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Exploring the Role of Educational Human Capital and Green Finance in Total-Factor Energy Efficiency in the Context of Sustainable Development

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Abstract: The problem of lower total-factor energy efficiency (TFEE) has become a bottleneck for economic growth, and how to break this bottleneck and achieve high-quality development is one of the urgent issues to be solved nowadays. The study selects 30 provincial units in mainland China during 13 years, from 2008 to 2020; then adopts slack-based measure (SBM) method to measure the TFEE values of each province; and on this basis, finally explores the impact of educational human capital and green finance on regional TFEE in China; It concludes as follows: (1) The average value of TFEE in China is 0.776, which is at a lower level, and TFEE shows a gradual increase during the study period; the mean value decreases from east to west in descending order. (2) Educational human capital's impact on the TFEE of the whole country and all regions is negative, and it does not show a significant U-shaped relationship; the effect of eastern region is the smallest; green finance's impact on TFEE shows a U-shaped relationship, except in eastern regions, where it is not significant; and the coefficient of the central region is stronger. (3) Environmental regulation's impact on TFEE show a U-shaped relationship in all regions; science and technology investment can improve TFEE all regions; and in the eastern region, it is most significant. Industrial structure is positively correlated with TFEE in all regions, and it has the most obvious effect on the improvement of TFEE in the central region; economic development can promote TFEE in all regions. This research has important theoretical implications for achieving regional TFEE improvement.

Keywords: human capital in education; green finance; TFEE; sustainable development; economy and environment

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1. Introduction

Economic growth has relied heavily on energy inputs, and the economic growth mode of "high input, high energy consumption, and high pollution" has brought economic prosperity to China but has led to problems of ecological destruction [1]. The Lucas mechanism [2] and the Nelson–Phelps mechanism [3] are regarded as two representative perspectives to explain the relationship between human capital and economic growth; however, there is no consistent conclusion on whether human capital brings significant economic growth. Human capital has a function to attract other factors and technological progress [4,5]. Human capital development in China shows a huge gap, and there is a significant shortage of high-quality labor in China compared with developed countries. The stock of human capital in rural areas of central and western regions is seriously lacking. More and more scholars have begun to explore the role of human capital in environmental pollution. As a unique factor of production, human capital not only helps to improve the efficiency of energy and capital use in the production process but also encourages enterprises to adopt strict environmental standards [6] and reduce energy intensity and pollutant emissions, which will have impacts on TFEE. Given the combination of the current emission-reduction goals with the current situation of human capital in China, it is urgent to study the relationship between educational human capital and TFEE and find effective ways to improve TFEE and alleviate environmental problems. To this end, the study tried to confirm human capital's impact on the improvement of TFEE by using multiple perspectives of educational human capital in order to propose relevant policy measures for energy conservation and emission reduction in each region.

Improving the input–output efficiency of energy is an effective way to reduce environmental pollution [7], and the core issue to be considered in solving the environmental pollution problem is improving TFEE. Energy is the foundation of industrial development, and the two are inextricably linked, and the advanced and green industrial production will promote the improvement of TFEE [8]. At the same time, it should be noted that green finance is one of the obvious features of the green development of regional economy; it is beneficial for the improvement of TFEE [9]. Green financial development can guide or directly invest funds into resource conservation and environmental protection, which can help improve environmental quality and increase resource utilization efficiency [10]. It needs to develop green financials to achieve China's sustainable development goals, promote the structural reform of the financial supply side under the new development pattern of "double cycle", and promote green development. Therefore, it is important to explore the relationship between green financial development and TFEE to accelerate the construction of ecological civilization in China.

To this end, this paper attempts to expand on the following aspects: first, use the SBM method to measure TFEE, taking into account the labor force differences of each province. To explore the impacts of educational human capital and green finance on the regional TFEE in China, it is of great practical significance for each region to promote energy-efficiency improvements, reach the carbon neutrality target as early as possible, and realize the green transformation of China's economy.

The main contributions of this paper are as follows: (1) Most of the studies are conducted at the national or industry level, and regional differences are not sufficiently considered, as there are large differences between the east and west of China in terms of economy, society, and resources. (2) Using the superefficient SBM method to calculate the total-factor energy-efficiency values of each province and city, we can make more-accurate judgments on the energy-efficiency level of each region and provide theoretical references for regional energy-efficiency revelation. (3) The inclusion of human capital in education and green finance in the same framework for total-factor energy-efficiency analysis fills the existing research gap and expands on and enriches existing research perspectives. (4) The corresponding policy recommendations based on the empirical results can provide a policy basis for policy implementation among regions, which is conducive to coordinated development between regions.

2. Literature Review

2.1. Definition and Measurement of TFEE

Patterson [11] was the first to propose the concept of "energy efficiency" and its indicators, but these indicators are single-factor indicators, resulting in large differences in energy efficiency. Later Boyd [12] and Hao et al. [13] proposed total-factor energy efficiency, which made the energy-efficiency measurement more realistic. Farrell [14] developed and proposed the concept of technical efficiency, i.e., the ability to minimize inputs at a given level of output or the maximum output achieved for a given variety of input factors. Hu and Wang [15] proposed the concept of TFEE on the basis of data envelopment analysis. This paper draws on Hu and Wang [15] to define TFEE as the minimum amount of energy input required according to best practice as a proportion of the actual energy input, given other factor inputs and given output.

The main methods for measuring TFEE are stochastic frontier function analysis (SFA) for parameter estimation and data envelopment analysis (DEA) for nonparametric estimation [16]. In terms of stochastic frontier research methods, many scholars applied the method to energy-efficiency measurements [17,18]. Qin et al. [19] measured the TFEE using a heterogeneous stochastic frontier model and interpreted industrial agglomeration impacts on energy efficiency in three dimensions, namely the technological progress effect, the structural optimization effect, and the price change effect. Hou et al. [20] established a stochastic frontier model to empirically analyze the TFEE and its influencing factors in the transportation industry in China from 1997 to 2016.

