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Exploring Financial Agglomeration and the Impact of Environmental Regulation on the Efficiency of the Green Economy: Fresh Evidence from 30 Regions in China

Ran Wang [1] and Rong Wang [2,*]

[1] Jincheng College, Nanjing University of Aeronautics and Astronautics, Nanjing 211156, China
[2] Business School, Nanjing Xiaozhuang University, Nanjing 211171, China
* Correspondence: rongwang@njxzc.edu.cn

Abstract: This research measures the green economic efficiency (GEE) of 30 regions in China from 2009 to 2021 and verifies the financial agglomeration and environmental regulation impacts on GEE with the Tobit model. The conclusions are as follows: (1) The average GEE value in China is 0.596—which is still at a low level—and is highest in the eastern region and lowest in the western region. (2) Financial agglomeration can promote GEE in the whole country, in both the eastern and western regions; however, the western region effect is very low. In the central region, due to the "siphon effect" produced by the eastern region, the financial resources concentrated in the east thus suppress GEE. Environmental regulation inhibits GEE nationally and in the western region while showing a promotion effect in the eastern and central regions, but it is not significant in the central region. (3) Industrial structures inhibit GEE nationally and in the central and western regions, while industrial structures promote GEE in the eastern region; the GDP (gross domestic product) per capita also inhibits GEE nationally and in the central and western regions and promotes GEE in the eastern region. Government intervention inhibits green economic development in all regions, and urbanization inhibits GEE nationally and in the central and western regions while promoting GEE in the eastern region.

Keywords: financial agglomeration; environmental regulation; green economic efficiency; sustainable development

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Citation: Wang, R.; Wang, R. Exploring Financial Agglomeration and the Impact of Environmental Regulation on the Efficiency of the Green Economy: Fresh Evidence from 30 Regions in China. *Sustainability* **2023**, *15*, 7226. https://doi.org/10.3390/su15097226

Academic Editor: Bruce Morley

Received: 6 March 2023
Revised: 19 April 2023
Accepted: 23 April 2023
Published: 26 April 2023

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1. Introduction

Along with the deepening of global industrialization, the resources and environmental issues brought about by industrial development have become the focus of global attention [1]. The development idea of the "pollute first, treat later" approach to development is no longer compatible with the requirements of sustainable development, and a green economy is necessary for sustainable development [2]. How to correct the short-sighted behavior of pursuing material accumulation, solve the problems of environmental pollution and resource wastage, reverse the previous trend of high energy consumption that overdraws the ecological environment in advance, and a sustainable development economy has become a major strategic issue related to global sustainable development [3–5].

Over decades of development, China's nonintensive development model has also brought serious environmental problems. Currently, China is still one of the few global economies with positive economic growth rates over the past two years or so, and the Chinese economy is showing a good trend of steady improvement. However, the irrational economic structure and the long-standing rough development model have led to significant negative externalities in economic development [6]. In 2020, carbon emissions from the energy sector accounted for 77% of the total national emissions in China; industrial process carbon emissions accounted for 14%; and agriculture and waste carbon emissions accounted for 7% and 2%, respectively [7]. China is facing problems of high energy consumption, wasting resources, and pressure on environmental protection. In this context, how to fully utilize the impact of innovation to drive the green economy to promote economic transformation and sustainable regional development is important in achieving high-quality development at this stage. How to improve GEE is becoming a hot topic of research for scholars [8,9]. GEE is a comprehensive economic efficiency that takes into account the costs of resources and the environment and is a different type of economic growth performance indicator compared to the traditional one that ignores the costs of resources and the environment [10].

The financial sector is regarded as a core element of the contemporary economy, and its "clean" and "dynamic" characteristics have an important impact on GEE. Financial agglomeration can promote continuous technological innovation and economic acceleration [11]. With economic development and technological progress, pollution hazards are reduced, and pollution reduction is facilitated, thus making the environmental pressure brought by economic activities less [12]. Sadorsky [13] argues that financial agglomeration helps enterprises to expand their production scale, which increases pollutant emissions, and then inhibits the GEE. Therefore, the financial agglomeration impact on GEE, including whether there are spatial differences in financial agglomeration on GEE, still has room for investigation.

Improving environmental regulations has become a consensus to prevent and control environmental pollution. There are two main views: the "compliance cost theory" and the "innovation compensation theory" [14]. The "compliance cost theory" argues that environmental regulations increase emissions costs, which reduce corporate profits, thus weakening corporate competitiveness. The "innovation compensation theory" or "Porter's hypothesis" suggests that well-designed environmental regulations can promote Pareto improvements or even win-win effects, not only for environmental protection but also to improve firm competitiveness [15]. Because the strengthening of environmental regulations could improve enterprise innovation, which can compensate for the problem of rising costs caused by environmental regulations, it also can promote enterprise competitiveness. However, in the process of increasing the intensity of environmental regulations year by year, China has found that since the promulgation and implementation of a series of policy instruments, the current environmental regulations in China have had a certain degree of inhibitory effect on economic growth since the enactment of a series of policy instruments [16]. In the face of an urgent need to solve the problem of excessive resource consumption and environmental pollution, the need to achieve environmental regulation and GEE improvement on the basis of economic development is an important task; however, whether environmental regulation can truly affect GEE improvement is another question that deserves deeper investigation.

The main contributions of this article are as follows: (1) The existing research mainly focuses on the measurement of green economic efficiency, lacking a comparison of different regions. This study can provide a theoretical reference for regional coordinated development. (2) The existing research on the relationship between financial agglomeration, environmental regulation, and green economic efficiency has not yet been found. Therefore, this study is an extension and improvement of the existing research, filling in existing research gaps, and has certain academic value. (3) The use of the super-efficiency SBM model with environmental considerations for green economic efficiency is an extension of the existing research methods. In view of this, this paper measures GEE in different regions of China, explores financial agglomeration and environmental regulation impacts on GEE, and then proposes a policy to promote GEE.

