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Article

Low-Carbon Efficiency Model Evaluation of China's Iron and Steel Enterprises Based on Data and Empirical Evidence

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Abstract: The aim of this study is to consider the economic, resource, energy and environmental factors in a low-carbon economic efficiency evaluation system and to analyze the factors affecting iron and steel enterprises. A combined data envelopment analysis and Malmquist index model have been used in this paper. We empirically investigate the low-carbon efficiency of the Chinese steel industry using observations of 17 listed enterprises from 2009 to 2013. The results show that the economic efficiency of China's iron & steel enterprises is generally low. The Malmquist productivity index also shows a decreasing trend. Based on our findings, some policies are proposed to improve the low-carbon economic efficiency of China's steel industry.

Keywords: Model evaluation; iron and steel enterprise; low-carbon efficiency; data-driver

1 Introduction

Low-carbon economic efficiency plays an important role in society and environmental protection. With the remarkable development of the Chinese economy, China's iron and steel industry, which has been the largest iron and steel producer in the world since 2010, is undergoing a transition. Unfortunately, this industry is now trapped in a dilemma due to its high energy consumption and low technical efficiency. In 2011, 44.68% of global crude steel production was provided by China. Nevertheless, the iron and steel industry, which is also regarded as one of China's largest pollution sources, accounts for 15.61% of China's total energy consumption and now faces great challenges. The Chinese government has launched a low-carbon transition strategy that involves an energy processing conversion that decreased carbon levels from 1.8 tons per ton of steel to 0.92 tons per ton of steel from 2009 to 2014, but this index still far exceeds the world average level based on reports of the World Steel Association, in addition to those of developed countries. Hence, feasibility studies have been conducted to study how to simultaneously conserve energy and increase economic efficiency. Demura and Johnson focused on the productivity efficiency of iron and steel enterprises [1–2]. Jung et al. studied the efficiency of 52 large-scale iron and steel enterprises in more than 23 countries [3]. To date, researchers from energy, ecology and economy backgrounds have examined the efficiency of Chinese iron and steel enterprises. For instance, Zhang et al. studied with the application of energy analysis to the sustainability of Chinese steel production for the period from 1998 to 2004 [4]. Han and Liu conducted a superefficient DEA to analyze the energy efficiency, energy savings and low-carbon potential of the Chinese steel industry [5]. Building on the impulse reaction function, Shi and Chen studied the relationship between TFEE and its factors influencing energy efficiency [6]. Liu et al. [5] and Zhang et al. [4] constructed and applied a DEA model to determine the ecological efficiency of iron and steel firms. They dynamically evaluated energy and socioeconomic development with the model. From previous studies, a two-step method was usually used to evaluate efficiencies and change trends. First, data environment analysis (DEA) or stochastic frontier analysis (SFA) was introduced to measure firm efficiencies. Second, some econometric methods, such as OLS, GLM and Tobit, were actualized to determine the true factors that affect efficiency. During the process, firm scale, production structure, age, labor and assets were often used as the inputs, and industry added value was used as the output. Currently, Li introduced five factors, namely, energy consumption, environmental pollution and carbon emissions, economic efficiency, and low-carbon sustainable development potential, to build a comprehensive evaluation system for an enterprise's a low-carbon economy, then they used a multilevel fuzzy evaluation method to calculate the low-carbon economic development index [7]. Chen et al. considered a low-carbon economy efficiency index and its influencing factors for the sustainable development of steel industries [8]. All of these previous studies shed light on the various practices and ideas employed by other researchers and have been shown to be positive and useful explorations. However, the results for the influencing factors were not entirely consistent, and there were also a number of shortcomings: (1) Based on an economic perspective, the existing research in the context of a low-carbon economy should be reflected in iron and steel enterprise efficiency evaluations of the economic, resource, energy and environmental elements of the evaluation but current and relevant studies rarely consider these factors. (2) Currently, a static analysis of the efficiency level is the focus of the study. Quantitative research on dynamic changes in efficiency and their influencing factors is not sufficiently comprehensive. (3) Empirical data used in previous studies are generally industry-wide data. There is a lack of sufficient research with enterprise-level data.