The nonparametric estimation of DEA is widely used. For example, Hu and Wang (2006) constructed a measure of TFEE using the nonparametric DEA method. Traditional TFEE is constructed in a multi-input–single-output framework, which usually evaluates the production relationship between multiple inputs such as capital, labor, energy, and GDP output, and this method does not include factors such as the environment, resulting in biased estimates of true performance. Zhou et al. [21] proposed including pollutants as nonexpected outputs in the accounting system, and since then, more and more scholars have constructed multi-input–multi-output DEA models to measure total-factor green energy efficiency [22,23]. Huang and Wang [24] used the SBM model to measure TFEE and found that regional energy-efficiency development was uneven and at a low level, and the energy-saving potential could reach 34–46%. The overall TFEE in China shows a trapezoidal characteristic decreasing from east to west [25]. Li et al. [26] measured the green total-factor productivity of the industrial sector by using the SBM efficiency measure model and found a decreasing trend, and China's industrial growth pattern increasingly showed the characteristics of sloppiness and extensiveness.

Through the comparison of the existing literature, it is found that the data envelopment analysis of nonparametric estimation is used by most scholars, and with the in-depth research and model improvement, the superefficiency SBM model solves the drawbacks of the previous traditional models, which can compare the part of efficiency greater than 1 and is more conducive to the comparison between regions. Therefore, this paper adopts the superefficiency SBM model used by most scholars to measure the total-factor energy efficiency.

2.2. Educational Human Capital Impact on TFEE

The endogenous economic growth theory considers human capital as one of the key elements of technological progress [27–29]. Current scholars, both domestic and foreign, have concluded that such growth has a greater facilitative and less inhibitory effect. Xu and Wang [30] examined human capital impact on energy efficiency. The results showed that the improvement of human capital was more beneficial to the energy efficiency of a region. Hao et al. [31] found that human capital accumulation strengthens energy-efficiency improvement by international technological spillover and has a more significant moderating effect on import trade. Yin et al. [32] concluded that human capital can improve energy efficiency in China. Li [33] also found that human capital can promote the energy efficiency of enterprises. Chen et al. [34] investigated human capital absorption impacts on industrial energy efficiency through foreign-owned enterprises in various provinces and regions. The results found that the overall absorption effect of advanced technology by foreign capital was not significant for all groups, while when including the absorption ability of different education groups, it was found that the overall technology absorption ability of foreign capital was better for middle and high school education levels. Studies have examined mostly those factors influencing energy-efficiency changes at the national level and have addressed less often the impact of regional variability on energy efficiency.

2.3. Green Finance Impact on TFEE

The existing literature examining the impact of financial development on energy efficiency is relatively large, while green finance as a variable is relatively small. Foreign scholars Jeanneney and Hua [35] argued that financial development offers a positive contribution to energy efficiency thanks to relevant financial policy instruments such as relevant credit policies that can motivate enterprises to utilize advanced environmental technologies. Shahbaz and Lean [36] used data from Tunisia as a research sample, and they argued that a country with a harmonious financial environment is able to attract more. Islam and Shahbaz [37], using data from Malaysia as a sample, concluded that financial development has an inverse relationship with energy consumption, through a vector error correction model. Domestic scholars have also conducted rich research in this area; for example, Shen et al. (2020) [38] studied the impact of green finance pilot policies on energy intensity by using a difference-in-differences (DID) model, and they concluded that the policy could significantly reduce energy intensity. Li and Wang [39] studied the effect of green finance policies on sulfur dioxide concentration by using the PSM-DID model with the panel data of each province. It was concluded that the policy effect was not significant in the short term, but there was a clear tendency for the policy to reduce SO_2 concentrations in the long term. By constructing a green finance development index in China, Shao et al. [40] found that China's non–fossil fuel energy consumption was influenced mainly by green finance and carbon intensity. Zhang et al. [41] showed that firms' access to finance is related to energy intensity. Su et al. [42] proposed that green finance can help improve the ecological environment.

In summary, through the study and analysis of existing literature, it is found that the current research on energy efficiency by Chinese scholars focuses mainly on the analysis of factors affecting energy efficiency. Moreover, it is found that technological progress, industrial structure upgrading, human capital, and green finance can significantly contribute to the improvement of energy efficiency, and there may be differences at different stages. For the related aspects of green finance and energy efficiency, scholars at home and abroad have made certain achievements, but there are relatively few studies on the impact of green finance on energy efficiency. Most scholars have qualitatively analyzed the impact of green finance on energy efficiency among them when studying the overall development of finance on energy efficiency, and the literature focusing on the impact of green finance is scant, and in the context of pursuing high-quality development, green finance is especially scant. In the context of pursuing high-quality development, green finance is particularly important. In addition, most of the existing studies have been carried out at the national or industry level, with insufficient attention paid to regional differences, which may have impacts on the results owing to the large differences between the east and west of China in terms of economy, society, and resources. On the basis of the existing studies at home and abroad, this paper plans to first explore the mechanisms and approaches of financial development on energy efficiency from a theoretical perspective and, second, conduct an empirical study at both national and regional levels using relevant domestic data. On this basis, we explore the impact of educational human capital and green finance on regional TFEE in China and explore how the optimization of green finance policies and educational human capital can promote energy efficiency with great practical significance.

3. Methodology

3.1. Theoretical Foundation

3.1.1. Theoretical Basis of the Impact of Green Finance on Energy Efficiency

The theory of externality is the main theory for studying green finance. The biggest difference between green finance and traditional finance is that it takes into account the benefits of both economic and environmental aspects. If financial institutions inject funds into society only from the perspective of profit, they will ignore the capital needs of green energy-saving and environmental protection industries and may even invest the funds in large enterprises with high energy consumption and high pollution, bringing negative externalities of production and causing problems such as wasting resources and environmental pollution. Green finance, on the other hand, takes negative environmental externalities into account in the cost, considers environmental risk factors in its business operations for financial product innovation, broadens financing channels for green and low-carbon projects in energy and other industries, solves the financing problems of enterprises with significant environmental benefits, encourages the development of start-up green industries, curbs the continued development of traditional enterprises that have not transformed to green energy, promotes the transformation of the overall industry to green energy, and promotes energy efficiency. Therefore, green finance can guide or directly invest funds into the fields of resource conservation and environmental protection, which helps to realize the effective allocation of resources, improve environmental quality, and enhance resource utilization efficiency. Based on this, we put forward the first hypothesis of this paper: green finance can help achieve the effective allocation of resources, improve environmental quality, and enhance resource efficiency.

