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Green Development Efficiency and Its Influencing Factors in China's Iron and Steel Industry

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Abstract: Analyzing the potential for green development and its influencing factors is an important part of the energy savings and low-carbon economic growth of China's iron and steel industry (ISI). Many studies have concentrated on improving the ISI's energy use and pollution control efficiencies, analyzing the influencing factors from the perspectives of regions and firms. However, no study has focused on measuring the provincial green development efficiency (GDE) in the ISI. The selected driving forces of the GDE do not consider regional or industrial characteristics. In this study, based on provincial panel data for 2006–2015 in China, the GDE of the Chinese ISI was evaluated using the super-slack-based measure (super-SBM) model. China's 28 provinces were divided into different groups through cluster analysis. Then, a Tobit model was constructed to explore the factors influencing the GDE. The key results show the following: (1) The GDE values decline, fluctuating from 0.628 in 2006 to 0.571 in 2015, decreasing by 1.1% annually. Among the provinces, wide differences exist in the GDE values for the ISI, with the highest average GDE value being observed in Beijing and the lowest in Shanxi. (2) The provinces with high R&D expenditure inputs and high GDE values are mostly located in the eastern region, while the provinces with low R&D expenditure inputs and low GDE values are located in the central and western regions. (3) The export demand, property structure, and capital investment have significant positive effects on the ISI's GDE in the eastern and western regions, while the energy consumption structure and industry scale have negative impacts on the improvement of the GDE in the central region. (4) Specific policy recommendations for sustainable development in the ISI mainly include further strengthening investment in R&D, expanding exports, adjusting energy consumption structures, and deepening the reform of stated-own enterprises.

Keywords: green development efficiency; low-carbon economic growth; super-SBM model; environmental policies; Tobit regression model

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1. Introduction

China's iron and steel industry (ISI) has rapidly developed since the beginning of the country's reform and opening-up processes. In 1996, China became the world's largest producer of crude steel. The country's past policy approaches affected its industry development and economic growth [1]. Especially during the 11th Five-Year Plan (2006–2010) and the 12th Five-Year Plan (2011–2015) periods, the crude steel output in China increased from 423 million tons (Mt) in 2006 to 804 Mt in 2015, which is an increase of 7.4% annually [2]. As a pillar promoting China's national economic growth, the ISI has played a key role by providing industrial products, promoting employment, and constructing national infrastructure. However, China's ISI is an energy- and emission-intensive industry. Its proportion of coal-related energy use was about 85.03% of the total energy consumption from 2000 to 2016 [3]. From 2006 to 2015, the energy consumption of the ISI increased 1.5 times from 428 to 640 Mt. The amount of CO_2 emitted by the ISI in 2015 was 1.53 times that in 2006. During this period, the ISI accounted for 14.7% and over 10% of the total Chinese energy consumption and CO_2 emissions, respectively [4], which is one of the main reasons for the frequent regional haze and air pollution in China, threatening human health and sustainable regional development.

Green development can overcome resource and environmental bottlenecks, provide guidance for industrial transformation and upgrading, and promote the construction of an ecological civilization in China [5]. To achieve the green and low-carbon development of the ISI, the Chinese government has promulgated a series of policies. In 2010, guidelines on energy conservation and emissions reductions for the ISI were issued to eliminate 125.4 Mt of blast furnace capacity under 400 m^3 as well as 28.2 Mt of converter and electric furnace steelmaking capacities under 30 t by the end of 2011. In 2012, a guidebook was published, requiring advanced and applicable energy savings and emissions reduction technologies to be applied in the ISI. The Iron and Steel Industry Adjustment and Upgrade Plan (2016–2020) was introduced by the Chinese government in 2016, emphasizing that the production capacity of crude steel would decrease by 100–150 Mt by 2020. In this context, exploring the ISI's green development and its driving forces could not only determine the potential for energy savings and carbon reduction, but could also identify a precise, green, and sustainable development path for other industries in China.

The concept of a green economy was first introduced in the Green Economy Blueprint in 1989 [6]. Since then, many institutions and scholars have defined green development from different perspectives [7,8]. The Organization for Economic Cooperation and Development (OECD) defined green development as "pursuing economic growth and development while offering resources and environmental services for human demands" [9]. The aim of green development is to promote the sustainable development of the economy, society, and environment [10]. Thus, factors related to the economy, society, and ecological environment should be considered in the evaluation of green development [11]. In China, green development means environment protection, improvement of resource use efficiency, and economic growth [12]. The 19th National Congress of the Communist Party of China (NCCPA) emphasized that the harmonious development of humans and nature is the new concept of green development.

In previous research studies, many scholars have focused on the relationship between economic growth and the environment, such as the relationships between carbon emissions and economic growth [13]; economic growth and energy consumption [14]; and economic growth, energy intensity, and carbon emissions [15]. Balancing the two systems is the key to achieving green development. The studies related to green development can be divided into two groups: those suggesting that green development should be formed by policy and regulations [16,17] and those focusing on evaluation methods for green development, mainly including composite evaluation index systems and green development efficiency (GDE) measures. Some scholars have measured the level of green development by constructing complex indicator systems, such as the evaluation index system for China's green economy development [18], the green development evaluation index system based on a multi-level evaluation method and the entropy method [19], the green development integrated weighting method [11], and the urban green growth efficiency evaluation index system [20]. However, the evaluation results for the green development produced using such methods may be biased because the selection of system indicators was subjective [21]. Two methods can be used to evaluate GDE: data envelopment analysis (DEA) [5,21] and stochastic frontier analysis (SFA) [22] models. The SFA model should include certain settings related to the form of the production function and shape of the efficiency boundary [23]. The DEA model does not require estimation parameters to be set, which may avoid bias in the estimation results caused by inappropriate assumptions [23] and is why this method has become a popular for evaluating GDE [24].