In this paper, we first conduct a comprehensive investigation of the low-carbon economy and development trends of China's iron and steel enterprises from the perspectives of economic, resource, energy and environmental evaluation efficiencies. Then, we build a DEA model to analyze the static influencing factors. In this model, the energy and low-carbon economy are involved when measuring the enterprise's economic efficiency compared to traditional methods. Malmquist indices are applied to China's iron and steel enterprises with 17 firm-level observations from 2009 to 2013. Then, we analyze the factors that can influence low-carbon economic efficiency. The conclusion of this paper provides scientific strategies and recommendations for low-carbon development in iron and steel enterprises.

The goals and main contributions of this paper are summarized as follows:

(1) Consider economic, resource, energy and environmental factors in the low-carbon economic efficiency evaluation system;

(2) Apply the input-oriented DEA model and Malmquist indices to analyze the dynamic changes and influencing factors of efficiency;

(3) Incorporate some of the unexpected outputs regarded as investment inputs in this evaluation;

(4) Investigate the low-carbon economic efficiency with Chinese firm-level data instead of the macroeconomy level or regional level data.

The remainder of this paper is summarized as follows. Section 2 presents an overview of related work and describes the methodology of the DEA model and Malmquist index. A novel input-oriented DEA model that is used in an economic efficiency evaluation system is also introduced. In Section 3, we propose an empirical design of iron and steel firms' low-carbon economic efficiency in China. In Section 4, we design a numerical analysis and conduct a model evaluation. Finally, we conclude our work in Section 5.

2 Methodology

2.1 DEA Model

The data envelopment analysis (DEA) model has gained great popularity for efficiency evaluations. This model, which does not show a strict relationship between the variables and any argument, is particularly suitable for multiple input and output indicators of efficiency evaluations. This DEA model is attractive for following accounts in iron and steel enterprise efficiency evaluations [9–10]. First, iron and steel enterprises invest in capital, labor, water, coal and other elements of the production process. In addition to producing primary products, such as pig iron and steel, they also produce large amounts of waste gas, wastewater, and other by-products. Therefore, the enterprises satisfy the typical characteristics of multiple input-output elements. Second, in China, most current iron and steel enterprises use mainly blast furnaces and electric furnaces for production. Because of the differences in the technology and standards between the two production methods, it is extremely difficult to compare results using the SFA model.

The CCR model and BCC model are the most widely used techniques within the DEA methodology [4]. In general, the CCR model is used to examine overall technical efficiency (TE) and can also be decomposed into scale efficiency (SE) and pure technical efficiency (PTE). PTE can be measured through the BCC model; therefore, SE is equal to the overall technical efficiency divided by PTE. When SE is equal to 1, the DMU is at the level of optimal scale efficiency. However, if SE < 1, the DMUs are in states of inefficient scale. In addition, we can determine whether the DMUs are in scale increment, decrement, or unchanged states based on the varying scale values. In this paper, these two kinds of models were used to evaluate scale efficiency, technical efficiency and pure technical efficiency to comprehensively assess low-carbon economic efficiency. TE can reflect the overall inputs-outputs, and through PTE, we can determine the resource allocation capability and low-carbon economic management.

