry data restricts the acquisition of GB data, resulting in time limitations and deviations from objective reality during EE analysis. Future research could focus on the practical applications and social appraisal of GBs, using social surveys and questionnaires to examine social determinants. Further research on the worldwide universal impact mechanisms will also be conducted.

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