Regarding the regional perspective of the above studies, the GDE evaluations have mainly been performed at the regional and city levels. At the regional level, Feng et al. found that GDE levels in developed regions and countries had been leading since the

21st century, while GDE levels in developing regions and countries showed a downward trend [25]. Zhu at al. explored China's interprovincial GDE using the super slack-based measure (super-SBM) model for 1999–2016 [5]. Zhou and Deng indicated that the green economic efficiency in coastal areas of China is higher than that in Western China [26]. At the city level, Zha et al. analyzed the development efficiency of the low-carbon tourism economy of 17 cities in Hubei province in China, adopting the SBM-DEA model [27]. Guo et al. measured the GDE of 34 cities in Northeast China based on the SBM-DEA model and indicated that significant spatial differences exist among the cities [21]. Chen et al. evaluated the industrial land green efficiency of 198 cities in China and found that cities with high industrial land green efficiency are mainly concentrated in the eastern region [28].

In addition, the forces driving GDE must be explored, as this is not only conducive to analyzing the potential and path of energy-savings and carbon emissions, but also provides specific guidance for policies and recommendations. Some scholars have found that energy price, technology progress, foreign direct investment, environmental protection, energy conservation, and emission reduction policies can promote the improvement of GDE [5,21,26,29], whereas openness, urbanization, industrial structure, climate change, energy consumption structure, and environmental regulation hinder its improvement [5,21,30]. Feng et al. found that the relationship between GDP per capital and GED for global 41 regions presents a significant inverted U-shape [31]. A U-shaped relationship exists between industrial agglomeration and GDE [21]. Zhu et al. found that industrial structure rationalization and advancement both positive affect the improvement of GDE [5]. Zhu et al. found that the carbon-trading mechanism, research and development intensity, and pollution control investment have a positive effect on GDE [32]. However, the same driving forces were reported to have different impacts on efficiency improvement because of the different research objects and methods. For instance, Su and Zhang found that urbanization promotes the improvement of the regional economy efficiency [33], whereas Zhu et al. indicated a negative effect of urbanization on the improvement of GDE [5].

Based on the above analysis of the literature, GDE has been comprehensively evaluated. However, some research gaps still exist follows: Firstly, existing studies on the ISI mainly concentrated on energy efficiency [34], pollution control efficiency [35], energy and carbon emission efficiency [3], green growth [29], and productivity evolution [31] from the perspectives of regions and firms. None of them constructed an integrated framework measuring China's provincial GDE in the ISI, which could promote technology progress and the development of a low-carbon industry. Secondly, in many studies, China's provinces were divided into different regions based on geographical location, which cannot reflect the changes in production technology [3]. Thirdly, the selected factors influencing GDE did not consider regional or industrial characteristics. Many scholars explored the factors influencing GDE based on the entire region or industry, which is not conducive to recognizing heterogeneous influences for different regions.

In this study, the above limitations were observed, and the main contributions are presented as follows: Firstly, a unified framework was constructed for evaluating the GDE of the ISI in China's 28 provinces using the super-SBM model, considering the research and development (R&D) expenditure input for the period of 2006–2015. Secondly, China's provinces were divided into different groups according to differences in R&D input and GDE value, and the differences and change trends of the ISI's GDE were analyzed from the nation, group, and region levels. Thirdly, we selected factors influencing GDE based on the characteristics of the ISI and explored their impact on GDE using a Tobit panel regression model.

The remainder of this paper is structured as follows. Section 2 describes the used methods, data sources, and variables. Section 3 introduces the empirical results and discussions. Section 4 summarizes our conclusions and related policy implications.

2. Materials and Methods

2.1. Super-SBM Model

Data envelopment analysis (DEA) was first proposed by Charnes et al. [36] and provides a measure of the relative efficiencies of decision-making units (DMUs) with multiple inputs and outputs [37]. DEA models include input-oriented models that seek to minimize inputs when the output is fixed and output-oriented models that seek to maximize outputs when the input is fixed [38]. However, traditional models of DEA efficiency evaluation ignore the undesirable outputs that are generated as by-products of desirable outputs in the production process [39]. They are radial and oriented measures that neglect the impacts of the input and output slack variables on the efficiency values. The efficiency evaluation results may be biased using traditional DEA methods. Tone introduced a slacks-based measure (SBM) model, which is a non-radial and non-angle model considering undesirable outputs [40] that can directly deal with input or output slacks variables.