The main research framework of this article is as follows: The first part is an introduction, which mainly introduces the background, motivation, and content of this study. The second part is a literature review, which mainly combs through the contributions of existing literature in this field and concludes the research innovation points of this article. The third part is an introduction to the research methods used in the paper, detailing the applicability of the methods used in the paper and providing a basis for further empirical analysis. The fourth part is the results, which mainly analyze the results of the empirical analysis and obtain the main viewpoints to provide support for further policy measures. The fifth part is the conclusion and suggestions section, which summarizes the research results of the paper and puts forward corresponding policy recommendations and the shortcomings of this study.

2. Literature Review

2.1. About the Meaning of GEE

In the context of the "new normal", the green economy, as a new driving force for the overall green transformation of society and the economy, emphasizes the correct handling of the relationship between resource elements, ecological environment, and economic development [17]. The GEE development index is a common indicator for evaluating economic development performance, which unifies resource, environmental, and economic factors into a function to unfold the assessment of green economic performance, considering both sustainable economic growth in the production stage and resource factor intensification and ecological and environmental protection [18,19]. Pittman [20] first treated the cost of combating environmental pollution as non-desired output, and Chung et al. [21] constructed the Malmquist–Luenberger productivity index to measure GEE. Since then, scholars have conducted relevant studies on GEE, such as Qian and Liu [22], who proposed the definition of GEE, which is based on the consideration of environmental costs and resource inputs.

The main methods for measuring GEE are the DEA (data envelopment analysis) model, the Malmquist index method and the SBM (slacks-based measure) model. Li and Yue [23] selected a four-stage DEA model to systematically analyze the evolutionary characteristics of inter-provincial GEE in China. Meng and Shao [24] analyzed the growth mechanism of GEE in China based on panel data from 2003 to 2016. Zofio et al. [25] chose to measure the green total factor by using the Malmquist model, while Wu [26] chose a combination of a three-stage DEA model and the more generally applicable Malmquist index to test the method of measuring GEE. In order to further optimize and upgrade this method and make our measured data results more valid, Fukuyama and Weber [27] and Li et al. [28] used the SBM model to construct a directional distance function to measure. The advantage of this combined model is that it can play a radial and directional role in measuring the distance function of the GEE process.

2.2. Financial Agglomeration Impact on GEE

According to the research related to financial agglomeration and GEE, most scholars conclude that financial agglomeration can improve GEE, such as Wang et al. [29], who believed that financial resources concentration in a certain region could improve resource utilization efficiency by optimizing resource allocations in that region, and thus promote industrial transformation and its upgrading. Bossone and Lee [30] thought that financial agglomeration improved green economic development. He et al. [31] discussed that financial agglomeration promoted economic growth by enhancing factor inflow and optimizing industrial structure. Qu et al. [32] argued that financial agglomeration also could effectively improve GEE. Miao et al. [33] and others found that the innovation effect and the corresponding conversion of results, as well as the corresponding green efficiency from financial agglomeration, are found to show fluctuating growth.

Fewer authors concluded the negative effect of them, such as Hu et al. [34], who concluded that the current financial agglomeration was lower, which generates more significant negative externalities, forming a phenomenon of high investment and low income, which inhibit GEE. Xu et al. [35] classified cities according to different city sizes and different city clusters and then studied the financial agglomeration impact on GEE. They found that it was only significant in big cities. Shi et al. [36] found the effect of the financial agglomeration impact on GEE shows a U-shaped relationship.

2.3. Environmental Regulation Impact on GEE

(1) Environmental regulation promotes GEE. According to Li and Liu [37], environmental regulation can improve GEE, and strengthening environmental regulation can achieve a "win-win" situation to a certain extent. Gong and Zhang [38] found that there is a positive spillover effect on GEE, and Telle and Larsson [39] showed that environmental regulation could promote GEE in Norwegian industries. The government, by imposing strict environmental regulations, can provide a certain degree of incentive for firms to carry out R&D activities [40]. He and An [41] found that environmental regulation promotes green development efficiency, and environmental regulation can protect the environment and promote high-quality economic development.

(2) Environmental regulation inhibits GEE. Wang and Li [42] believed that environmental regulation inhibited GEE, and Huang and Shi [43] concluded that public participation-type environmental regulation hinders GEE. Li et al. [44] believed that environmental regulation and private investment impact on the green total factors show an inhibitory effect. Based on inter-provincial data, Wu and You [45] found that environmental regulation inhibits technological innovation at the national level.

(3) The relationship is uncertain. Shuai and Fan [46] show that the environmental regulation impact on GEE shows a "U"-shaped curve. Yin and Gu [47] constructed a panel regression and threshold regression model to observe their relationship, and the study shows that the effect is in an "N"-shape. Song et al. [48] argue that the relationship is an "inverted U-shaped", while Qian and Liu [49] argue that the relationship is also "U-shaped". Jiang et al. [50] show that the effect depends on the strength of environmental regulation. Li et al. [51] indicated that there is a nonlinear relationship between them. Wang and Sun [52] found that the effect is different in variable regions.

It can be concluded that more and more attention is paid to GEE, and its influencing factors are mostly explored from the perspectives of manufacturing agglomeration and industrial agglomeration, etc., and few analyses are carried out from the perspective of financial agglomeration. Many studies have come to different conclusions from their studies on this issue. Some argue that environmental regulation inhibits GEE, some argue that there is an inhibitory and then promotional effect of environmental regulation on GEE, and some argue that there is a promotional and then inhibitory effect. Therefore, the study first measures GEE and then studies the financial agglomeration and environmental regulation impacts on GEE, which helps to provide a theoretical reference for different regions to formulate policies to enhance GEE.

3. Methodology

3.1. Methodological Choices for Measuring GEE

3.1.1. Super-Efficiency SBM

Green economic efficiency is a comprehensive efficiency measurement index that takes into account the cost of resources and the environment while measuring economic efficiency. It includes energy and environment in the input and output factors, respectively, in order to minimize economic growth and unexpected output. There are two methods for measuring efficiency: the parametric method, based on a quantitative relationship, and the non-parametric method, which contains assumptions. Stochastic frontier production function analysis (SFA) is an important part of the parametric method, which has the advantage of considering production inside the frontier boundary for more comprehensive reasons, taking into account both stochastic shocks and technical inefficiencies, as well as the possibility of using panel data for estimations and studying the temporal trends of different individuals. Data envelopment analysis (DEA) is an important part of the non-parametric method. Its advantages over SFA are that it does not require the standardization of indicator data, omits the steps of function construction and subjective weighting, and is a linear optimization problem in the production domain. Its disadvantage is that the corresponding efficiency values are still measured in the absence of a relationship between the input and output indicators [53].