3.1.2. Theoretical Basis for the Impact of Educational Human Capital on Energy Efficiency

Human capital investment has a double effect on energy-efficiency improvement: on the one hand, human capital investment can promote a change in the energy consumption mode from rough to intensive by improving workers' education, vocational skills, technical proficiency, and energy conservation awareness, thus improving energy efficiency; on the other hand, human capital investment can improve energy efficiency by enhancing enterprises' technological absorption capacity, improving and innovating energy utilization technologies and equipment, and managing and organizing the optimal use of energy factors. In addition, human capital as the main carrier of knowledge products is considered as an important indicator of technological progress in the new growth theory. The accumulation of human capital also directly promotes the continuous renewal of physical capital. Lai et al. [43] found that absorptive capacity plays a key role in technology absorption outcomes, using economic openness and human capital as measures of a country's absorptive capacity. Huang et al. [44] found that human capital contributes to the role of (foreign direct investment) FDI technology spillover effects. In addition, human capital, as the main carrier of knowledge products, is considered an important indicator of technological progress in new growth theory. In addition, the difference in human capital stock may be one of the main reasons for the different effects of international R&D spillovers on energy efficiency in different energy-efficiency sectors. It is through the dynamic mediating role of human capital that energy efficiency increases and dynamically counteracts the law of diminishing returns to scale. Based on this, we propose the second hypothesis of this paper: human capital has the function of enhancing the ability of enterprises to create new technologies and absorb existing technologies.

3.2. Measurement Methods of TFEE

The main methods for measuring TFEE are SFA and DEA. Although SFA does not require the establishment of a production function, it has relatively strict assumptions on the model, which makes the parametric method less frequently used in academic circles. The nonparametric approach requires the establishment of a production function, but it is more convenient and widely used because there is no need to set the form of the production function and the weights of the inputs and outputs in advance. The nonparametric approach uses mainly the DEA model to measure TFEE. In contrast, DEA can be applied to complex multi-input–multi-output decision types, and it is now widely used in academia.

3.2.1. SBM Model

The traditional measure of TFEE is measured mainly by radial DEA, which can eliminate random error on TFEE and make the value of TFEE more realistic, but radial DEA cannot consider the influence of slack variables, and an nonexpected output on the TFEE measurement SBM model is a good solution to this problem because SBM takes into account the problem of slack. On the other hand, it also solves the problem of nonexpected output in the output variable. In the case of energy consumption causing more and more serious pollution problems, this method is able to measure a more realistic TFEE. However, the disadvantage of this method is that it doesn't consider external environmental factors. From the existing studies, the current measurement of energy efficiency is dominated by the nonparametric approach, and most scholars choose the DEA-SBM model, but this model has a problem: multiple efficiency values are 1 and effectively incomparable at the same time. Tone (2003) proposed an SBM efficiency-evaluation model that addressed nondesired outputs and includes two components in the outputs: desired outputs and nondesired outputs. Given the environmental effects, environmental pollutants are added to the input–output framework as nondesired outputs. According to the approach of introducing nondesired outputs into the SBM model, nondesired outputs are introduced into the superefficient SBM model. The relaxation variable of the superefficient SUPER-SBM-DEA model is distinguished from the original SBM model that calculates efficiency values greater than 1 without the constraint that efficiency values are less than or equal to 1. A valid decision unit is one whose efficiency value is not affected by input and output variables, whose optimal solution has unquantified characteristics, and whose input ratio increases while its efficiency value remains unchanged, and whose input increase ratio is the superefficiency evaluation value of the decision unit. So this paper adopts the super-SBM model improved to measure regional energy efficiency. The model is constructed as follows: assuming that each province has N factor inputs $x = (x_1, \cdots, x_N) \in R_N^+$, M expected outputs $y^g = \left(y_1^g, \cdots, y_k^g\right) \in R_M^+$, and K nonexpected outputs $y^b = \left(y_1^b, \cdots, y_k^b\right) \in R_K^+$, at each period t (t = 1,..., T), the TFEE of the i-th province is

$$\rho = \min \frac{\frac{1}{m} \sum_{i=1}^{m} \frac{\overline{x_i}}{x_{i0}}}{\frac{1}{M+K}\left(\sum_{r=1}^{M} \frac{y_r^{-g}}{y_{i0}^g} + \sum_{r=1}^{K} \frac{y_r^{-b}}{y_{i0}^g}\right)} \quad (1)$$

$$\text{s.t.}\overline{x} \geq \sum_{j=1,\neq 0}^{n} \lambda_j x_j, y^{-g} \leq \sum_{j=1,\neq 0}^{n} \lambda_j y_j^g, y^{-b} \leq \sum_{j=1}^{n} \lambda_j y_j^b \quad (2)$$

$$\overline{x} \geq x_0, y^{-g} \leq y_0^g, y^{-b} \leq y_0^b \quad (3)$$

$$\sum_{j=1,\neq 0}^{n} \lambda_j = 1, y^{-g} \geq 0, \lambda \geq 0 \quad (4)$$

where ρ is the total-factor energy efficiency; x, y^g, y^b represent the input variables, desired output variables and nondesired output variables of the decision unit, respectively; λ is the respective weight vector; and the subscript "0" in the model is the evaluated unit. The objective function value ρ is the measured total-factor energy efficiency. In this paper, the optimal orientation is chosen on the basis of the empirical results, to measure the TFEE of each province.

3.2.2. Input and Output Variables Selection

According to the existing studies, the measurement of TFEE includes into two forms: single factor and full factor. Among them, full factor is more scientific because it takes into account the correlation between multiple factors. In terms of indicator selection, with the increasing improvement of academic theories, more and more experts and scholars have noticed that while energy consumption brings economic benefits, it also brings certain negative impacts on the environment. Therefore, this study adopts the SBM model, chooses the popular three-factor input in the academic field in the input index, and adds CO_2 emissions as the nonexpected output in the output index.