In the SBM approach, suppose there are n DMUs, each of which has three factors: inputs, desirable outputs, and undesirable outputs, represented by three vectors $X \in R^m$, $Y^g \in$, and $Y^b \epsilon R^{S_2}$, respectively. Each DMU uses m input factors to produce the s_1 number of desirable outputs and the s_2 number of undesirable outputs. The matrices X, Y^g, and Y^b are defined as follows:

$$X = [x_1, x_2, \ldots, x_n] \in R^{m \times n}, Y^g = \left[y_1^g, y_2^g, \ldots, y_n^g\right] \in R^{s_1 \times n}, Y^b = \left[y_1^b, y_2^b, \ldots, y_n^b\right] \in R^{s_2 \times n}.$$

Then, we define the production possibility set (P) as follows:

$$P = \left\{ \left(x, y^g, y^b\right) \middle| x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \lambda \geq 0 \right\} \tag{1}$$

where λ denotes a non-negative vector. The SBM model with undesirable outputs based on Tone's SBM model for evaluating (x_0, y_0^g, y_0^b) are defined as follows:

$$\beta = \min \frac{1 - \frac{1}{m}\sum\limits_{i=1}^{m} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1+s_2}\left(\sum\limits_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum\limits_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b}\right)},$$

$$\text{s.t. } x_0 = X\lambda + S_0^-,\ y_0^g = Y^g\lambda - S^g,\ y_0^b = Y^b\lambda + S^b,$$
$$S_0^- \geq 0, S_0^g \geq 0, S_0^b \geq 0, \lambda \geq 0, \tag{2}$$

where S^-, S^g, and S^b represent the excess of inputs, the shortage of desirable outputs, and the excess of undesirable outputs, respectively. The estimated value of the DMU is denoted by the objective of function value β, which ranges in [0, 1]. The DMU is efficient in the presence of undesirable outputs if $\beta = 1$, meaning that all the slack variables are 0 ($s_0^- = s_0^y = s_0^d = 0$). The DMU is inefficient if $\beta < 1$; it can be improved and become efficient by optimizing the inputs and outputs.

In most efficiency evaluation research, the efficiency status of plural DMUs is denoted by 100%. Thus, discriminating ranking efficiency and analyzing influencing factors are important among these efficient DMUs. The super-slacks-based measure (super-SBM) model proposed by Tone [41] not only ranks the same efficient DMUs as in SBM model, but also relaxes the restriction on efficiency score to be less than 1. The super-SBM model with undesirable outputs based on Tone [41] is as follows:

$$\varepsilon = \min \frac{\frac{1}{m}\sum\limits_{i=1}^{m} \frac{\bar{x}_i}{x_{i0}}}{\frac{1}{s_1+s_2}\left(\sum\limits_{r=1}^{s_1} \frac{\bar{y}_r^g}{y_{r0}^g} + \sum\limits_{r=1}^{s_2} \frac{\bar{y}_r^b}{y_{r0}^b}\right)},$$

$$\text{s.t. } \bar{x} \geq \sum_{j=1,\neq 0}^{n} \theta_j x_j,\ \bar{y^g} \leq \sum_{j=1,\neq 0}^{n} \theta_j y_j^g,\ \bar{y^b} \geq \sum_{j=1,\neq 0}^{n} \theta_j y_j^b,$$

$$\bar{x} \geq x_0, \bar{y^g} \leq y_0^g, \bar{y^b} \geq y_0^b, \bar{y^g} \geq 0, \theta \geq 0, \tag{3}$$

where the efficiency score of the DMU is represented by the objective function value of θ. We hypothesized that the above-discussed models are constant returns-to-scale. In addition, $\sum_i^n \lambda_i = 1$ in Equation (2) and $\sum_{i=1,\neq 0}^n \theta_i = 1$ in Equation (3) are the conditions of the variable returns-to-scale.

2.2. Tobit Regression Model

Using the ordinary least square (OLS) model may cause bias and inappropriate parameter estimation. The Tobit model can deal with this problem, which we used as the main estimation method in analyses of factors influencing efficiency. In the regression model, the GDE calculated by the super-SBM model was taken as the dependent variable. The independent variables included export demand, energy consumption structure, industry scale, state-owned output, and capital investment, which are explained below:

(1) Export demand: The market demand plays an important role in an enterprise's production and operations [42]. The higher is the demand for a product in the international market, the higher are the green environmental standards. This promotes green innovation, technological upgrade, and changing the production process for local enterprises. In this paper, the proportion of export delivery value to the gross value of industrial output is used as the indicator of export demand.

(2) Energy consumption structure: The energy consumption in the ISI is very large; the ISI emits many pollutants. As an important fossil energy source, the high proportion of coal in the total energy use may indicate low GDE. The energy consumption structure is represented by the proportion of coal consumption to the total energy consumption in this paper.

(3) Industry scale: A large industry scale creates the accumulation of labor, capital, technology, energy, and other elements. It not only enhances production and technology innovation capacities, but also promotes economic development and improves the use of resources [43]. However, the expansion of industry scale leads to increases in energy and resources consumption, which result in increased pollutant emissions. A large industrial scale may result in market monopoly, which is not conducive to the efficient improvement in production and operation [44]. Industry scale was measured by the proportion of the gross value of the industrial output to the number of industrial enterprises in this study.

(4) Property structure: State ownership is the main form of property structure in ISI. Capital, technology, and energy use are intensive in state-owned enterprises. This may influence the improvement in GDE. The proportion of the industrial output value of state-owned enterprises to the total gross industrial outputs represents the property structure in this paper.

(5) Capital investment: The higher is the capital investment, the higher is the productivity of labor and technology progress. Capital investment can promote economic development and green innovation. The proportion of net fixed assets to the number of employees is used to represent the capital investment in this paper.

The Tobit regression model was built as follows:

$$GDE_{it} = \beta_0 + \beta_1 ED_{it} + \beta_2 ES_{it} + \beta_3 IS_{it} + \beta_4 PS_{it} + \beta_5 CI_{it} + \varepsilon_{it}, \tag{4}$$

where i and t indicate the iron and steel industry of each province and time, respectively; β_i (I = 0, 1, . . . , 5) is the estimated parameters; and ε is the error term. GDE, ED, ES, IS PS, and CI denote green development efficiency, export demand, energy consumption structure, industry scale, property structure, and capital investment, respectively.