DEA models can be divided into four categories: angular versus radial, non-angular versus radial, angular versus non-radial, and non-angular versus non-radial. Among them, angle refers to the output-oriented or input-oriented analysis of efficiency, while radial indicates that the input and output are scaled up or down according to a certain ratio to measure efficiency. Most of the traditional DEA models belong to the type of "angle and radial"; thus, they cannot measure all the slack, and the efficiency results obtained are not accurate [54]. Tone [55] proposed an SBM model that does not include undesired outputs, which assumes that there are n DMUs and each DMU (decision-making unit) contains two vectors of inputs and outputs, denoted as $\mathrm{X} = (x_{ij}) \in R^{t\times n}, Y = (y_{ij}) \in R^{c\times n}, X > 0, Y > 0$. Then, the production possibility set P is:

$$\mathrm{P} = \{(x, y)|x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0\} \tag{1}$$

Define the expression of $\mathrm{DMU}(x_0, y_0)$ as:

$$\begin{cases} x_0 = X\lambda + S^- \\ y_0 = Y\lambda - S^+ \\ \lambda \geq 0, S^- \geq 0, S^+ \geq 0 \end{cases} \tag{2}$$

where S^- and S^+ are the slack in the inputs and outputs, respectively, indicating redundant inputs and insufficient outputs. When $X > 0$ and $\lambda > 0$, $x_0 \geq S^-$. Combining the slack variables, the expression of the index $\rho(0 < \rho \leq 1)$ is defined as follows:

$$\rho = \frac{1 - \frac{1}{t}\sum_{i=1}^{t}\frac{S_i^-}{x_{i0}}}{1 + \frac{1}{c}\sum_{r=1}^{c}\frac{S_r^+}{y_{r0}}} \tag{3}$$

To obtain the efficiency value, Tone [55] proposed the SBM model:

$$\min\rho = \frac{1 - \frac{1}{t}\sum_{i=1}^{t}\frac{S_i^-}{x_{i0}}}{1 + \frac{1}{c}\sum_{r=1}^{c}\frac{S_r^+}{y_{r0}}} \tag{4}$$

$$s.t.\begin{cases} x_0 = X\lambda + S^- \\ y_0 = Y\lambda - S^+ \\ \lambda \geq 0, S^- \geq 0, S^+ \geq 0 \end{cases} \tag{5}$$

Tone and Sahoo [56] propose an SBM model that contains non-expected outputs, which can be divided into expected and non-expected outputs in detail. It assumes that there are n DMUs, and each DMU contains input, desired output and non-desired output vectors, denoted as $X \in R^t, y^g \in R^{c1}, y^b \in R^{c2}$. The matrix can be defined as X, Y^g, Y^b, which are denoted as $X = (x_{ij}) \in R^{t\times n}, Y^g = (y_{ij}) \in R^{c1\times n}, Y^b = (y_{ij}) \in R^{c2\times n}, \mathrm{X} > 0, Y^g > 0, Y^b > 0$. Then, the set of production possibilities P is:

$$\mathrm{P} = \left\{\left(x, y^g, y^b\right)\middle| x \geq X\lambda, y^g \leq y^g\lambda, y^b \geq y^b\lambda, \lambda \geq 0\right\} \tag{6}$$

where λ represents weight. Based on this, the equation of the SBM model, including the non-desired outputs, is:

$$\min\rho = \frac{1 - \frac{1}{t}\sum_{i=1}^{t}\frac{S_i^-}{x_{i0}}}{1 + \frac{1}{c_1 + c_2}\left(\sum_{r=1}^{c1}\frac{S_r^g}{y_{r0}^g} + \sum_{r=1}^{c2}\frac{S_r^b}{y_{r0}^b}\right)} \tag{7}$$

$$\text{s.t.}\begin{cases} x_0 = X\lambda + S^- \\ y_0^g = Y^g\lambda - S^g \\ y_0^b = Y^b\lambda + S^b \\ \lambda \geq 0, S^- \geq 0 \\ S^g \geq 0, S^b \geq 0 \end{cases} \tag{8}$$

where t, c_1, and c_2 are the quantities of input, desired output, and non-desired output in the DMU, and S^-, S^g, and S^b are the slack variables of input, desired output, and non-desired output, respectively. If ρ = 1, $S^- = 0$, $S^g = 0$, $S^b = 0$, the DMU is effective; if ρ < 1, it is non-effective.

In the efficiency measurement, the use of the basic SBM model that deals with non-desired output often encounters many decision units with 1, which affects the comparison and ranking among decisions if some value all equal to 1. Therefore, Tone [57] found the super-efficiency SBM model, which has the advantage that the efficiency values are not limited by the [0, 1] interval and can be well-evaluated for those efficiency units.

Suppose there are n DMUs, each DMU has t inputs, c_1 is the desired outputs, c_2 is the non-desired outputs and X, Y^g, and Y^b are the matrices of inputs, desired outputs, and non-desired outputs, respectively. Then, the specific formula is as follows:

$$\rho = \min \frac{\frac{1}{t}\sum_{i=1}^{t}\frac{\overline{x_i}}{x_{i0}}}{\frac{1}{c_1+c_2}\left(\sum_{r=1}^{c1}\frac{\overline{y^g}}{y_0^g} + \sum_{r=1}^{c2}\frac{\overline{y^b}}{y_0^b}\right)} \tag{9}$$

$$\begin{cases} \overline{x} \geq \sum\limits_{j=1, j\neq 0}^{n} x_{ij}\lambda_j \\ \overline{y^g} \leq \sum\limits_{j=1, j\neq 0}^{n} y_j^g\lambda_j \\ \overline{y^b} \geq \sum\limits_{j=1, j\neq 0}^{n} y_j^b\lambda_j \\ \overline{x} \geq x_{ij}, \overline{y^g} \leq y_j^g, \overline{y^b} \geq y_j^b, \overline{y^g} \geq 0, \lambda \geq 0 \end{cases} \tag{10}$$

where $\overline{x}$, $\overline{y^g}$, and $\overline{y^b}$ are the average values; λ is the non-negative weight vector assigned to the inputs and outputs; x_{ij}, y_j^g, and y_j^b are the i-th input, g-th desired output, and b-th non-desired output of DMUj; ρ represents the DMU efficiency value, which can exceed 1.