2.2 Malmquist Index

The CCR and BCC models are usually used to statically analyze the efficiency of DMUs. However, the low-carbon economic behavior and energy consumption of iron and steel enterprises are uncertain, and all of the multiple input and outputs are complex. The Malmquist indices, which are based on the DEA approach, are well-suited for productivity measurement in evaluating low-carbon economic efficiency. The combined DEA–Malmquist index model is used to measure changes in total factor productivity. The Malmquist productivity index is defined as follows:

$$M_0^{t,t+1}(x_{t+1},y_{t+1},x_t,y_t)=\left[\frac{D_0^t(x_{t+1},y_{t+1})}{D_0^t(x_t,y_t)}\times\frac{D_0^{t+1}(x_{t+1},y_{t+1})}{D_0^{t+1}(x_t,y_t)}\right]^{1/2} \tag{1}$$

The equation contains k observations between time periods t (base period) and t+1, where y_t and y_{t+1} are the outputs, respectively, and x_t x_{t+1} are the inputs in periods t and t+1, respectively. D_0^t and D_0^{t+1} are output efficiency scores that are related to the observations. We denote the Malmquist productivity index using $M_0^{t,t+1}$. Productivity improves if $M_0^{t,t+1}$ > 1, declines if $M_0^{t,t+1}$ < 1, or remains unchanged if $M_0^{t,t+1}$ = 1.

We consider the technical efficiency change index (EC) and technological progress index (TC). Eq. (1) can be changed to Eq. (2).

$$M_c^{t,t+1}(x_{t+1},y_{t+1},x_t,y_t)=EC\times TC=\frac{D_c^{t+1}(x_{t+1},y_{t+1})}{D_c^t(x_t,y_t)}\times\left[\frac{D_c^t(x_{t+1},y_{t+1})}{D_c^{t+1}(x_{t+1},y_{t+1})}\times\frac{D_c^t(x_t,y_t)}{D_c^{t+1}(x_t,y_t)}\right]^{1/2} \tag{2}$$

where $EC=\frac{D_c^{t+1}(x_{t+1},y_{t+1})}{D_c^t(x_t,y_t)}$ shows the relative distance between the frontiers, and EC can be further divided into variations in scale efficiency (SEC) and pure technical efficiency (PEC). Then, we can obtain Eq. (3) from Eq. (2).

$$\begin{aligned}M_{v,c}^{t,t+1}&=EC\times TC=PEC\times SEC\times TC\\&=\frac{D_v^{t+1}(x_{t+1},y_{t+1})}{D_v^t(x_t,y_t)}\times\left[\frac{D_v^t(x_t,y_t)}{D_c^t(x_t,y_t)}\times\frac{D_c^{t+1}(x_{t+1},y_{t+1})}{D_v^{t+1}(x_{t+1},y_{t+1})}\right]\times\left[\frac{D_c^t(x_{t+1},y_{t+1})}{D_c^{t+1}(x_{t+1},y_{t+1})}\times\frac{D_c^t(x_t,y_t)}{D_c^{t+1}(x_t,y_t)}\right]^{1/2}\end{aligned} \tag{3}$$

Therefore, by using the Malmquist index method in the evaluations of low-carbon economy efficiency, we can dynamically analyze all of the changeable factors in more detail, which can help us deeply understand the reasons for low-carbon steel enterprise economic efficiency, as well as the various contributions to it.

2.3 Model and Variables

Iron and steel enterprises invest not only capital, labor, and technology but also in natural resources such as water and coal for their low-carbon economic activities. Unexpected output and expected output are two different types of outputs. Therefore, we can only minimize undesired outputs while increasing the expected outputs to achieve a win-win outcome between environmental protection and economic development. Because of the input-oriented DEA model used in this paper, we regard waste gas, wastewater, waste residue and other undesired outputs as productive investments to process. Our approach is inspired by the previous investigations of Jiao et al. [11] and Yang et al. [12], we combine the characteristics of low-carbon production in China and the acquisition possibility of firm-level data. We select net fixed assets, employee numbers, energy consumption, water consumption and emissions of waste gas, wastewater and residue as inputs. Unexpected outputs, total industrial waste gas, water and residue are regarded as investment inputs and are considered in this efficiency index as well.