2.3. Data

Based on the availability of data, we included China's 28 provinces' panel data for the iron and steel industry from 2006 to 2015; Tibet, Ningxia, and Hainan were excluded. Labor, capital, R&D expenditure, and energy were selected as input variables. The gross value of industrial output was selected as the desired output variable; CO_2 emission was selected as the undesirable output variable. Table 1 provides the descriptive statistics of the input and output variables.

(1) Labor input: Labor refers to the number of people employed at the end of each year. Data were obtained from the China Industry Economy Statistical Yearbook, 2007–2016. The missing data were obtained using linear interpolation.

(2) Energy input: The total energy consumption (coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas, and electricity) at the end of each year was used to represent energy input. We obtained the missing data using linear interpolation. We converted each energy resource into standard coal based on the converting coefficients. The energy data were obtained from the statistical yearbook of each province.

(3) Capital input: Because data on the capital stock in China's iron and steel industry cannot be obtained from the statistical yearbook, following Lin and Wang [34], the perpetual inventory method (PIM) was used to calculate the capital stock, which is expressed as follows:

Table 1. Description of inputs and outputs.

Variables	N	Mean	SD	Max	Min
Labor	280	125,011	119,720	619,500	5600
Capital (10^4 RMB)	280	2.614,188	2,731,766	11,999,600	18,5716
R&D expenditure (10^4 RMB)	280	373,528	448,038	2,056,759	5110
Energy (10^4t)	280	1929	2093	14,336	23
Industrial Output (10^4 RMB)	280	14,428,496	16,552,573	88,965,725	681,800
CO_2 emission(10^4t)	280	6068	6643	45,445	72

$$K_t = K_{t-1}(1 - \delta_t) + I_t, \tag{5}$$

where K_t and K_{t-1} are the capital stock at periods t and t + 1, respectively. Net fixed assets of 2006 were used as the capital stock of the base year, and they were obtained from the statistical yearbook of each province during 2007–2016. I_t denotes investment at period t, which is equal to the fixed assets at period t minus the fixed assets at period t + 1 based on the study of Lin and Wang [34]. δ is the depreciation rate. The value of the depreciation rate in the iron and steel industry is 9.6%.

(4) R&D expenditure input: We cannot obtain the expenditure on R&D in China's iron and steel industry from the statistical yearbooks. Following Luo et al. [45], the perpetual inventory method (PIM) was used to calculate the R&D expenditure, which is expressed as follows:

$$R_t = R_{t-1}(1 - \delta) + E_{t-1} \tag{6}$$

where R_t and R_{t-1} are the R&D expenditure at periods t and t + 1, respectively; E_{t-1} denotes the internal expenditure of R&D expenditure at period $t - 1$, which was obtained from the statistical yearbook of each province during 2007–2016; and δ is the depreciation rate. The value of the depreciation rate is 15% according to Hu et al. [46].

(5) Industrial output: Data on the gross value of industrial output were obtained from the statistical yearbook of each province during 2007–2016. We converted industrial output value into constant price in 2006.

(6) CO_2 emission output: We estimated CO_2 emission from burning fossil fuels based on the Intergovernmental Panel on Climate Change guidelines (IPCC, 2006) [47], which is expressed as:

$$CO_{2,t} = \sum_{i}^{8} E_{i,t} \times CEF_i \times HE_i \times COF_i \times (44/12), \quad (7)$$

where i refers to coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas, and electricity; E denotes the consumption of each energy at period t; the carbon emission factor, heat equivalent, and carbon oxidation factor are represented by CEF, HE, and COF, respectively; and 44/12 denotes the molecular weight proportion of CO_2 (44) to carbon.

3. Results

3.1. Analysis of Green Development Efficiency

3.1.1. Change Trends of 28 Provinces' Green Development Efficiency in the Iron and Steel Industry

The GDE value of the ISI in the 28 provinces during 2006–2015 is shown in Table 2. The average GDE of China's ISI showed a fluctuating downward trend, declining from 0.628 in 2006 to 0.571 in 2015, with an annual average decline of 1.1%. During 2006–2008, the GDE demonstrated an upward trend, and the efficiency value in 2008 (0.653) was the highest point, which was confirmed by Zhu et al. [5]. In 2005, China government issued the Steel Industry Development Policy, which played a significant role in enhancing technology innovation, promoting structural adjustment, and achieving the sustainable development of the ISI by increasing R&D expenses and introducing advanced foreign technology. China's ISI has the ability to improve resource use and pollution emissions. From 2009 to 2015, the average GDE of China's ISI showed a downward trend; this is consistent with the findings reported by Chen et al. [28]. The possible explanations are as follows: First, in 2009, the international financial crisis occurred. China government issued a series of polices to simulate economy growth, which may not have balanced environmental protection and economic development. Second, the 12th Five-Year development plan of the ISI issued by the Chinese government implemented stricter limitations on energy conversation and environment protection. Many iron and steel enterprises had to limit outputs of production and increase environmental protection investments to meet the new environmental standards. Third, in 2013, foggy and hazy weather frequently occurred in central and eastern regions of China. A number of iron and steel enterprises temporarily shut down or limited production to reduce pollutant emissions. These may have negatively impacted the improvements in the GDE of China's ISI.