3.1.2. Indicator Selection

(1) Input indicators

Labor input. The hourly wage can represent labor input, which can visually reflect the value created by the labor force in a certain period of time; however, considering the availability of data, this paper uses the sum of the number of units, private and self-employed workers, at the end of the year in each region to represent the labor input indicator.

Capital input. The capital input indicator is selected from the year-end physical capital stock and is estimated using the perpetual inventory method. The calculation formula is:

$$K_{it} = K_{it}(1 - \delta_{it}) + I_{it} \tag{11}$$

where K_{it} represents the fixed capital stock, I_{it} represents the fixed asset investment completion, and δ_{it} represents the depreciation rate, which is taken as 10.96%.

Energy input. Energy is both necessary for product development and a source of environmental pollution. Due to the variety of energy sources, this paper will use a "million tons of standard coal" as the unit of measurement and use the total energy consumption to represent the energy input index.

(2) Output indicators

Expected output. In this paper, the real regional gross product is taken as the expected output indicator of the economy.

Non-desired output. Industrial wastewater emissions, SO_2 emissions from industrial waste gas, and industrial solid waste are selected as non-desired output indicators, and the time period is cut off from 2009 to 2021, with 2009 as the base period. The monetized data are adjusted to make them comparable. The indicator system is selected, as demonstrated in Table 1 below.

Table 1. Indicator system.

Indicators	Indicator Composition	Indicator Measurement
Input Indicators	Capital Inputs	Physical capital stock (billion yuan)
	Labor input	Number of employees (million people)
	Energy Inputs	Energy consumption (million tons of standard coal)
Output Indicators	Desired output	Real GDP (billion yuan)
	Non-desired output	Industrial wastewater emissions (million tons)
		Industrial sulfur dioxide emissions (million tons)
		Industrial smoke and dust emissions (million tons)

3.2. Regression Analysis Methods

3.2.1. Tobit Model

The efficiency value, calculated by the data envelopment model, is discrete, and its value distribution is between 0–2. In general, when conducting coefficient regression analysis, the commonly used method is the ordinary least squares method. However, when regress parameters with discrete values of dependent variables are used, this method may lead to biased and inconsistent parameter estimates [58]. In order to prevent this situation, Tobin [59] proposed a truncated regression model using the maximum likelihood method instead of the ordinary least squares method in 1958, referred to as the Tobit model. The main characteristics of this model are as follows: (1) The values of dependent variables are truncated, not continuous; that is, they are observed in a limited manner. (2) Theoretically, the maximum likelihood method is also a coefficient regression method used to estimate the regression parameters in a model, and currently, many economists have used this model to analyze certain problems. Therefore, theory and practice have proven that using the Tobit model to replace the ordinary least squares method for regression analysis is indeed feasible; that is, the Tobit model has strong predictability and feasibility. Therefore, Stata 15.1 software was used to analyze the factors affecting GEE using the Tobit model. Due to the large time span of the sample, the two-way fixed-effects of both region and year were controlled in the study to avoid the effect of omitted variables. The Tobit model is shown below:

$$y_i^* = \beta x_i + \mu_i, \mu_i \sim N\left(0, \sigma^2\right) \tag{12}$$

$$y_i = \begin{cases} y_i^*, y_i^* > 0 \\ 0, y_i^* \le 0 \end{cases} \tag{13}$$

where x_i denotes the explanatory variable, y_i^* denotes the explained variable, β denotes the regression parameter, and μ_i denotes the random disturbance term.

3.2.2. Variable Selection

(1) Explained variables

GEE: The values of GEE, in this paper, come from the measurement results of the resource super-efficiency SBM.

(2) Core explanatory variables

Financial agglomeration (FA): The location entropy index is used as an indicator to evaluate the degree of financial agglomeration. When FA > 1, it means that financial agglomeration is high; when FA < 1, it means the phenomenon of financial agglomeration is lower.

$$\text{FA} = \frac{F_j/G_j}{F/G} \tag{14}$$

F_j denotes the value added of the financial sector in regions j; G_j denotes the regional GDP in regions j; F denotes the value added of the financial sector nationwide; G denotes the national GDP.

Environmental regulation (ER). In the study, based on research from Han and Liao [60], we selected industrial wastewater, sulfur dioxide, and smoke (dust) emissions to obtain the comprehensive index.

First, the pollutant emission data of each region are standardized as follows:

$$UE_{ij}^{s} = \frac{UE_{ij} - min(UE_j)}{max(UE_j) - min(UE_j)} \tag{15}$$

where UE_{ij}^{s} denotes pollutant standardized value j in region i. UE_{ij} is the pollutant emission j in region i, and UE_j denotes the values of each pollutant. Secondly, because of the large gap among the three pollutants, the adjustment factor W_j is added in this paper, and its calculation formula is as follows:

$$W_j = \frac{UE_{ij}}{\overline{UE_{ij}}} \tag{16}$$

where $\overline{UE_{ij}}$ is the average of the j pollutant emissions in the regions during the sample period. Finally, the environmental regulation intensity is calculated.

$$ER_i = \frac{1}{3}\sum_{j=1}^{3} W_j UE_{ij}^{s} \tag{17}$$

(3) Control variables

Industrial Structure. The industrial structure refers to the share of the primary, secondary, and tertiary sectors in a country's economic structure. The industrial structure impact on GEE is through a change in the share of each industry to change the flow and consumption structure of energy, which in turn affects the consumption demand of different energy sources. At the same time, different types of energy have different conversion rates, making the inputs and outputs different. Therefore, changes in industry structure directly affect GEE. Usually, the secondary industry is a relatively energy-intensive and inefficient industry, and the change in its share in the national economy will directly change the energy consumption structure. The proportion of the relatively low energy-consuming and efficient tertiary industry increases, and the proportion of the high energy-consuming and inefficient secondary industry decreases. Therefore, in this paper, we use the ratio of secondary industry to GDP to represent the industrial structure.