(1) The choice of input indicators is capital stock. The calculation of capital stock is a difficult issue, and no international unified calculation method yet exists. Many scholars have selected the perpetual inventory method to measure capital stock, which is reasonable. In this paper, we also follow this method, and the formula is as follows:

$$K_{it} = K_{it-1}(1-\delta) + I_{it} \quad (5)$$

In this formula, i represents provinces (cities and districts), t represents time, K represents capital stock, I represents capital investment amount, and δ is the depreciation rate. In this paper, we use the measurement results of previous studies, from 2008 to 2020, and take the value of 10.96% for depreciation according to the estimation method of Shan et al. [45].

Second is the labor force. The current indicator of labor force is the number of people currently employed, which is commonly used in academic circles. It is reasonable to use current employment as a proxy for labor input, but it is not entirely accurate. In some overseas studies, labor input is expressed by worked hours, which is more scientific. However, because of the incomplete statistics in China, this paper still uses the number of people currently employed to represent labor input, and the unit is 10,000 people.

Third is energy consumption. Energy inputs are expressed in terms of total energy consumption by region.

(2) Output indicators selection

Expected output: For energy consumption, the most important expected output is the economic benefit, which is expressed as the increase in GDP. In the study, the real GDP of each province from 2008 to 2020 is used, and the unit is billion yuan.

Nonexpected output: As for the measurement of nonexpected output, the majority of scholars have expressed the nonexpected output in terms of CO_2 emissions. However, because there is no officially issued data on CO_2 emissions, most scholars refer to the IPCC guidelines, and this paper also adopts this approach by calculating the product of energy consumption and the corresponding CO_2 emission factor as CO_2 emissions. Coal, oil, and natural gas are three types of energy that emit more carbon dioxide. In this paper, for the sake of comprehensiveness in the measurements, we combine the practices of other scholars at home and abroad and choose eight energy resources that are most used in social life, namely raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas, to make a comprehensive calculation of carbon dioxide emissions, as shown in Equation (6):

$$CO_2 = \sum_{i=1}^{8} E_i \times CEF_i \times NCV_i \times COF_i \times \frac{44}{12} \tag{6}$$

where E_i denotes the energy consumption of the ith energy resource; CEF_i, NCV_i, COF_i are the carbon content, net heating value, and oxidation factor of the ith energy resource, respectively; and the product of the last four terms represents thus the carbon dioxide emission factor of the ith energy source. Here 44 and 12 are the molecular weights of carbon dioxide and carbon, respectively. The relevant data of carbon emission factors of eight energy resources are obtained from China Carbon Trading Network.

3.3. Factor Analysis Method of TFEE

3.3.1. Tobit Model

From the results of the above analysis, it is known that the interval range of the distribution of TFEE values is [0, 2], so the general panel regression model cannot be used for validation. This study chooses the Tobit model to analyze the influencing factors. The probability distribution of the variables in the Tobit model is as follows:

$$P(y_i = 0) = P(y_i^* \leq 0) = P\left(\frac{y_i^* - x_i\beta}{\sigma} \leq \frac{0 - x_i\beta}{\sigma}\right) = \varphi\left(-\frac{x_i\beta}{\sigma}\right) = 1 - \varphi\left(\frac{x_i\beta}{\sigma}\right) \tag{7}$$

$$P(y_i) = P(y_i^*) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(y_i - x_i\beta)^2}{2\sigma^2}} \tag{8}$$

The maximum likelihood estimate of the Tobit model is:

$$L = \prod_{y_i > 0} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(y_i - x_i\beta)^2}{2\sigma^2}} \prod_{y_i = 0} 1 - \varphi\left(\frac{x_i\beta}{\sigma}\right) \tag{9}$$

$$\ln L = \sum_{y_i > 0} -\frac{1}{2}\left(\ln(2\pi) + \ln\sigma^2 + \frac{(y_i - x_i\beta)^2}{\sigma^2} + \sum_{y_i = 0} \ln\left(1 - \frac{x_i}{\sigma}\right)\right) \tag{10}$$

In this paper, the regression model is built as follows:

$$y_j^* = \beta x_j + \varepsilon_j \tag{11}$$

$$y_j = \begin{cases} 0, otherwise \\ y_j^*, 0 < y_j^* \leq 2 \end{cases}, i = 1, 2, \cdots, 30 \tag{12}$$

where p is the distribution probability, y_j is the TFEE value of the jth region, β represents coefficients to be estimated, x_j is the vector of factors influencing TFEE, ε_j represents random disturbance term, and y_j^* is the potential TFEE.

3.3.2. Variable Selection

(1) Explanatory variables

Total-factor energy efficiency (TFEE): we measure the regional TFEE in China according to the SBM model, and the measured results are substituted into the regression model for analysis.

(2) Core explanatory variables

Educational human capital (HC): because of the limited data, the measurement of educational human capital shows the status quo of "emphasizing educational dimensions but not other dimensions", which is slightly different from the comprehensive definition from Schultz [46]. Measuring educational human capital on the basis of the years-of-education approach has become a common approach for researchers. In studies on China, educational human capital measures based on the years-of-education approach can also be divided into two categories: those based on age-specific population samples (e.g., population aged 6 years and older) and those based on a sample of employed persons involved in actual production activities. In this paper, as in most studies, we use the average years of schooling on the basis of the former type of sampling caliber to characterize educational human capital, and we include a squared term in the empirical analysis to verify the nonlinear relationship. Specifically, the average years of education can be obtained by using Equation (13):

$$\mathrm{HC} = \frac{pri}{pop} \times 6 + \frac{middle}{pop} \times 9 + \frac{hig}{pop} \times 12 + \frac{coll}{pop} \times 16 \tag{13}$$

where *pri*, *middle*, *hig*, *coll*, and *pop* denote the number of people with primary, middle, high school, and postsecondary education and the total population in each region, respectively; 6, 9, 12, and 16 are the years of education for the corresponding education level.

Green finance (GF): because of the relatively short development time of green finance, a unified measurement method has not been formed for green finance development, and the studies have generally referred to the method from Zeng et al. [47], where the index system includes green credit, green securities, green insurance, green investments, and carbon finance to measure the development level of green finance. The studies have adopted the entropy value method to objectively and accurately reflect the weights of indicators and added the squared term to verify their nonlinear relationship. The details are shown in Table 1.

Table 1. Evaluation index system.