The average GDE values of 75% of the provinces were less than 1.000 in the ISI, meaning that GDE was being lost in many provincial ISIs. Beijing's ISI's average GDE value was the highest (1.273) with an annual average increase of 13.56%, while Shanxi has the lowest average GDE value (0.219). Beijing is an important ISI base in China and has advanced production equipment and management experience. Since Beijing's Shougang Group moved to Hebei province, a green and scientific development system in the ISI has gradually taken shape in Beijing. Beijing lies in the eastern developed area and has many R&D institutions and schools. Thus, it has strong technical innovation ability and R&D investment capability, which are conducive to the improvement of energy-saving and emission reduction technologies in ISI. Conversely, Shanxi is located in Central China, and it has poor technical innovation and production management in the ISI. Shanxi has abundant coal resources. Poor resource use and unreasonable energy consumption structure may hinder the improvement in GDE in Shanxi. Thus, the ISI in Shanxi has great potential for GDE improvement.

Table 2. The green development efficiency (GDE) of the iron and steel industry (ISI) in China's 28 provinces during 2006–2015.

Province	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Mean
Beijing	0.554	0.646	1.075	1.064	1.253	1.432	1.453	1.750	1.762	1.741	1.273
Tianjin	1.060	1.051	1.041	1.034	1.045	1.031	1.035	1.030	1.033	1.034	1.039
Hebei	0.665	0.662	0.718	0.656	0.589	0.653	0.656	0.530	0.539	0.527	0.619
Shanxi	0.231	0.251	0.284	0.272	0.235	0.204	0.186	0.179	0.176	0.174	0.219
Inner Mongolia	0.477	0.471	0.512	0.500	0.555	0.673	0.857	0.603	0.606	0.683	0.594
Liaoning	0.314	0.316	0.358	0.319	0.277	0.243	0.227	0.216	0.213	0.210	0.269
Jilin	1.264	1.269	1.264	1.260	1.253	1.262	1.237	1.218	1.216	1.224	1.247
Heilongjiang	0.310	0.314	0.330	0.315	0.277	0.252	0.240	0.232	0.231	0.230	0.273
Shanghai	1.239	1.376	1.440	1.448	1.276	1.188	0.376	0.296	0.285	0.268	0.919
Jiangsu	1.158	1.136	1.147	1.118	1.059	1.031	1.036	1.036	1.039	1.039	1.080
Zhejiang	1.000	1.006	0.790	0.786	0.780	1.002	0.858	0.871	0.841	0.811	0.875
Anhui	0.421	0.408	0.403	0.371	0.317	0.274	0.251	0.240	0.233	0.229	0.315
Fujian	0.473	0.462	0.503	0.451	0.434	0.433	0.404	0.382	0.377	0.373	0.429
Jiangxi	0.393	0.416	0.437	0.415	0.407	0.399	0.414	0.412	0.412	0.404	0.411
Shandong	0.428	0.453	0.502	0.456	0.383	0.355	0.326	0.317	0.314	0.308	0.384
Henan	1.237	1.137	1.189	1.209	1.206	1.121	1.105	1.214	1.175	1.132	1.173
Hubei	1.325	1.296	1.296	1.221	1.125	1.083	1.064	1.024	1.021	1.016	1.147
Hunan	0.296	0.298	0.310	0.293	0.252	0.220	0.206	0.199	0.196	0.192	0.246
Guangdong	0.478	0.486	0.534	0.501	0.432	0.379	0.359	0.346	0.341	0.335	0.419
Guangxi	0.339	0.353	0.370	0.346	0.326	0.329	0.325	0.317	0.319	0.311	0.334
Chongqing	0.413	0.439	0.442	0.427	0.353	0.306	0.293	0.279	0.274	0.271	0.350
Sichuan	0.256	0.265	0.299	0.262	0.241	0.217	0.207	0.200	0.197	0.196	0.234
Guizhou	0.483	0.474	0.604	0.626	0.627	0.730	1.019	1.009	1.018	1.043	0.763
Yunnan	0.235	0.250	0.240	0.269	0.239	0.218	0.205	0.200	0.199	0.198	0.225
Shaanxi	1.061	1.060	1.057	1.059	1.057	1.054	1.053	1.053	1.053	1.054	1.056
Gansu	0.295	0.306	0.314	0.294	0.246	0.223	0.206	0.199	0.188	0.188	0.246
Qinghai	0.275	0.275	0.262	0.268	0.255	0.250	0.244	0.240	0.238	0.238	0.254
Xinjiang	0.905	0.502	0.554	0.498	0.480	0.580	0.926	0.444	0.466	0.547	0.590
Mean	0.628	0.621	0.653	0.634	0.606	0.612	0.599	0.573	0.570	0.571	0.607

3.1.2. Provincial Differences of Green Development Efficiency

To further analyze provincial differences in GDE in China's ISI, we classified the 28 provinces by two indicators, GDE and R&D expenditure input, based on the method followed by Lin and Wang [34]. Because R&D expenditure plays a large role in technology innovation and the improvement in GDE, we used R&D expenditure input as a key indicator for analyzing provincial differences. First, we divided the provinces into two categories in accordance with R&D expenditure input in the ISI. During 2006–2015, the provinces whose average R&D expenditure input was within [0, 500] million RMB were classified as the low input group. Other provinces were classified as the high input group. Second, for each R&D expenditure input group, provinces were divided by average GDE values. The provinces whose average values of GDE were within [0, 0.5] were classified as the low GDE group. The other provinces were classified as the high GDE group. All 28 provinces were divided into four groups: High R&D expenditure input, High GDE; High R&D expenditure input, Low GDE; Low R&D expenditure input, High GDE; and Low R&D expenditure input, Low GDE. The specific classifications are described in Table 3.