Economic development level. Differences in the strength of regional economic development affect the development trend of regional GEE, and this paper uses the real GDP per capita to measure this. Its value is obtained by deflating the GDP per capita index of each region, using 2009 as the base period, which better reflects the actual level of economic development.

Degree of Government Intervention. The increase in the proportion of fiscal expenditures in science and technology and education can, to a certain extent, significantly promote talent quality levels, further optimizing the development mode of regions and thus improving GEE. However, when the government's administrative expenditures favor administrative management, the redundancy consumption is larger, which, in turn, will hinder the improvement in GEE in the regions. In this paper, we chose (total fiscal expenditure—science and technology education expenditure)/regional GDP for the measurement.

Urbanization. On the one hand, cities and towns are important carriers of modernization, and regions with high urbanization levels tend to have more complete industrial structures, which are convenient for optimizing resource allocation and improving economic efficiency. On the other hand, cities are densely populated and have concentrated pollution emissions, and the rapid expansion of the urban population will aggravate resource scarcity and environmental pollution, which may have a negative impact on green economic development. The proportion of the urban resident population to the total population is used to measure urbanization. The specific variable selection is shown in Table 2 below:

Table 2. Variable selection.

Variable	Symbol	Meaning	Data Sources
Green economic efficiency	GEE	Results of super-efficiency SBM measurement	China Statistical Yearbook China Energy Statistics Yearbook China Industrial Statistical Yearbook
Financial agglomeration	FA	Using the location entropy index as an indicator to evaluate the degree of financial agglomeration	China Statistical Yearbook
Environmental regulation	ER	Comprehensive index of environmental regulation intensity	China Statistical Yearbook
Industrial structure	IS	Ratio of secondary industry output value to regional GDP	China Statistical Yearbook
Economic development level	PGDP	Real per capita GDP	China Statistical Yearbook
Degree of Government Intervention	GOV	(Total financial expenditure—science and technology education expenditure)/regional GDP	China Statistical Yearbook
Urbanization	UR	Proportion of permanent urban residents in the total population	China Statistical Yearbook

Based on the above variable selection, the Tobit model is set as below:

$$GEE_{it} = \alpha_0 + \alpha_1 FA_{it} + \alpha_2 ER_{it} + \alpha_3 IS_{it} + \alpha_4 PGDP_{it} + \alpha_5 GOV_{it} + \alpha_6 UR_{it} + \mu_i + \varepsilon_{it} \quad (18)$$

where i denotes the 30 regions, and t is the year. GEE_{it} denotes the GEE of regions i in year t, calculated by the DEA model in the previous section. FA_{it}, ER_{it}, IS_{it}, $PGDP_{it}$, GOV_{it}, and UR_{it} represents financial agglomeration, environmental regulation, industrial structure, economic development level, government intervention, and urbanization, respectively; ε is a random perturbation term.

4. Results

4.1. GEE Measurement Results

According to the GEE measurement method and the evaluation index system constructed above, the work measures the GEE level of 30 regions from 2009 to 2021, and the results are demonstrated in Table 3.

Table 3. GEE measurement results.