The expected output is defined as the industrial added value, total profit and tax on enterprises. There are three points that of specific importance: 1) In general, capital investment usually uses capital stock or depreciation. In this paper, we use fixed assets that represent capital stock to avoid the uncertainty of depreciation. 2) Because of the lack of statistical data in recent years, labor input is measured by the number of employees instead of by employee working hours. 3) Steel technological procedures are complicated because of the necessity for both long and short processes for different products. It is possible to ignore the intermediate goods output in the long process if the total output value of the enterprise is used instead of the added value. In addition, the output indicators of total profits and taxes were chosen instead of profit mainly because the different tax policies of local governments affect corporate profits. Nonetheless, profits and taxes paid can avoid this side effect.

3 Empirical Analysis

The empirical data cover 17 listed iron and steel enterprises with designated annual sales amounts of more than 100 million yuan. The financial data used in the survey are taken from announced annual enterprise report data during the period from 2009 to 2013 and the China Statistic Yearbook. Energy consumption and environmental pollutant data were obtained from the China Environment Statistics Yearbook (2009–2013) and the database of the China Ministry of Environmental Protection. In addition, we consulted the data reported by China's Iron and Steel Industrial Association.

3.1 Static Analysis of the Low-Carbon Economic Efficiency of the Iron and Steel Firms

The relative scale variables of the 17 listed iron and steel enterprises are defined as dummy values that distinguish small, medium and large categories according to labor, sales and total assets.

We conducted a static analysis of low-carbon economic efficiency for iron and steel enterprises per models (1) and (2) by using the DEAP 2.1 software package. Based on an input-oriented model, the 17 listed enterprises were examined, and their efficiency values were measured from 2009 to 2013. We can see from Tab. 2 that the low-carbon economic efficiency of China's iron and steel enterprises presents the following characteristics: 1) The enterprise technical efficiency is generally low. From 2009 to 2013, the average low-carbon economic and technological efficiency of China's iron and steel enterprises was only 0.578. China's iron and steel enterprise production still has much room for improvement. 2) The technical efficiency difference between individual enterprises is obvious. Kim, Wu and Zhang stated that iron and steel enterprises had the property of increasing returns to scale, which means that larger firms had higher efficiency [13–15]. Tab. 1 shows that smaller-scale firms have higher efficiency than some larger-scale firms. Examples are Xining Special Steel and Xining Ductile Iron Pipes, whose scales are smaller than others but whose technical efficiency values are 1. The technical efficiency values of most small enterprises are above the average. This is followed by middle-sized enterprises, such as Nanjing Iron and Steel and Jiu Steel, whose technical efficiency values are close to 1. Some large enterprises, such as He Steel, Angang Steel, Wuhan Iron and Steel, and Baotou Steel Union, have technical efficiency values that are below average. Tab. 2 shows that the overall pure technical efficiency is low in China with an average of 0.676.

Generally, low pure technical efficiencies imply that the production technology and management level are still backward. The scale efficiency average is 0.848, which indicates that enterprise developments are relatively more dependent on scale expansion and scale effectively. The evidence shows that most large-scale enterprises are in a state of scale return decrease, but some smaller firms' scale returns increase. This means that blindly expanding investments is not the best choice for these larger firms in China. For larger-scale enterprises, it is very important to achieve technological progress and product and process upgrades but not solely by increasing inputs and expanding scales.

Table 1: Firm scale classification

Classification Standard	Unit	Small	Medium	Large
Total asset	1 Million	<500	500–1000	>1000
Sales	1 Million	<200	200–400	>400
Labor	person	<1000	1000–3000	>3000

3.2 Analysis of the Trends of Low-Carbon Economic Efficiency with the Malmquist Index Model

The results presented above are based on a simple static analysis of the low-carbon economic efficiency of Chinese iron and steel enterprises based on the CCR and BBC models. We further investigated the change trends of the 17 listed iron and steel enterprises. We applied the Malmquist index model based on panel data for 2009–2013. All of these data were the inputs for the DEAP2.1 software for calculations. The results are shown in Tab. 3 and Tab. 4.