Table 3. Classification by R&D expenditure input and GDE.

	High R&D Expenditure Input	Low R&D Expenditure Input
High GDE	Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Henan, Hubei	Beijing, Inner Mongolia, Jilin, Guizhou, Shaanxi, Xinjiang
Low GDE	Liaoning, Anhui, Fujian, Shandong, Hunan, Guangdong, Sichuan, Shanxi	Heilongjiang, Jiangxi, Gansu, Guangxi, Chongqing, Qinghai, Yunnan

First, in the high R&D expenditure input and low GDE group, Fujian, Shandong, and Guangdong are coastal provinces. The ISIs in these provinces are in the early stages of green transformation and low-carbon development. The improvement in GDE may lag in the ISI. In Liaoning and Anhui provinces, the institutional innovation is poor, and transformation of scientific and technological achievements in the ISI is low, preventing the improvement in GDE. For Shanxi, Hunan, and Sichuan provinces, the average R&D expenditure input was more 1500 million RMB, and the GDE values were below 0.2. The main aims of these provinces are to promote economic development through the ISI, and demands are large for iron and steel in urban construction, transportation, and other infrastructure. Thus, it is difficult to balance economic growth and environmental protection targets. Second, provinces in the low R&D expenditure input and low GDE group are located in central and western regions of China, and they have a relatively low degree of market openness. The low technology diffusion and lagging economy are not conducive to investing in technology R&D and improving production in the ISI. These provinces have huge potential for improvement of GDE. Third, provinces with high R&D expenditure input and high GDE are mostly located in the eastern region (72.4% of all provinces). The rational industry structure and abundant technology investments have improved the GDE in the ISI. In addition, R&D expenditure in provinces with low R&D expenditure input and high GDE should be continuously increased.

3.1.3. Region Differences of Green Development Efficiency

Following Song et al. [48] and Zhu et al. [5], we divided China's 28 provinces into three areas: eastern, central, or western region based on the National Bureau of Statistics of the People's Republic of China. The eastern region consists of ten provinces (Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, and Guangdong). The central region is composed of eight provinces (Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan). The western region includes ten provinces (Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, and Xinjiang).

The change trends in GDE in each region are shown in Figure 1. The GDE of the ISI of the three regions are significantly different. During 2006–2015, the average GDE in the eastern and central regions was 0.731 and 0.629, respectively, which are higher than the overall value of 0.607 in China's ISI. The average GDE in the western region was 0.465, which is lower than the national, eastern, and central values.

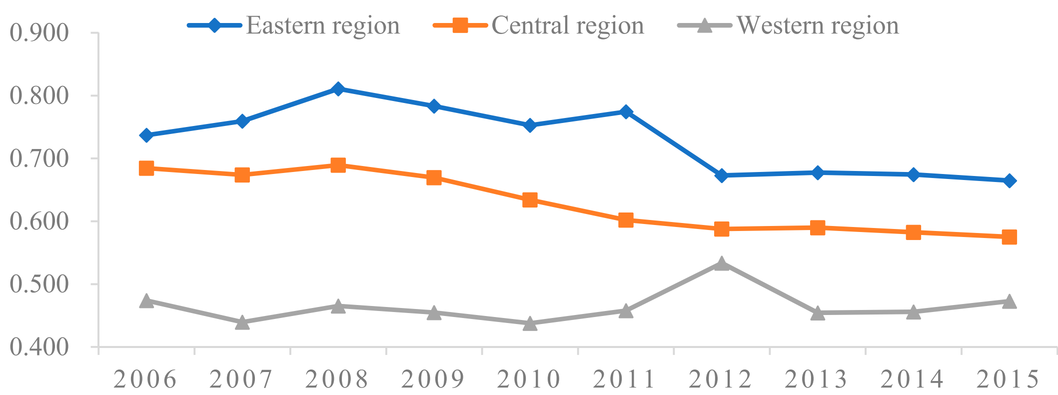

Figure 1. Average change trends in green development efficiency (GDE) in different regions in China.

The ISI's GDE in the eastern and central regions showed a downward trend with an annual average decline of 1.14% in the eastern region and 1.92% in the central region. However, from 2006 to 2015, the GDE in the western region remained steady: the GDE value in 2006 was 0.474, and 0.473 in 2015. In the eastern region, iron and steel enterprises paid more attention to investing in green technology innovation and low-carbon transformation development, which produced a crowding-out effect on economic development. This produced a decrease in GDE in the eastern region. In the central region, many iron and steel enterprises have high energy consumption and high emissions. The lack of special financial investment in environmental treatment and advanced technology caused a reduction in the GDE in the central region [5]. For the western region, regional development policies issued by China's government promoted the efficient use of resources and upgrading of equipment in the iron and steel industry. However, because the level of economic development, ability of technology innovation, and environmental carrying capacity were relatively low, the change in GDE in the ISI in the western region was very slow.

3.2. Impact of Forces Driving Green Development Efficiency

3.2.1. Panel Unit Root Test Results

To analyze the data stability and avoid spurious regression, we tested the stationary of each variable before implementing the Tobit panel regression model in this study. We tested the panel unit root using the Levin–Lin–Chu and Im–Pesaran–Shin tests. The results of the unit root test are shown in Table 4.

Table 4. Results of the stationary test. LLC, Levin–Lin–Chu; IPS, Im–Pesaran–Shin.