	Region	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**Mean**
Eastern	Beijing	0.859	0.903	0.953	0.995	1.136	1.131	1.212	1.287	1.319	1.346	1.424	1.546	1.553	1.205
	Tianjin	0.538	0.545	0.578	0.538	0.505	0.628	0.657	0.717	0.743	0.856	0.961	1.018	1.112	0.723
	Hebei	0.426	0.531	0.542	0.522	0.538	0.512	0.619	0.634	0.713	0.724	0.735	0.818	0.927	0.634
	Liaoning	0.437	0.548	0.503	0.433	0.448	0.603	0.678	0.685	0.691	0.708	0.719	0.732	0.821	0.616
	Shanghai	0.776	0.798	0.845	0.901	0.977	1.116	1.245	1.264	1.283	1.226	1.336	1.418	1.456	1.126
	Jiangsu	0.757	0.768	0.795	0.851	0.848	0.835	0.893	0.921	1.089	1.143	1.286	1.328	1.388	0.992
	Zhejiang	0.797	0.805	0.896	0.895	0.805	0.916	0.929	0.938	1.041	1.159	1.265	1.325	1.361	1.010
	Fujian	0.626	0.647	0.722	0.779	0.747	0.722	0.845	0.881	0.912	0.961	0.985	1.011	1.112	0.842
	Shandong	0.481	0.496	0.532	0.587	0.576	0.592	0.623	0.635	0.743	0.857	0.972	1.014	1.139	0.711
	Guangdong	0.968	0.984	0.996	0.968	0.924	0.926	0.935	1.041	1.089	1.112	1.226	1.352	1.417	1.072
	Hainan	0.468	0.485	0.528	0.568	0.555	0.628	0.657	0.657	0.683	0.716	0.841	0.868	0.932	0.660
Eastern mean		0.648	0.683	0.717	0.731	0.733	0.783	0.845	0.878	0.937	0.983	1.068	1.130	1.202	0.872
Central	Shanxi	0.357	0.396	0.449	0.477	0.424	0.427	0.562	0.593	0.629	0.665	0.771	0.812	0.824	0.568
	Jilin	0.357	0.387	0.465	0.468	0.443	0.421	0.511	0.526	0.533	0.606	0.758	0.822	0.884	0.552
	Heilongjiang	0.353	0.383	0.441	0.483	0.448	0.405	0.525	0.526	0.536	0.643	0.733	0.741	0.772	0.538
	Anhui	0.397	0.427	0.485	0.397	0.362	0.328	0.423	0.551	0.673	0.732	0.864	0.911	0.958	0.578
	Jiangxi	0.355	0.385	0.443	0.495	0.437	0.422	0.546	0.552	0.574	0.631	0.738	0.855	0.891	0.563
	Henan	0.361	0.391	0.438	0.471	0.441	0.433	0.548	0.567	0.659	0.764	0.806	0.928	0.959	0.597
	Hubei	0.352	0.388	0.443	0.482	0.448	0.423	0.534	0.541	0.548	0.632	0.762	0.816	0.973	0.565
	Hunan	0.353	0.393	0.446	0.393	0.347	0.438	0.554	0.577	0.615	0.622	0.734	0.803	0.925	0.554
Central mean		0.361	0.394	0.451	0.458	0.419	0.412	0.525	0.554	0.596	0.662	0.771	0.836	0.898	0.564
Western	Neimenggu	0.249	0.259	0.251	0.249	0.263	0.221	0.236	0.343	0.357	0.362	0.467	0.564	0.627	0.342
	Guangxi	0.248	0.253	0.267	0.258	0.223	0.221	0.335	0.353	0.342	0.359	0.372	0.481	0.583	0.330
	Chongqing	0.247	0.267	0.271	0.347	0.341	0.328	0.412	0.437	0.559	0.593	0.622	0.648	0.752	0.448
	Sichuan	0.373	0.388	0.392	0.363	0.345	0.336	0.484	0.493	0.595	0.603	0.711	0.716	0.518	0.486
	Guizhou	0.189	0.199	0.162	0.259	0.246	0.237	0.233	0.236	0.238	0.242	0.244	0.258	0.361	0.239
	Yunnan	0.377	0.397	0.381	0.372	0.366	0.353	0.355	0.365	0.372	0.326	0.431	0.555	0.662	0.409
	Shanxi	0.187	0.193	0.268	0.253	0.243	0.229	0.254	0.282	0.315	0.413	0.522	0.637	0.742	0.349
	Gansu	0.279	0.299	0.257	0.259	0.241	0.234	0.236	0.237	0.345	0.442	0.548	0.465	0.559	0.339
	Qinghai	0.217	0.218	0.226	0.231	0.228	0.216	0.228	0.239	0.242	0.252	0.261	0.272	0.388	0.248
	Ningxia	0.153	0.153	0.168	0.253	0.243	0.329	0.354	0.382	0.415	0.513	0.622	0.637	0.642	0.374
	Xinjiang	0.183	0.193	0.181	0.186	0.176	0.169	0.214	0.282	0.315	0.352	0.412	0.527	0.632	0.294
Western mean		0.246	0.256	0.257	0.275	0.265	0.261	0.304	0.332	0.372	0.405	0.474	0.524	0.588	0.351
National mean		0.418	0.444	0.475	0.488	0.472	0.485	0.558	0.588	0.635	0.683	0.771	0.830	0.896	0.596

From the time dimension, from 2009 to 2021, China's GEE level, in general, shows a fluctuating upward trend, growing from 0.418 in 2009 to 0.896 in 2021. From the sub-regional dimension, there are significant differences in the GEE levels between the whole country and the east, central, and western regions; however, the trend of the GEE changes in the east, central, and western regions is more consistent with the national change trend, and the GEE values in the east, central, and western regions all show an upward trend, and the upward trend is faster after 2018.

From the spatial dimension, the GEE average value in China is 0.596 at a low level and is highest in the east and lowest in the west. This is related to the economic foundation of each region and the national economic development strategy. China's development started with the priority development of the eastern coastal region, which accumulated strong economic development strength for the eastern region and made it gradually become the main contributor to the national GEE. The central part is the second, and the western part is the lowest, while the GEE of western regions, such as Guizhou, Qinghai, and Xinjiang, is lower than 0.3.

4.2. Empirical Analysis

4.2.1. Multicollinearity Test

If there is multicollinearity, it may lead to an unreasonable estimation of the coefficients of the variables, a failure of the *t*-test of the regression coefficients of individual variables, a failure to clearly distinguish the effect of individual explanatory variables on the explained variables, and bring errors to the empirical results. Therefore, it is necessary to use the VIF (variance inflation factor) test to determine whether there is multicollinearity among the variables. From Table 4, we can see that the VIF values of the variance inflation factor of all variables are at a low level, with a maximum VIF value of 3.27 and a mean VIF of 2.505, which can be considered as no multicollinearity, and all variables can be analyzed using regression via the panel data model.

Table 4. Test results.

Variable	**FA**	**ER**	**IS**	**PGDP**	**GOV**	**UR**
VIF	2.44	3.27	1.77	2.56	3.22	1.77
Mean VIF			2.505			

4.2.2. Unit Root Test

This paper performs a unit root test before empirical analysis to verify whether the sample data are stationary. The tests are carried out using the usual LLC (Levin-Lin-Chu) and IPS (Im-Pesaran-Shin) for panel data, respectively. Table 5 shows that all variables are stationary in the horizontal condition.

Table 5. Unit root test results.

Variable	**LLC Test**	**IPS Test**	**Test Results**
FA	−34.567 ***	−4.993 ***	stationary
ER	−22.249 ***	−5.842 ***	stationary
IS	−9.774 ***	−2.364 ***	stationary
PGDP	−10.358 ***	−8.334 ***	stationary
GOV	−8.449 ***	−4.329 ***	stationary
UR	−9.228 ***	−5.971 ***	stationary

Note: *** means $p < 0.01$.

4.2.3. Model Selection

The panel data models can be generally classified into three types: mixed estimation model (ME), fixed-effects model (FE) and random-effects model (RE). In this study, the F-test and Hausman test are selected to verify the panel model's selection. Table 6 shows that the panel data should preferably be estimated by the fixed-effects model.

Table 6. Model selection results.

Test Method	*p* Value	Result
F-test	0.0002	Selecting a fixed-effects model
Hausman test	0.0000	Selecting a fixed-effects model

4.2.4. Regression Analysis Results

In this paper, a Tobit model was established with the help of the Eviews 8.0 software based on data related to the factors influencing the GEE in each region of China from 2009 to 2021. Regression analysis was conducted. Table 7 reports the results.