First Indicators	Secondary Indicators
Green Credit	Total green credit/total loans Interest expenses of high-energy-consuming industries/total interest expenses of industrial industries
Green Securities	Total market value of environmental protection enterprises/total market value of A-shares Total market value of high-energy-consuming industries/total market value of A-shares

Table 1. *Cont.*

First Indicators	Secondary Indicators
Green Insurance	Agricultural insurance revenue/total agricultural output Agricultural insurance expenditure/total insurance expenditure
Green Investment	Fiscal expenditure in energy-saving and environmental protection industry/total fiscal expenditure Investment in environmental pollution control/ gross domestic product (GDP)
Carbon Finance	Number of participating clean development mechanism (CDM) projects

(3) Control variables

Industrial structure (IS): the tertiary industry is the industry with the lowest energy consumption; the tertiary industry can cause changes in TFEE. The industrial structure is expressed by the ratio of the added value of the tertiary industry to the GDP of each region, which is expressed by IS.

Science and technology input (TE): the science and technology input is expressed as the ratio of regional R&D input to regional GDP, denoted by TE.

Environmental regulation (ER): this paper selects three kinds of wastes, namely industrial wastewater, industrial waste gas, and industrial solid waste, as proxy variables to measure the intensity of environmental regulation, and it calculates the comprehensive evaluation index of environmental regulation intensity through the entropy weight method. Because environmental regulation impacts on the environment have dual characteristics, this paper includes its squared term in the empirical analysis for the ER, which is calculated by the entropy power method.

Economic development level (PGDP): economic development brings more and more advanced equipment and technology, as well as raises the organizational management level of enterprises, and people prefer to use efficient and clean energy to replace traditional high-pollution and energy-inefficient resources such as coal, which will lead to improvements in TFEE. The regional GDP per capita can reflect the developed level of the region and people's living standards. In this paper, we use GDP per capita to reflect the economic development level of a region, and we use the price index to convert GDP per capita into comparable prices with 2008 as the base period, which is denoted by PGDP. The Tobit model is constructed as follows:

$$TFEE_{it} = C + \beta_1 HC_{it} + \beta_2 GF_{it} + \beta_3 IS_{it} + \beta_4 TE_{it} + \beta_5 ER_{it} + \beta_6 PGDP_{it} + \mu_{it} \quad (14)$$

HC_{it}, GF_{it}, IS_{it}, TE_{it}, ER_{it}, and $PGDP_{it}$ are the following: educational human capital, green finance, industrial structure, science and technology investment, environmental regulation, and economic development level, respectively. μ_{it} is an independent random perturbation term. The data of indicators in this paper are obtained mainly from the China Statistical Yearbook, the China Statistical Yearbook of Provinces, the China Energy Statistical Yearbook, and the China Macroeconomic Database, and they are calculated by the authors. For the scope of data selection, in view of the availability of data and in order to maintain the uniformity and completeness of the data, Tibet and Hong Kong as well as Macao and Taiwan, which have serious data deficiencies, are excluded from this paper. A total of 30 provincial units in China are selected for the study, for the period 2008–2020, with a total of 390 observations. The results of the descriptive statistics are shown in Table 2.

Table 2. Descriptive statistics results.

Variable	Obs	Mean	Std.Dev.	Min	Max
TFEE	390	0.7570	0.8120	0.2170	1.6220
HC	390	0.2248	0.1235	0.1097	0.5543
TE	390	0.2214	0.2890	0.0783	1.9924
GF	390	0.7783	0.4519	0.3489	1.6671
IS	390	0.4522	0.5109	0.1125	0.4987
ER	390	0.3565	0.3316	0.0057	0.9865
PGDP	390	43,576	45,334	24,100	71,800

4. Results

4.1. Regional TFEE Measurement Results in China

With the help of MYDEA software [48], the TFEE is measured by using the SBM model on the basis of the above input–output data. The calculation results are shown in Table 3.

Table 3. Calculation results of TFEE.