Variables	LLC (Level)	IPS (Level)	LLC (First Difference)	IPS (First Difference)
GDE	−0.296 ***	−1.658	−1.519 ***	−3.199 ***
Trade	−0.670 ***	−2.777 ***	−1.607 ***	−3.241 ***
Energy	−0.837 ***	−3.557 ***	−1.322 ***	−4.197 ***
Scale	−0.550 ***	−1.485	−1.540 ***	−2.238 ***
State	−0.284 ***	−1.352	−1.547 ***	−3.069 ***
Capital	−0.574 ***	−1.709	−1.463 ***	−3.262 ***

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

All variables showed nonstationary in the two tests, and the variables were stable at the 1% significance level after their first differences. Therefore, there is no unit root.

3.2.2. Regression Results of Tobit Model

The multicollinearity test was used as a variance inflation factor (VIF) before the Tobit regression model. The VIF values of the explanatory variables are less than 10, indicating that there is no multicollinearity in this regression model. The evaluation results were calculated using Stata 14.0 software and are shown in Table 5.

Table 5. The results of the Tobit model.

Variable	Country	East Region	Central Region	West Region
ED	0.888 ** (2.54)	1.520 * (1.94)	0.403 * (1.78)	1.382 ** (2.54)
ES	−0.220 ** (−2.58)	−0.123 (−0.38)	−0.114 * (−1.83)	−0.239 *** (−2.61)
IS	−0.010 *** (−2.66)	−0.024 *** (−2.81)	−0.006 ** (−2.22)	−0.005 (−0.72)
PS	0.232 *** (3.16)	0.324 * (1.83)	0.198 *** (4.02)	0.230 ** (2.29)
CI	21.046 *** (5.59)	39.171 *** (4.27)	0.496 (0.13)	10.295 * (1.78)
constant	0.647 *** (5.41)	0.581 ** (2.11)	0.795 *** (10.33)	0.449 *** (2.94)
Log likelihood	81.239	1.363	82.348	54.656
LR	86.85	33.53	83.25	40.93

Note: *, **, and *** present their significant levels of 10%, 5% and 1%, respectively.

Export demand (ED) had a significant positive effect on GDE in the eastern, central, and western regions and the entire country in the ISI. With a 1% increase in export demand, the GDE of the eastern, central, and western regions and the country increases by 1.52%, 0.403%, 1.382%, and 0.888%, respectively. The results were provided by Li and Zeng [42]. Iron and steel enterprises have to update production equipment, enhance management capacity, and increase R&D investment to meet environmental protection requirement and the fierce competition in the foreign market, which will result in low energy consumption and high export quality. The eastern region has more advanced production technology and abundant financial capital than other regions. Thus, export demand has had a large effect on the improvement in GDE in the eastern region.

The coefficient of energy consumption structure (ES) was significantly negative. If the proportion of energy consumption structure increases by 1%, the GDE of ISI in the central and western regions and the country will drop by 0.114%, 0.239%, and 0.22%, respectively. This is in line with the findings of Guo et al. [21]. The coal consumption accounted for 67% of the energy structure of the ISI during 2006-2015. However, the energy-saving and emission reduction technology for coal use is unpopular in China [43]. The rapid development of the ISI has resulted in high coal consumption, which increases undesirable outputs and hinders the improvement in GDE. In addition, the western region has a fragile ecological environment and poor awareness of environmental protection. Energy consumption structure had a more negative effect on the improvement in the GDE in the western region than in the other regions.

The correlation coefficient of industrial scale (IS) was found to negatively influence GDE in the eastern region, central region, and the country in the ISI. With a 1% increase in industry scale, the GDE in the eastern region, central region, and country drops by 0.024%, 0.006%, and 0.01%, respectively. The correlation coefficient is small, but IS contributes to the green development. The result is consistent with the findings reported by Li and Shi [44]. The increase in industry scale would consume more energy and raw materials, leading to the increase in undesirable outputs. However, at present, ISI is in the key stage of structure transformation and green development. The bigger is the industry scale, the greater are the R&D investment and fiscal expenditure. This may cause a crowding-out effect on GDE improvement.

The coefficient of property structure (PS) was found to be significantly positive. If the proportion of state-owned output increases by 1%, the GDE in the ISI of the eastern, central, and western regions and country will increase by 0.324%, 0.198%, 0.23%, and 0.232%, respectively. We obtained an opposite result compared to the findings of Wang et al. [43]. A possible explanation for the positive influence of state-owned enterprises is that, after years of reform and development, a modern state-owned iron and steel enterprises system may have formed. State-owned enterprises not only have large industry output, but have market competitiveness, technology innovation, and anti-risk ability. They can also invest more in resource-saving and pollutant reduction [3]. These are conducive to promoting the improvement in GDE.

Capital investment (CI) had a significant positive effect on the GDE in the ISI in the eastern, central, and western regions and country. With a 1% increase in capital investment, the GDE of the eastern region, western region, and country will increase by 39.171%, 10.295%, and 21.046%, respectively. The results were provided by Wang et al. [43]. Capital investment had a large effect on GDE improvement. There may be two reasons for this finding. First, CI can increase the R&D expenditure and enhance the technology innovation ability, producing a positive effect on the green economic development of the ISI. Second, CI promotes updating of production equipment and adjustment of industry structure. These reduce carbon emissions and improve the efficiency of energy use, which can promote GDE improvement.

