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Exploring the impact of green finance development on energy efficiency in China: Evidence from panel data and threshold modelling

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ABSTRACT

Energy efficiency is critical for green growth, which is conducive to economic transformation and meeting the challenges associated with climate change. This research employs provincial data from China covering 2010 to 2022 to analyze the progress of energy efficiency under the impact of green finance using Driscoll-Kraay standard errors, feasible generalized least squares, and panel threshold regression methods, and draws the following conclusions. Nationwide, energy efficiency has continued to improve, but there are regional imbalances. The performance of the eastern area is obviously superior compared to that of the middle and western areas, and the optimization effect is more significant. Both green credit and green bonds have an obvious positive association with energy efficiency. With the rise in economic development and R&D expenditure, the benefits of green credit and green bonds on energy efficiency have also increased, especially green bonds showing a stronger threshold effect. Additionally, there is regional heterogeneity between green credit and green bonds in boosting energy efficiency. Eastern provinces have higher impact coefficients, central provinces have moderate values, and western provinces have the lowest. Therefore, we recommend implementing targeted green financial policies, increasing the supply of green finance, and promoting technological innovation to enhance energy utilization.

Contribution/ Originality: This research enhances our understanding of how green finance affects energy efficiency in China and emphasizes the significance of green bonds in advancing green development. Moreover, it offers empirical evidence on the threshold effect and regional heterogeneity between green credit, green bonds, and energy efficiency, providing a reference for policymakers to implement targeted management strategies.

1. INTRODUCTION

The traditional economic growth model prioritizes industrial expansion but often neglects environmental sustainability (Sarkar, 2022). In the 21st century, China's economic development has achieved significant progress, but the characteristics of past economic development were extensive growth, mainly relying on energy consumption, especially long-term coal consumption (Iqbal, Tang, Chau, Irfan, & Mohsin, 2021). Additionally, China's current economic scale is huge, and energy demand is gradually increasing. It is not feasible to address issues of natural resource depletion and energy difficulties by focusing solely on reducing energy consumption. The Chinese government is also actively transforming the mode of economic growth, promoting energy reform, innovation, and efficient, energy-saving development. "Energy efficiency" is a commonly used term that has different definitions and measures. Bosseboeuf, Chateau, and Lapillonne (1997) defined it as the energy inputs in fixed-output production of goods and services. In particular, economic energy efficiency indicates achieving the same or higher levels of output with reduced or unchanged energy consumption (Jaffe & Stavins, 1994; Wang & Shao, 2023).

Energy efficiency is important for improving the quality of economic development. Improving energy efficiency is conducive to optimizing resource allocation, enhancing productivity, and helping to achieve goals related to energy saving and emission reduction (Jiakui, Abbas, Najam, Liu, & Abbas, 2023). Driven by the pressure to promote environmentally friendly and sustainable development, enhancing energy efficiency is a crucial strategy for addressing energy-related challenges (Zoppolato & Jiang, 2023). According to the data, during the period from 2014 to 2024, China's energy usage grew at a generally annual rate of 3.1%[1]. We compare the 2024 energy consumption data for the top six countries or regions and find that China is the largest energy consumer; it contributed 26.8% to global total energy consumption (see Figure 1). At the same time, China has improved its energy utilization efficiency by promoting energy reform, and the GDP generated per unit of energy consumption has been continuously increasing. However, its energy utilization efficiency performs below the level of European, U.S., and Japanese standards (see Figure 2).

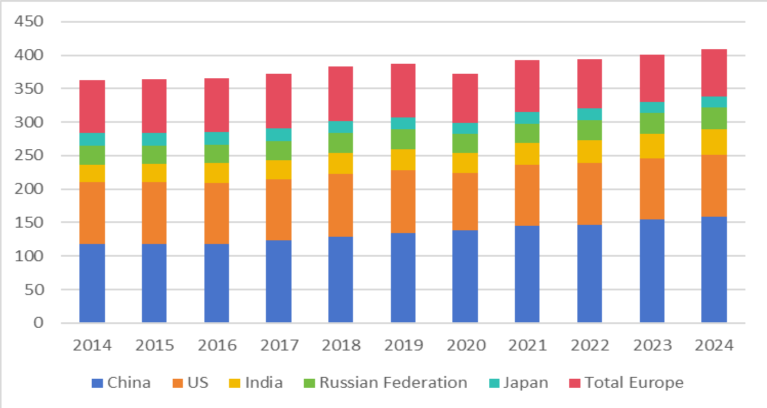

Figure 1. Energy consumption in major countries around the world.

Note: China's energy consumption data only includes the Chinese mainland.

Source: BP Statistical Review of World Energy 2025.