Tab. 3 shows the decomposition of total factor productivity for the 17 listed iron and steel enterprises from 2009 to 2013. The total factor productivity is less than 1 for the 17 iron and steel enterprises except for the 2010–2011 period, which indicates that the average annual total factor productivity of Chinese iron and steel enterprises is not ideal. The main reason is that the technical efficiency change index decreased at an annual rate of 12.9%. Changes in pure technical efficiency are another cause for this decline. A series of policies and regulations forced iron and steel enterprises to pay more attention to their low-carbon economic efficiencies. Therefore, we can see that TEC and PTEC increased by more than 10% in this year.

Tab. 4 shows the decomposition of total factor productivity of the 17 listed iron and steel enterprises. The total productivity indices of Beijing Shougang Steel, Hunan Valin Steel, Taigang Stainless, Xining Special Steel, Liuzhou Iron & Steel and Xinxing Ductile Iron are greater than 1. Among these six enterprises, their technical efficiency change indices remained unchanged or improved, except those for Taigang Stainless. The technology index is greater than 1 for the Pangang Group. Among the remaining 11 firms, the total factor productivity indices are less than 1. From the technical efficiency change index perspective, only Anyang Iron and Steel's index was greater than 1 and the indices of the remaining 10 firms were less than 1. From the technological progress index perspective, only the Baoshan Steel, Angang Steel and Wuhan Iron and Steel indices were greater than 1. This indicates that technical weakness and technical efficiency declines both affected the decline of a firm's total factor productivity.

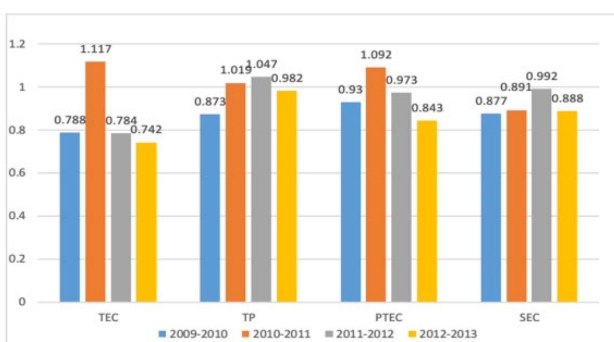

Figure 1: Trends of factor decomposition of the Malmquist index from 2009 to 2013

Table 2: DEA evaluation of the 17 listed iron and steel enterprises from 2009 to 2013

Firm	Relative Scale	TE	PTE	SE	RS
Baotou Steel Union	Large	0.315	0.338	0.938	Decreasing
Jiu Steel Group	Medium	0.784	0.885	0.887	Increasing
Nanjing Iron & Steel	Small	0.952	1	0.950	Increasing
Pangang Group	Medium	0.244	0.301	0.874	Decreasing
SGIS Songshan	Medium	0.514	0.655	0.829	Decreasing
Beijing Shougang Steel	Medium	0.998	1	0.993	Unchanged
Xining Special Steel	Small	1	1	1	Unchanged
Anyang Iron & Steel	Small	0.433	0.481	0.956	Decreasing
Xinxing Ductile Iron Pipes	Small	1	1	1	Unchanged
Liuzhou Iron & Steel	Small	0.963	0.847	0.991	Decreasing
Baoshan Steel	Large	0.639	1.000	0.659	Decreasing
He Steel	Large	0.224	0.350	0.705	Decreasing
Angang Steel	Large	0.369	0.571	0.710	Decreasing
Wuhan Iron&Steel	Large	0.434	0.746	0.592	Decreasing
Hunan Valin Steel	Small	0.231	0.241	0.930	Increasing
MaanShan Steel	Medium	0.222	0.246	0.776	Increasing
Taigang Stainless	Small	0.502	0.832	0.619	Increasing
Mean		0.578	0.676	0.848	
Stand-Dev		0.308	0.297	0.140	

Table 3: Annual Malmquist index change trends of iron and steel enterprises from 2009 to 2013