	Region	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
	Beijing	1.114	1.122	1.214	1.223	1.315	1.339	1.405	1.436	1.484	1.538	1.545	1.613	1.622	1.382
	Tianjin	0.889	0.907	1.056	1.129	1.172	1.235	1.309	1.326	1.341	1.416	1.423	1.522	1.547	1.252
	Hebei	0.471	0.522	0.538	0.612	0.659	0.664	0.713	0.724	0.735	0.815	0.797	0.825	0.839	0.686
	Liaoning	0.329	0.333	0.348	0.463	0.478	0.485	0.491	0.508	0.519	0.532	0.541	0.625	0.641	0.484
	Shanghai	1.026	1.117	1.129	1.186	1.245	1.264	1.313	1.326	1.336	1.424	1.446	1.517	1.584	1.301
Eastern	Jiangsu	0.722	0.741	0.768	0.785	0.803	0.821	0.835	0.843	0.856	0.978	1.028	1.155	1.179	0.886
	Zhejiang	0.732	0.746	0.805	0.816	0.829	0.838	0.841	0.859	0.865	0.975	1.071	1.143	1.262	0.906
	Fujian	0.518	0.626	0.647	0.722	0.745	0.781	0.792	0.811	0.825	0.836	0.848	0.855	0.862	0.759
	Shandong	0.572	0.581	0.468	0.692	0.723	0.735	0.743	0.857	0.872	0.884	0.889	0.896	0.934	0.757
	Guangdong	0.934	0.968	1.211	1.256	1.335	1.341	1.389	1.452	1.432	1.453	1.512	1.527	1.689	1.346
	Hainan	0.341	0.368	0.445	0.478	0.528	0.547	0.643	0.656	0.761	0.778	0.822	0.872	0.889	0.625
Eastern mean		0.731	0.766	0.818	0.888	0.930	0.950	0.983	1.014	1.027	1.057	1.084	1.141	1.186	0.967
	Shanxi	0.419	0.427	0.524	0.537	0.542	0.653	0.659	0.765	0.771	0.782	0.794	0.897	0.912	0.668
	Jilin	0.345	0.367	0.443	0.461	0.511	0.526	0.533	0.656	0.758	0.862	0.874	0.979	0.981	0.638
	Heilongjiang	0.321	0.383	0.398	0.445	0.515	0.526	0.536	0.643	0.733	0.841	0.882	0.954	0.965	0.626
Central	Anhui	0.645	0.677	0.722	0.738	0.743	0.751	0.773	0.882	0.894	0.901	0.917	0.967	0.989	0.815
	Jiangxi	0.623	0.635	0.637	0.642	0.646	0.652	0.654	0.666	0.678	0.695	0.711	0.827	0.929	0.692
	Henan	0.518	0.521	0.631	0.643	0.648	0.752	0.759	0.764	0.766	0.878	0.879	0.911	0.935	0.739
	Hubei	0.593	0.612	0.618	0.723	0.734	0.841	0.848	0.852	0.862	0.916	0.931	0.959	0.963	0.804
	Hunan	0.526	0.633	0.647	0.648	0.754	0.777	0.815	0.863	0.872	0.923	0.935	0.958	0.963	0.793
Central mean		0.499	0.532	0.578	0.605	0.637	0.685	0.697	0.761	0.792	0.850	0.865	0.932	0.955	0.722
	Neimenggu	0.521	0.529	0.533	0.521	0.636	0.643	0.657	0.662	0.777	0.784	0.793	0.821	0.976	0.681
	Guangxi	0.627	0.638	0.643	0.651	0.665	0.673	0.681	0.689	0.692	0.691	0.713	0.822	0.864	0.696
	Chongqing	0.515	0.548	0.521	0.528	0.632	0.636	0.641	0.653	0.662	0.678	0.682	0.711	0.742	0.627
	Sichuan	0.372	0.373	0.375	0.383	0.384	0.393	0.395	0.403	0.411	0.416	0.422	0.432	0.441	0.400
	Guizhou	0.315	0.319	0.326	0.327	0.433	0.436	0.438	0.442	0.544	0.548	0.551	0.559	0.565	0.446
Western	Yunnan	0.421	0.522	0.556	0.643	0.651	0.655	0.672	0.686	0.691	0.705	0.712	0.722	0.761	0.646
	Shaanxi	0.418	0.523	0.613	0.639	0.654	0.682	0.715	0.813	0.822	0.837	0.963	0.942	0.956	0.737
	Gansu	0.217	0.229	0.231	0.299	0.316	0.337	0.345	0.352	0.358	0.456	0.459	0.478	0.526	0.354
	Qinghai	0.566	0.571	0.578	0.586	0.588	0.589	0.592	0.612	0.621	0.632	0.642	0.633	0.635	0.603
	Ningxia	0.322	0.363	0.416	0.489	0.554	0.582	0.615	0.613	0.622	0.737	0.738	0.742	0.756	0.581
	Xinjiang	0.561	0.572	0.583	0.585	0.589	0.601	0.616	0.627	0.629	0.634	0.658	0.651	0.669	0.613
Western mean		0.453	0.482	0.496	0.516	0.555	0.565	0.575	0.594	0.621	0.638	0.660	0.677	0.714	0.580
National mean		0.561	0.594	0.631	0.670	0.707	0.733	0.752	0.790	0.813	0.848	0.870	0.917	0.951	0.757

From Table 3, on TFEE values for each province and city in China in previous years, we can see that the average value of national TFEE is 0.757, which is still in the middle and low level and has a lot of room for improvement. For 2008 to 2020, the TFEE values of Beijing, Shanghai, Tianjin, and Guangdong in China are all greater than 1, which means that these provinces and cities have the best energy utilization efficiency, and under the condition of certain output, the input energy is the lowest. The energy use efficiency of Ningxia, Qinghai, Gansu, Guizhou, and Sichuan is relatively low, indicating that these provinces and cities have relatively more energy input for a certain output. This is not conducive to the sustainability of the cities. In addition, in terms of time, it can be seen that from 2008 to 2020 as a whole, the energy utilization rate of the country is improving.

It can be seen that TFEE values in the east, central, and west regions of China show a gradual increase in the state of affairs, with the most obvious increase in the east and the least obvious increase in the west. Further, the TFEE shows a decreasing pattern from the central east to the west. The eastern part of the country has an average TFEE of 0.967, with a favorable climate, developed transportation, dense population, and high openness to the outside world. The central region, with moderate climate, relatively low openness, and less-developed transportation, has a TFEE of 0.722, which is rich in primary consumption energy resources but with a poor climate. The TFEE of the western part of the country, which is not well developed in transportation, is only 0.580 on average.

4.2. Analysis of the Effects of Educational Human Capital and Green Finance on TFEE

4.2.1. Multicollinearity Test and Smoothness Test

This paper uses the variance inflation factor (VIF) to test for the presence of multi-collinearity. If the VIF value is greater than 10, it means that the multicollinearity is very serious, which needs to be dealt with, and if the VIF value is below 5, it does not need to be dealt with, the results as Table 4.

Table 4. Results of multicollinearity test.

Variables	HC	TE	GF	IS	ER	PGDP
VIF	2.33	2.56	1.89	3.47	2.55	1.34
1/VIF	0.43	0.39	0.53	0.29	0.39	0.75

The sample data has a large dimension and small time, according to this characteristic; the test of smoothness was performed with reference to Harris and Tzavalis [49]. Table 5 shows the results of the stationarity test, which shows that they are all stationary, allowing the next stage of the econometric empirical study to be carried out.

Table 5. Stability test results.

Variable	HTtest	*p*-Value	Stability
EE	−11.342	0.000	stable
HC	−9.213	0.002	stable
TE	−12.338	0.000	stable
GF	−5.781	0.001	stable
IS	−7.510	0.000	stable
ER	−10.116	0.000	stable
PGDP	−6.449	0.000	stable

4.2.2. Formal Test of Model Setting

The Hausman test is used to select the appropriate panel data model, mainly to determine fixed effects or random effects. By performing Hausman's test on the model in this section (Table 6), p = 0.0000, which would be better by using a fixed effect.

Table 6. Hausman's test results.

Test Summary	Chi-Sq.Statistic	Chi-Sq.d.f	Prob.
Cross section random	44.123	6	0.0000

4.2.3. Tobit Regression Results Analysis

According to the above analysis, the regression was conducted using a fixed-effects panel Tobit model. Table 7 shows the results.