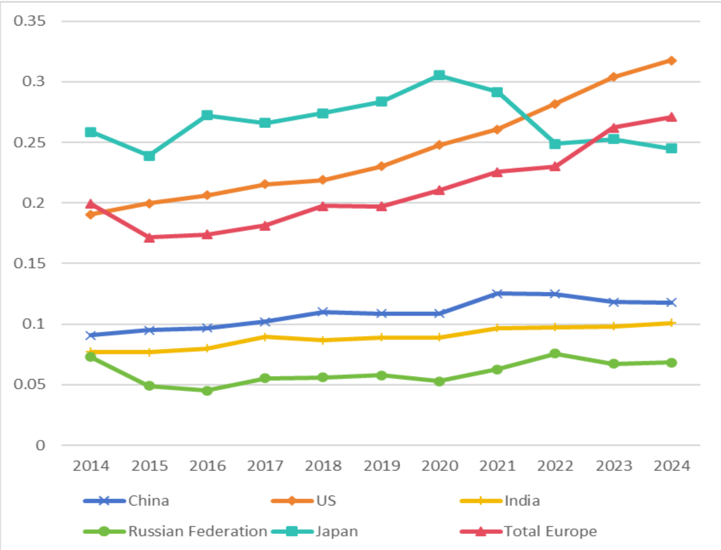

Figure 2. Energy efficiency in major countries around the world.

Note: Energy efficiency = GDP / Energy consumption.

Source: World Bank.

[1] Data source: BP Statistical Review of World Energy 2025.

Green finance offers a new approach to enhancing energy efficiency by optimizing financial tools, providing appropriate environmental funding, and developing green project financing solutions (Ahmed, Ahmad, Rjoub, Kalugina, & Hussain, 2022). In domestic and international practices, green finance includes green credit, green bonds, and other elements. Green finance promotes the distribution of financial and economic resources (Mohammad & Kaushal, 2018) focusing on using new financial instruments and policies to broaden financing channels for green development, guiding social funds to provide targeted financing (Sachs, Woo, Yoshino, & Taghizadeh-Hesary, 2019) and using funds for renewable energy investment and green technology improvement projects (Madaleno, Dogan, & Taskin, 2022). Additionally, the positive attributes of green finance are affected by many factors. Cai and Zhang (2024) found that economically developed regions can promote greater capital allocation for green development, which further supports the energy-saving benefit of green finance. Yu, Zhou, Cheok, Kubiczek, and Iqbal (2022) discovered that green finance improves the financing of green projects, especially increasing R&D expenditure and promoting technological advancement, and technological progress helps to boost energy utilization efficiency and production optimization. Currently, the Chinese government has strengthened its green financing policy framework to guide more financial resources to the green field.

So far, research has explored the effect of green finance on energy efficiency. Chien-Chiang Lee, Wang, He, Xing, and Wang (2023) pointed out that green finance has made significant contributions to improving energy efficiency. Chi-Chuan Lee and Lee (2022) highlighted that green finance helps to enhance green productivity. According to previous research, green finance has made significant contributions to advancing energy efficiency. However, there is little existing literature comparing the energy efficiency (EE) benefits of green credit (GC) and green bonds (GB), and the study on how economic development and R&D expenditure affect the effectiveness of green finance is also very limited. Therefore, this article will analyze and compare the effects of GC and GB on EE and explore whether there are threshold effects and regional heterogeneity.

This research deepens the understanding of GC and GB to promote EE from four aspects. First, the use of the kernel density assessment method offers the possibility of a more detailed and intuitive understanding of changes in EE. Second, the Driscoll-Kraay standard error and FGLS methods are used to reveal and compare the benefits of GC and GB (two key green development tools) for EE and provide policymakers with a detailed perspective. Third, the threshold regression estimation approach is used to reveal the nonlinear effect of GC and GB on EE and to verify the roles of economic development and R&D expenditure. Fourth, it explores the regional heterogeneous effects of GC and GB on EE to support targeted policy design. These discoveries offer a foundation for optimizing GC and GB policies to enhance EE in different areas.

2. LITERATURE REVIEW AND RESEARCH HYPOTHESES

2.1. Green Credit and Energy Efficiency

Green credit comes from the equatorial principle, sustainable finance, or environmental finance. Thompson and Cowton (2004) believe that green loans are derived from the equatorial principle and aim to promote sustainable development; Jeucken (2010) defines green credit as a sustainable form of finance, emphasizing the expansion of funding for green projects through bank loans to support sustainable development; and Zhang, Li, Qi, and Shao (2021) and Luo, Yu, and Zhou (2021) believe that green credit is a policy that promotes environmentally friendly development. Generally speaking, green credit is a credit distribution mechanism that focuses on environmental quality management, promoting the balanced development of economic benefits and environmental results through the development of environmentally friendly financial projects (Dong, Xue, Xiao, & Liu, 2021; Nobanee & Ellili, 2017). It aims to advance energy efficiency through the allocation of credit resources.

Bank loans are the primary external funding sources for Chinese businesses. Green credit controls the financing scale of energy-intensive industries, curbs the excessive expansion of enterprise production capacity, and encourages investment in environmentally friendly innovations and green projects, thus increasing energy utilization efficiency

(Wu, Wu, & Zhao, 2022). Additionally, green credit strategies can significantly promote green development and provide loans for renewable energy projects and environmental protection industries (Sharma & Choubey, 2022). A large number of studies have shown that green credit also contributes to technological progress, optimization of industrial structure, and improvement of energy utilization patterns, ultimately helping to enhance energy efficiency (Hu, Jiang, & Zhong, 2020). Therefore, the first hypothesis is

Hypothesis 1: Green credit is beneficial for improving energy efficiency.