Table 7. Regression results.

Explanatory Variables	National	East	Central	West
FA	0.2314 ***	0.3316 ***	−0.1124 ***	0.0043 *
ER	−0.1453 ***	0.0983 ***	0.1256	−0.0563
IS	−0.1123 *	0.0943 *	−0.1678 ***	−0.2341 ***
PGDP	−0.087 ***	0.034 *	−0.067 ***	−0.1054 ***
GOV	−0.2341 ***	−0.1543 ***	−0.2149 ***	−0.2818 ***
UR	−0.1675 ***	0.1268 ***	−0.2238 **	−0.3568 **

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

At the national level, financial agglomeration can promote GEE, indicating that as the level of agglomeration increases, abundant financial resources bring higher-quality financial products and services. By allocating more capital to the energy conservation and environmental protection industry, the financing constraints for technological R&D activities are alleviated while enhancing the regional innovation capacity and environmental benefits, thus creating GEE enhancement.

From different regions, financial agglomeration can improve GEE in the eastern region, i.e., the eastern region can promote GEE in the long run because financial products can utilize capital market rules to efficiently and accurately adjust capital flows, allocate more financial capital to the tertiary industry with low consumption, low pollution, and low resource dependence, thereby increasing the proportion of the tertiary industry in the national economy, and optimizing China's economic structure. Thus, the "three high" polluting industries are relocated to the outside world so that the industry clusters tend to be highly energy efficient and reasonably laid out, making the GEE significantly improved. Secondly, with the continuous improvement and upgrading of financial markets and institutions in the eastern region, the financial system tends to develop with high quality, and the selection of bank loans and capital market financing targets are more resource-saving and green. Additionally, the green investment system provides a strong boost to the upgrading of sewage equipment and green technology innovation of the "three high" enterprises, which makes GEE increase continuously. The central and western regions show significant differences. One possible explanation for the significant difference is that the central and eastern regions are close to each other, and the eastern region has a large amount of financial resources, resulting in a "siphon effect", thus leading to a lack of financial resources in the central region and inhibits GEE. In the western region, under the "Western Development Strategy", China attaches great importance to its economic development, thus leading to the continuous financial agglomeration in the western region. However, from the estimation results of the western region, the financial agglomeration on the GEE of western regions shows the promotion effect; however, the significance level is not high, and the elasticity coefficient is small, which means that the improvement in GEE is a slow process. Although its financial development is improving, the promotion function on the GEE of regions has not been fully developed.

Based on Table 7, the coefficient of the impact of environmental regulations on green economic efficiency at the national level is −0.1453, which means for every 1 unit increase in environmental regulation, GEE decreases by an average of 0.1453. This indicates that environmental regulation is not conducive to China's GEE improvement, which is in line with Lei [61], who points out that the current implementation of environmental regulations in China has increased the "environmental compliance costs" of enterprises, limiting their green economic efficiency. Lanoie et al. [62] also verified the same conclusion. This may be due to the fact that environmental regulations are not in line with the development rules of enterprises and do not promote regional GEE, and the production costs of enterprises are limited in the short term. In the long run, even if environmental regulations play a certain degree of "innovation compensation effect", they cannot compensate for the environmental investment of enterprises or reduce the cost and expense of enterprises, which further leads to a reduction in the enterprises' incentives to innovate, thus entering into a vicious circle. As a result, green technology innovation stagnates and inhibits the improvement in enterprises' GEE.

From the comparison of coefficients, the influence in the eastern region is large. From a significance level, only the eastern region can improve GEE, indicating that the environmental regulation policies in this region have achieved the expected effect, while the results in the other two regions are not significant, indicating that the environmental regulation policies do not work in these two regions. Environmental regulation, implemented in the central part of the country, has a promoting effect but is not significant, which may be explained by the fact that the central part of the country has a certain economic base. Therefore, increased investment in capital operations will lead to a more obvious effect—the western part of the country may lack the environment or construction facilities for capital operations; therefore, the environmental regulation effect on GEE improvement is slower compared to the central part of the country. Although the implementation of the western strategy brings great opportunities for the development of the western part of the country, the western government has pursued economic growth to such a degree that it does not discriminate between internal and external industrial undertakings, thus sacrificing ecology and repeating a large number of construction projects for political achievements, where the environmental regulation impact on GEE is not obvious.

Based on Table 7, the industrial structure inhibits GEE, and for every 1 percentage point increase in industrial structure, GEE decreases by 0.1123 percentage points. This is mainly because of the fact that China's secondary industry still dominates, and its green contribution to economic growth is still low. Regarding the different regions, the industrial structure promotes GEE in the eastern region, indicating that the tertiary industry in the eastern region is more developed, which is conducive to improving GEE. In contrast, the central and western regions are mainly resource-based industries, and the development of the tertiary industry is still far from being achieved in the eastern region because of the large gap of tertiary industry development, thus inhibiting the improvement in GEE.

The negative impact of the GDP per capita on national GEE is mainly due to the fact that the economic growth of many regions in China still relies on traditional growth models. In the traditional growth models, the waste of resources is caused by extensive growth patterns, which are the efficiency of economic growth and the environmental pollution caused by the one-sided pursuit of GDP growth while ignoring environmental protection. This is the environmental problem of economic growth. The GDP per capita inhibits the GEE of the central and western regions, probably because the transformation of the old and new dynamics has not yet been completed, and the traditional high-consumption production method still exists in society. The GDP per capita can improve the GEE of the eastern regions, probably because the eastern region has advanced technology. The core pursuit of technology innovation is to achieve green development, focusing on providing new products, processes, services, and market solutions through innovation, reducing natural resource consumption, reducing ecological and environmental damage, and improving resource allocation efficiency. This can provide dynamic support and implementation paths for China's high-quality economic development. Therefore, it is conducive to the synergistic effect of technology and thus promotes the GEE of the region.