Table 7. Tobit regression results.

Variable	National	East	Central	West
HC	−0.109 ***	−0.005 ***	−0.197	−0.227 ***
	(4.91)	(3.44)	(3.89)	(6.18)
HC2	−0.072 *	−0.001	−0.141 **	−0.197 ***
	(−1.97)	(−3.66)	(−2.15)	(−4.32)
GF	−0.212 ***	0.139	−0.142 ***	−0.203 ***
	(−4.22)	(0.22)	(−4.94)	(−3.78)
GF2	0.124 ***	0.037	0.253 ***	0.126 ***
	(3.44)	(0.78)	(3.32)	(5.22)
ER	−0.075 ***	−0.073 ***	−0.131 **	−0.087 *
	(−3.56)	(2.98)	(−2.38)	(−0.77)
ER2	0.125	0.137 ***	0.094 ***	0.083
	(5.18)	(3.44)	(2.85)	(4.61)
TE	0.2344 ***	0.4336 ***	0.2666 ***	0.1238 ***
	(5.32)	(3.12)	(4.78)	(6.13)
IS	0.128 ***	0.206 ***	0.339 ***	0.233 ***
	(3.44)	(4.16)	(5.43)	(2.96)
PGDP	0.085 ***	0.126 ***	0.103 ***	0.118 ***
	(4.55)	(2.88)	(4.87)	(4.92)
-cons	0.1124 (0.98)	0.2341 (0.34)	0.1785 (1.02)	0.4533 (1.21)
Log-likelihood value	56.235	72.665	52.138	71.668
Wald test	41.234 ***	51.238 ***	42.169 ***	61.109 ***

Note: ***, ** and * means $p < 0.01$, $p < 0.05$ and $p < 0.1$.

(1) Core explanatory variables

The educational human capital variable coefficient is significantly negative, and the squared term is also negative, so educational human capital has no U-shaped relationship. The difficulties and challenges in accurately measuring educational human capital make it difficult to introduce information such as migration and health in empirical studies. In addition, educational human capital measured by average years of education may ignore more-accurate, but difficult to fully observe, information on the structure and spatial agglomeration state of educational human capital and the matching efficiency with physical capital in each region, which may inhibit the improvement effect of educational human capital on TFEE. Peng [50] argues that the level of human capital affects total-factor productivity only if it exceeds certain "threshold conditions", and if the conditions are not met, it can affect output only as an input factor. Under the given condition of educational human capital level, the increase of educational human capital return brought by the reasonable optimization of educational human capital allocation structure will promote industrial structure upgrading and economic development. Therefore, the negative coefficient in the east may be related to the application of educational human capital, i.e., the poor matching of educational human capital with physical capital. The coefficient is significantly negative in the east; the middle and west are similar to the overall national test, and in comparison; the coefficient of this variable is smaller in the eastern region and relatively higher in the eastern region, but the proportion of professional educational human capital is still low compared with that in developed countries. The lower level of educational human capital may not achieve a good match between educational human capital and physical capital, which eventually manifests as the lower level of human capital in education may not achieve a good match between human capital in education and physical capital, and eventually the educational human capital will hinder the improvement of TFEE. In the central and western regions, the human capital stock is low compared with the eastern regions, and the labor force is mostly basic educated human capital that can perform only simple manual labor, and the impact of educated human capital on TFEE is still expressed in terms of output.

The difficulties and challenges in accurately measuring human capital make it difficult to bring in information on migration and health in empirical studies. In addition, human capital measured by average years of education may ignore more-accurate, but difficult to fully observe, information on the structure and spatial agglomeration status of human capital in each region, and the efficiency of matching with physical capital, which may inhibit the improvement effect of human capital on total-factor energy efficiency. Clearly, there is much room for discussion on the relationship between human capital, energy, and total-factor energy efficiency under carbon emission constraints and even environmental efficiency, which should attract the attention of researchers in future studies [51,52].

The primary coefficient of green finance's impact on national TFEE is negative, the quadratic term is positive, and both pass the significance test, indicating that there is a significant U-shaped relationship between these two. That is, green finance realizes the trend of first decreasing and then increasing, and at the early stage, when the development of green finance is low, it is not conducive to the improvement of TFEE, because the development of green finance affects the level of regional economic development, and the level of economic development affects the level of regional environmental pollution, thus having an impact on TFEE. When the level of green finance is low, it shows that the economic growth mode stays in the pursuit of economic. When the level of green finance is low, it shows that the economic growth mode is stuck in the pursuit of speeding up economic growth, and the quality of economic growth is ignored, which sacrifices the environment and causes a large amount of energy development and consumption, which is not conducive to the improvement of TFEE. When the level of financial development rises, a large amount of capital can be directed to the energy conservation and environmental protection industry, which can significantly promote TFEE.

In the central and western regions, the coefficient of the primary term of green finance is less than zero, and the coefficient of the secondary term is greater than zero. The relationship between the two also shows a U-shaped relationship, and the coefficient of the central region is larger than that of the western region, so the central region shows a strong effect. The coefficient of green finance in the eastern region does not pass the significance test, but its positive coefficient also indicates the tendency to promote total-factor energy efficiency, and it is necessary to strengthen the support for the development of green finance to realize its promotional effect.

It can be seen that green finance and energy efficiency are to some extent in a complementary relationship. The core question of this paper is, how can we bring into play the financing function of green finance, mobilize social resources to the green development field with maximum efficiency, cope with the increasingly severe ecological environment, and then improve energy-efficiency development (which is also a key direction to be explored in the future)?

(2) Control variables

The primary term of environmental regulation is negative and the secondary term is positive. The relationship shows a U shape, i.e., as the intensity of environmental regulation increases, TFEE first decreases to a certain level and then tends to increase. When the intensity of environmental regulation is weak, the impact on TFEE is negative. After reaching the inflection point, the effect becomes positive, which is in line with the views of existing scholars. Environmental regulation's impact on TFEE in the eastern, central, and western regions shows that the primary coefficients are negative and the secondary coefficients are positive, indicating a U-shaped relationship. In addition, the effect is most obvious in the eastern region, followed by the central region, and least obvious in the western region. The main reason is that the western region is the least developed and has certain advantages in resource endowment and lower labor costs, so the adoption of more-intensive environmental regulations would restrict its industrial development and thus offset the positive effects brought by environmental regulations.