Years	TEC	TP	PTEC	SEC	Malmquist
2009–2010	0.788	0.873	0.930	0.877	0.780
2010–2011	1.117	1.019	1.092	0.891	1.037
2011–2012	0.784	1.047	0.973	0.992	0.943
2012–2013	0.742	0.982	0.843	0.888	0.871
Means	0.858	0.980	0.958	0.912	0.907

TEC Technology efficiency change, *TP* Technology progress, *PTEC* Pure TEC, *SEC* Scale returns change

Table 4: Average Malmquist indices of the 17 listed iron and steel enterprises from 2009 to 2013

Firms	TEC	TP	PTEC	SEC	Malmquist indices
Baotou Steel Union	0.887	0.911	0.889	1.058	0.885
Jiu Steel Group	0.913	0.880	0.975	0.933	0.833
Nanjing Iron & Steel	0.863	0.915	0.860	0.941	0.764
Pangang Group	1.150	0.933	1.204	0.987	1.135
SGIS Songshan	0.903	0.932	0.991	0.912	0.883
Beijing Shougang Steel	1.000	1.037	1.010	1.003	1.039
Xining Special Steel	1.000	1.014	1.000	1.000	1.034
Anyang Iron & Steel	1.020	0.952	1.031	0.995	0.968
Xinxing Ductile Iron Pipes	1.000	1.033	1.000	1.000	1.028
Liuzhou Iron & Steel	1.000	1.012	0.997	1.003	1.022
Baoshan Steel	0.819	1.077	1.010	0.810	0.911
He Steel	0.818	0.897	0.813	1.006	0.775
Angang Steel	0.349	1.005	0.672	0.404	0.275
Wuhan Iron & Steel	0.702	1.018	0.746	0.997	0.782
Hunan Valin Steel	0.889	0.975	0.856	1.040	0.883
MaanShan Steel	0.941	0.930	0.917	1.038	0.931
Taigang Stainless	0.970	1.066	1.084	0.974	1.019
Means	0.878	0.966	0.943	0.938	0.888

4 Analysis and Conclusion

4.1 Variables and Hypothesis

Based on the previous studies of Sheng et al. [16], Wu et al. [17] and Chen et al. [18], this paper introduces technology, energy structure, product structure, environment and government regulation to study their effects on the low-carbon economic efficiency of iron and steel enterprises.

In the transition process of China's iron and steel industry, technological progress, such as production process improvement, product upgrades, and management improvements, contributed substantially to the increase in production output and the reduction in energy consumption.

Hypothesis 1. The higher the technological progress in the production process, the higher the energy and low-carbon economic efficiencies of iron and steel enterprises are in China. These factors have a positive correlation.

Hypothesis 2. The higher the rate of coal use in energy consumption, the lower the carbon economic efficiency is of the iron and steel firms. These two factors have a negative correlation.

Hypothesis 3. The lower the rate of crude steel in the product structure (PS), the higher the low-carbon economic efficiency is. These two factors have a positive correlation.

Hypothesis 4. The higher the environmental conservation investment (EC), the higher the low-carbon economic efficiency is. These two factors have a positive correlation.

Hypothesis 5. Government regulation of iron and steel enterprises will improve low-carbon economic efficiency.

Hypothesis 6. An enterprise whose scale is larger has a higher low-carbon economic efficiency.

Hypothesis 7. An older enterprise has higher low-carbon economic efficiency.

We denoted the i enterprise at the time t period technology progress using T_{it} and we adopted full element productivity (TFP) to describe the technology progress in this paper. ES_{it} is the energy structure of enterprise i at the time period t using the coal consumption proportion of total energy consumption;

PS_{it} is the product structure of enterprise i at time period t using the crude steel proportion in iron and steel production. EC_{it} is the environmental production investment of enterprise i at time period t. GR_{it} represents government regulation at time period t, and we use the sewage charge of the added value of iron and steel enterprises. FS_{it} and FA_{it} represent the enterprise i scale and age at time period t, respectively.