The coefficient of government intervention is negative and significant, which indicates that the higher the government intervention, the more it will hinder GEE. This is because government intervention distorts the leading role of the market in resource allocation and leads to the misallocation of financial resources. It shows a significant negative correlation in different regions, which indicates that more government intervention will inhibit GEE, and the market should be fully utilized to allocate resources so as to improve GEE.

Urbanization is significantly negative nationally and in the central and western regions. The reason may be that the increase in urbanization and infrastructure levels often depends on traditional infrastructure industries, such as steel and cement and their related supporting industries, and most of these industries are high-emission industries. The negative externalities, based on environmental damage, will lead to a decrease in the GEE level, thus inhibiting GEE. Urbanization can improve GEE in the eastern region, with an increase of 0.1268 percentage points for each 1 percentage point increase in the urbanization level. This is mainly because of its developed economy, the people's pursuit of a better quality of life, the country's emphasis on improving quality of life and environmental protection awareness in the process of urbanization, and the increase in energy conservation, emission reduction, and ecological management, which is conducive to GEE. Therefore, the increase in the level of urbanization can effectively promote the improvement in GEE.

5. Conclusions and Implications

5.1. Conclusions

This paper first measures China's GEE and then studies the influence of financial agglomeration and environmental regulation on the GEE of different regions in China and draws the following conclusions.

(1) Examining the time dimension, from 2009 to 2021, the GEE average value in China is 0.596 at a low level. China's GEE level, in general, shows a fluctuating upward trend. There are significant differences, with the value being highest in the east, lowest in the west, and inefficient regions being mainly concentrated in the west.

(2) There is a significant promotion effect of financial agglomeration on GEE in the country and the eastern and western regions, meaning that with an increase in the agglomeration level, there is a homogeneous change in GEE. However, the significance level of the western region is very low, meaning that the promotion effect in the west is not obvious yet, and because of the "siphon effect" produced by the eastern financial resources agglomeration, many financial resources are concentrated in the east. Thus, the financial concentration in the central region is lower and inhibits GEE. Environmental regulation inhibits China's GEE significantly, and for every 1 unit increase in environmental regulation, GEE decreases by an average of 0.1453. Only the eastern region can improve GEE, while the results in the other two regions are not significant, indicating that the environmental regulation policies do not work in these two regions. Environmental regulations implemented in the central part of the country have a promoting effect but are not significant; however, they hinder the effect in the western region but are also not significant.

(3) Industrial structures hinder GEE nationally and in the central and western regions while promoting GEE in the eastern region, but the significance level is not high. The GDP per capita inhibits GEE in the national, central, and western regions, indicating that traditional high-consumption production methods still account for a large proportion, while the GDP per capita can improve GEE in the eastern region; government intervention inhibits GEE in all regions, and more government intervention is detrimental to improve GEE. Urbanization inhibits GEE, except in the eastern region.

5.2. Suggestions

(1) Strengthen the innovation of financial institutions, markets, products, systems and the other main elements. Build a systematic ecological environment of perfect systems, technologies, and talents, etc., and promote the breadth and depth of the financial resource concentration. Establish a good external ecological environment for financial concentration

and provide a more efficient financial support system for regional industrial structures. Regional central regions should focus on becoming regional financial centers. Regional financial agglomeration can promote GEE; therefore, all regions—especially the less developed regions—should focus on building regional financial centers and playing the role of financial services for the real economy.

(2) Create a multi-level financial network radiation system, break the administrative division boundaries, optimize the financial agglomeration and adaptation effects, and guide more financial resources for allocation in the green industry. Regional financial centers in provincial capitals need to be built, the scope of radiation needs to be expanded, and emphasis is required on the spatial spillover effect of financial agglomeration to form a linkage development with the surrounding satellite financial centers. At the same time, different regions will formulate differentiated policies according to the local conditions, and for developed coastal areas, financial resources will be directed to low-carbon industries to accelerate the upgrading of industrial structures. For the less developed regions on the mainland, a favorable business environment should be created through timely adjustments of fiscal and financial policies to enhance the interconnection of financial services in the region and avoid possible resource mismatches of financial institutions to traditional enterprises.

(3) Provide full play to urbanization, government intervention, industrial structures, and other factors to promote the growth of GEE. In accelerating and upgrading urbanization, the government should focus on energy consumption structures, the development of quality and efficiency for the tertiary industry sector and new energy consumption. The government should also reduce the level of government intervention and allow full play with the market allocation of resources to effectively enhance GEE.

(4) A continuous and stable investment in environmental regulation is an important guarantee for improving environmental quality. It is necessary to continue to increase the investment in human, material, and financial resources for environmental regulation, increase the proportion of investment in environmental pollution control to the regional GDP, and, while playing a leading role in public finance, actively expand the channels of fundraising, improve the investment structure, and actively explore other financing means, such as environmental funds and debt financing to increase the investment in environmental control. Additionally, pay attention to the reasonable allocation of resources to improve environmental control efficiency so as to effectively enhance GEE and realize green economic development.

5.3. Limitations and Prospects

(1) There are many factors that affect the efficiency of the green economy, but this article does not list too many. Based on the results of the previous research by scholars, some important factors have been selected for in-depth analysis, and there is still room for further exploration.

(2) There may be a spatial effect relationship between the variables. This article does not test the spatial effect of the variables. In future research, spatial econometric methods can be used to verify this, and more meaningful conclusions are expected.

(3) This article mainly studies the linear relationship between variables without studying the nonlinearity of variables, which is also a future research direction of this article.

Author Contributions: Conceptualization, R.W. (Rong Wang); methodology, R.W. (Ran Wang); formal analysis, R.W. (Ran Wang); investigation, R.W. (Ran Wang); resources, R.W. (Ran Wang); data curation, R.W. (Ran Wang); writing—original draft preparation(Rong Wang), R.W.; writing—review and editing, R.W. (Ran Wang); visualization, R.W. (Rong Wang); supervision, R.W. (Ran Wang); project administration, R.W. (Ran Wang). All authors have read and agreed to the published version of the manuscript.

Funding: The Jiangsu Department of Education University Philosophy and Social Science Fund Project (2022SJYB0601).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest: The authors declare no conflict of interest.

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