Science and technology investment is positively correlated with the improvement of national TFEE. The eastern region has higher technology investment and a higher developed economic level, so the TFEE is higher, and the promotion effect of technology investment on TFEE in the eastern region is greater than that in the central and western regions. The eastern region is technologically developed, and over time, technology spillover and technology transformation will gradually drive the level of technological development in the central region, thus further improving energy utilization and reducing pollution, which is more conducive to sustainable economic development. For the western regions, the role of technology investment in improving TFEE is low, probably due to the lack of high-end talent, the lack of advanced equipment and management experience in these regions, fewer research institutions and schools, etc.

In addition, more foreign direct investment in the eastern coastal regions brings advanced technology and management experience, so technology plays an obvious role in the progress of TFEE. The improvement of industrial structure on TFEE confirms the view of most scholars that for every percentage point change in the value added of tertiary industry in the eastern region to the GDP of the region, TFEE increases by 0.206 percentage points, but the horizontal comparison shows that the increase in the central region is 0.339 percentage points and the increase in the western region is 0.233 percentage points, which has the most significant effect on central region TFEE. The TFEE improvement is most obvious in the central region.

The economic development level in all regions will promote the improvement of TFEE, and the degree of influence of economic development level on TFEE does not differ much among regions. The fact that economic development will improve TFEE and the pursuit of economic development can lead to the improvement of TFEE at the same time.

5. Conclusions and Recommendations

5.1. Conclusions

In this paper, the SBM method was selected to evaluate the TFEE values of each province in China over 13 years, from 2008 to 2020. On this basis, the impact of educational human capital and green finance on the regional TFEE in China is explored, and the following conclusions are drawn.

(1) Chinese TFEE average value is 0.776, which is still at a lower level and has a lot of room for improvement, and the TFEE of China's eastern, central, and western regions shows a gradual increase; the TFEE in the east is the most obvious, and least obvious in the west.
(2) The coefficient of educational human capital variable is significantly negative, the squared term is also negative, and educational human capital does not show a signifi-

cant U-shaped relationship at the national level. The coefficient of educational human capital is significantly negative in the eastern, central, and western regions, similar to the overall national test. In the central and western regions, the stock of educational human capital is low compared with that in the eastern regions, and the labor force is mostly basic educational human capital that can perform only simple manual labor, which has no significant contribution to TFEE.

The coefficients of the primary term and the quadratic term of the impact of green finance on national TFEE are negative and positive, and both pass the significance test, indicating that there is a significant U-shaped relationship between these two. There is also a significant U-shaped relationship in the central and western regions. The coefficient of green finance in the eastern region does not pass the significance test, but its positive coefficient also indicates a tendency to promote total-factor energy efficiency, and it is necessary to strengthen the support for the development of green finance to realize its promotional effect.

(3) The following are the control variables. Environmental regulation's impact on national TFEE shows a U shape in all regions; science and technology investment can improve the TFEE of the whole country and each region. The improvement of industrial structures on TFEE shows a positive correlation in all regions; economic development promotes TFEE improvement in all regions; and the degree of influence of economic development level on TFEE does not differ much among regions.

5.2. Suggestions

(1) Efforts should be made to increase investment in education, attach importance to the strategy of developing the country with talents, make full use of regional resource advantages to introduce high-quality talent, and promote human capital level in each region. As an important source of technological progress, human capital can accelerate the improvement of TFEE in China. Because of the differences in human capital levels in different regions, regional governments in China should adopt different human capital optimization strategies. The eastern region should vigorously develop higher education and vocational education, gradually increase the proportion of professional human capital, and alleviate the inhibiting effect of the overall improvement of human capital on TFEE. The central and western regions should expand the establishment of teachers in remote areas, accelerate the work of universal compulsory education, guarantee the right of low-income people to receive formal compulsory education, and fundamentally improve the education quality and population quality in remote areas.

(2) Optimize the efficiency of human capital. The free flow of talents can bring economic or noneconomic returns to workers, and migration benefits such as higher wages and improved labor environment become important factors in the career choice of high-quality workers; at the same time, the flow of talents also forces local workers to continuously improve their own human capital investment in order to improve their competitiveness and achieve high efficiency in human capital. The eastern and central regions of China rely on the introduction of foreign investment to improve the local technology level, while the western regions mainly undertake technology transfers from the east and central regions.

Therefore, in order to enhance the ability of laborers around the world to absorb, improve, and utilize technology and improve the overall human capital level of each region, the flow of talent should be reasonably guided. The government should establish a sound talent-incentive mechanism to guide the flow of human capital from big cities to small and medium-size cities, gradually alleviating the idle and wasted human capital in big cities and the lack of human capital in small and medium-size cities. Improving the flow of technology and talent between regions will break down the barriers to factor flow between regions that hinder the improvement of TFEE.

(3) Construct a cross-regional cooperation platform to promote the cross-regional flow of green financial resource elements because the problem of uneven development of energy efficiency among regions in China is still prominent. To effectively promote a balanced development of TFEE in each region, a cross-regional cooperation platform should be constructed to enhance the flow of green finance–related resource elements among different regions [53,54]. For example, regular lectures should be held to strengthen the exchange of green financial professionals between regions and improve the professional capacity of green financial professionals, especially to strengthen the training of green financial professionals in the central and western regions, where energy efficiency is low, so as to improve green finance in the central and western regions, bring into play the role of green finance in promoting energy efficiency, and solve the problem of the uneven development of energy efficiency.

(4) Increase preferential subsidies for environmental protection enterprises and increase taxes on high-polluting enterprises. To promote the development of green finance for environmental protection enterprises, the government has to reduce the development of high-polluting enterprises, of which the most important means is taxation [55]. By adjusting and increasing the tax rate of the environmental protection tax, the cost of high-pollution enterprises will be controlled to a certain extent, as will the development of high-pollution enterprises through the green financial policy to reduce the financing costs of environmental protection enterprises [56]. Expand the scale of environmental protection enterprises, because environmental protection enterprises developed in turn promote the development of energy efficiency, thus promoting the improvement of energy efficiency [57].

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