4.2 Model and Analysis

We studied a total of 85 observation points through a panel dataset that contained 17 sections from 2009 to 2013. These data are derived from the released data in the annual reports of the listed companies, as well as the China Iron and Steel Association statistics collation. We can assume that the differences in low-carbon economic efficiency of these firms are mainly associated with individuals. We first consider variable intercept models. Through determinations by the Hausman test, as are shown in Tab. 5, we should reject the hypothesis of random effects and use a fixed effect model. The basic model is described in Eq. (4).

$$TE = \beta_0 + \beta_1 T_{it} + \beta_2 ES_{it} + \beta_3 PS_{it} + \beta_4 EC_{it} + \beta_5 GP_{it} + \beta_6 FS_{it} + \beta_7 FA_{it} + \varepsilon \tag{4}$$

where β_0 is a constant; β_1, β_2 β_3, β_4, β_5, and β_6 are the regression coefficients for the variables; i is the enterprise number; $i = 1, 2, \cdots, 17$; and t is the time period, $t = 2009, \cdots, 2013$. ε is a residual term.

We conducted an evaluation of model (4) with Eviews 7.0 software, and the results are listed in Tab. 5.

Table 5: Correlated random effects–hausman test

Summary	Chi-Sq.	Chi-Sq. d.f.	Prob.
Cross-section	14.130439	5	0.0197

By examining the results from Tab. 5, we find the following:

(1) Technical progress has a positive influence on low-carbon economic efficiency, but this influence is not dramatic. This may be related to R&D investment in China. Currently, most enterprises are in a low-profit or loss state. Investments in R&D are limited especially because environmental protection R&D funding is insufficient.

(2) The energy structure shows a significant negative correlation with the low-carbon economy of iron and steel enterprises. In the energy structure, coal accounts for 71% of the total energy consumption in China, which leads to high levels of pollutant emissions, which reduce the low-carbon economic efficiency.

Table 6: Regression analysis of the factors affecting low-carbon economic efficiency

Variable	**Regression Coefficient**	**Standard Deviation**	***T* Test**	***P* Value**
C	186.1461***	62.05952	2.830116	0.0046
T	0.335461	0.194031	1.378034	0.1897
ES	–0.855858***	0.250934	–3.367950	0.0011
PS	–1.483545**	0.661349	–2.158474	0.0409
EC	0.942156	3.657950	0.256727	0.8121
GP	0.032561	0.477268	0.071477	0.9323
FS	–0.601391**	0.194611	–2.073423	0.0023
FA	0.458361	1.138017	0.124442	0.9411
Adjusted R-squared 0.808099	Durbin-Watson stat 1.946640	F-statistic 17.63353		

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

(3) The negative influence of the product structures on low-carbon economic efficiency is obvious. High performance and high value-added products, such as some special steels, still need to be imported. This unreasonable product structure is an important factor that influences the low-carbon efficiency in China.

(4) Environmental protection investments have positive influences but are not significant. This suggests that environmental protection investments to increase the economic efficiency of iron and steel enterprises are not obvious.

(5) Governmental regulations for iron and steel enterprises have a positive correlation. Theoretically, all regulations or policies may significantly improve the efficiency of the low-carbon economy, but the empirical results show that is not the case. Based on the economic development differences among different regions of China, different regions have their own advantages, which include political advantages, economic advantages, and geographical advantages. Each regional iron and steel enterprise may take full advantage of these distinctive features to improve development. Some local governments at all levels have not thoroughly implemented these policies.

(6) The GDP of a region and the scale of its enterprises have a positive effect on low-carbon economic efficiency. However, the per capita income of the enterprises does not show a significant effect. The empirical results indicate that small-enterprise efficiency is highest and is followed by middle-enterprise efficiency. In contrast, large enterprises have the lowest efficiency, a finding opposite to the traditional hypothesis based on economy of scale.

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