3.2.3. Robustness Test

In this study, a fixed-effect regression model was used to replace the Tobit regression model for the robustness test. The estimation results are shown in Table 6. The symbols of the variables are consistent with the Tobit regression results. As a result, the empirical results of the Tobit regression were found to be robust.

Table 6. Results of the robustness test.

Variable	Coefficient	*p*-Value	Standard Error
ED	1.091 **	0.016	0.448
ES	−0.486 ***	0.000	0.105
IS	−0.014 ***	0.001	0.004
PS	0.175 **	0.040	0.085
CI	19.797 ***	0.000	3.744
constant	0.780 ***	0.000	0.098

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

4. Conclusions and Policy Implications

4.1. Conclusions

Measuring GDE is important for upgrading the structure and green development of China's iron and steel industry. Adopting the super-SBM model, we evaluated the GDE of the ISI in China's 28 provinces during the period of 2006–2015. The empirical results were analyzed from three perspectives: nation, province, and region. We divided the 28 provinces into different groups according to their R&D expenditure inputs and GDE values. Then, a Tobit model was used to explore the factors influencing the improvement in GDE. The main conclusions were drawn as follows:

Firstly, the GDE value declined over time from 0.628 in 2006 to 0.571 in 2015, showing an average decrease of 1.1% annually. However, during 2006–2008, the GDE demonstrated an upward trend, and the efficiency value in 2008 (0.653) was the highest in the study period. The average GDE values of 75% of the provinces were less than that in the ISI, indicating that many provinces have huge potential for energy conversion and reduction of carbon emissions in the ISI. Beijing had the highest average GDE value for the ISI, while Shanxi had the lowest.

Secondly, provinces were divided into four types based on R&D expenditure and GDE value. (1) Provinces with high R&D expenditure and low GDE were Liaoning, Anhui, Fujian, Shandong, Hunan, Guangdong, Sichuan, and Shanxi. They showed huge potential to enhance the ISI's GDE. (2) Some provinces, i.e., Beijing, Inner Mongolia, Jilin, Guizhou, Shaanxi, and Xinjiang, had low R&D expenditure input and high GDE, showing that green transformation has produced considerable effects in these provinces' ISI. (3) Provinces with high R&D expenditure input and high GDE were mostly located in the eastern region. (4) Provinces with low R&D expenditure input and low GDE were located in the central and western regions.

Thirdly, during the research period, the GDE of the ISI showed significant heterogeneity among the different regions. The average GDE of the ISI in the eastern and central regions was 0.731 and 0.629, respectively, which are higher than the 0.465 in the western region. Further, the GDE in the eastern and central regions showed a declining trend, decreasing by an average of 1.14% and 1.92%, respectively, per year. In contrast, the ISI's GDE in the western region was steady at 0.474 in 2006 and 0.473 in 2015.

Fourthly, certain factors, i.e., export demand, property structure, and capital investment, had significant positive effects on the ISI's GDE in the eastern and western regions, while energy consumption structure and industry scale had negative impacts on the improvement in GDE in the central region.

4.2. Policy Implications

The specific policy recommendations for the improvement of GDE in China's ISI are proposed as follows:

Firstly, for provinces with high R&D expenditure input and low GDE, the government should focus on the impact of R&D investment in technology on the updating of industry structure and strengthening the application of green technology in the ISI. The technology innovation capacities should be improved by strengthening the relationship between scientific research institutions and production sectors [21]. In addition, supervising the use of R&D investment is important to avoid the crowding-out effect of industry development. For provinces with high R&D expenditure input and high GDE, R&D expenditure should be increased in energy-saving and emission reduction technologies in the ISI. For provinces with low R&D expenditure input and low GDE, the government should continuously increase the R&D investment in technology innovation and green development. Investment should be accelerated to improve opening up and promote the spillover and diffusion of knowledge and technology in provinces with lagging economic development. For provinces with low R&D expenditure input and high GDE, advanced technology should be cultivated and highly-skilled workers should be introduced.

Secondly, resource and energy use should be improved. It is necessary to change the structure of energy consumption and increase the proportion of green and renewable energy in total energy consumption. The government should strengthen and popularize the application of clean coal technology in the ISI. In addition, the industry scale of the ISI should be controlled. It is necessary to inhibit the crowding-out effect caused by expanding industry scale on the efficiency of improvement.

Thirdly, increasing the ISI's exports should apply advanced production technology and obtain management experience from foreign industries, as well as force enterprises to improve the quality of the product and increase awareness of environmental protection. The government should issue some policies, such as tax credits and subsidies, to enhance the international competitiveness of enterprises [42]. In addition, the reform of stated-own enterprises should be continuously deepened, playing a more significant role in the green and low-carbon development of the ISI.

4.3. Limitations and Future Research

There are some limitations in this study. First, the DEA method assumes the homogeneity of DMUs. However, the production technology is widely different in the ISI of each province. Second, the undesirable output only included carbon emissions calculated based on the Intergovernmental Panel on Climate Change guidelines because of data availability. Third, we did not analyze the ISI's GDE in specific economic zones in China, such as Central Bohai, Pearl River Delta, and Yangtze River Delta. In the future research, the following should be emphasized. First, we would further expand the research period to analyze the GDE in China's ISI. Second, the research results should be calculated using and compared with other models. Third, we should further investigate the relationship between environmental regulation and GDE from the perspective of spatial correlation. Fourth, the ISI's GDE in China's specific economic zones could be further explored, such as Central Bohai, Pearl River Delta, Yangtze River Delta, etc.

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