2.2. Green Bonds and Energy Efficiency

Green bonds have emerged as an important channel to advancing energy efficiency (Linton, Clarke, & Tozer, 2021). Green bonds are a concept first proposed by the World Bank at the end of 2010, aiming to provide effective solutions to environmental pollution and climate change (Zhou & Cui, 2019). Similarly, the International Capital Market Association (ICMA) describes green bonds as providing financing or refinancing mainly for qualified green projects to support environmental sustainability. The green bond project covers many categories, such as efficient energy utilization, clean energy development, and environmental pollution prevention and control (Rasoulinezhad & Taghizadeh-Hesary, 2022). Further, green bonds have higher certification issuance requirements to regulate the use of funds from bond issuance (Alamgir & Cheng, 2023). This also encourages private investment funds to participate in sustainable projects (Azhgaliyeva, Kapoor, & Liu, 2020).

Many studies demonstrated that green bonds can help strengthen energy efficiency (Auffhammer, 2018; Liu, Saydaliev, Lan, Ali, & Anser, 2022; Nguyen, Naeem, Balli, Balli, & Vo, 2021). Tolliver, Keeley, and Managi (2020) noted that the issuance of green bonds can attract investors to participate in energy-saving projects. It helps satisfy the financing requirement of energy-saving transformation and clean energy development (Ning et al., 2023). Similarly, Polzin and Sanders (2020) believe that green bonds can encourage the growth of green energy and help to reduce the intensity of energy usage (Ye & Rasoulinezhad, 2023). However, Chang, Moldir, Zhang, and Nazar (2023) emphasized that green bond financing can improve energy efficiency, but there are differences between different countries. The government needs to analyze specific problems when formulating green bond financing measures. Hence, the second hypothesis is

Hypothesis 2: Green bond financing can effectively improve energy efficiency.

2.3. Green Finance, Economic Development and Energy Efficiency

Green finance can support the development of sustainable practices and foster energy efficiency (Ziolo, Bak, & Cheba, 2021). However, whether green finance can truly play a role depends largely on economic development. This is because the economic level affects the efficiency of capital allocation, as well as the ability of technological innovation, policymaking, and implementation, which together determine the effectiveness of green finance. Inefficient capital allocation will weaken the financing effectiveness of green projects (Gibon, Popescu, Hitaj, Petucco, & Benetto, 2020). And through environmental risk management policies, it is possible to effectively encourage companies to lower energy usage (Jiancheng Bai, Chen, Yan, & Zhang, 2022).

Numerous research papers have confirmed this theoretical perspective. Sultanuzzaman, Yahya, and Lee (2024) consider that green finance affects energy efficiency significantly differently across economic development stages. More developed regions typically have more sophisticated green finance oversight and management policies, which can regulate green fund use and significantly boost energy efficiency (Zeng & Zhang, 2024). Conversely, in underdeveloped economies, green bonds tend to be less effective due to insufficient financial systems (Hafner, Jones, Anger-Kraavi, & Pohl, 2020). Further, Wang and Wang (2022) discover that economic growth has a favorable influence. The more developed the economy in a city, the greater the beneficial influence of green finance on energy performance. The third hypothesis is

Hypothesis 3: Green finance initiatives and energy efficiency show a nonlinear relationship across different stages of economic development.

2.4. Green Finance, R&D Expenditure and Energy Efficiency

Green finance offers monetary support for sustainability technologies (Bhatnagar & Sharma, 2022) and uses green investment signals to drive the implementation of energy-efficient technologies in production (Agarwal, Bhadauria, Rajwanshi, & Bharti, 2024). However, to fully utilize the technological incentive and transformation functions of green finance, it is crucial to rely on the R&D expenditure of enterprises. According to the resource-based theory, enterprises and regions with high R&D expenditure can more effectively use green finance to transform technological achievements in energy consumption reduction (Barney, 1991). The diffusion of green innovative technologies or clean energy projects requires sufficient R&D expenditure. Low R&D expenditure will hinder the ability of green funds to be converted into energy efficiency improvements (Zhang & Fu, 2022).

Empirical research confirms the effect of R&D expenditure. Jafary, Ashani, and Afsharirad (2024) identified R&D expenditure as a threshold variable, revealing that financial development has a greater impact on encouraging energy efficiency in regions with high R&D expenditure. Irfan, Razzaq, Sharif, and Yang (2022) pointed out that R&D expenditure drives regional green technological innovation through green finance. Similarly, Chen, Huang, and Zheng (2019) demonstrated that financial development improves by lowering energy consumption intensity through driving innovation and advancing technology, with R&D expenditure being particularly important for technological progress. An appropriate green finance mechanism enhances energy efficiency by increasing R&D expenditure. The fourth hypothesis is stated below.

Hypothesis 4: Green finance promotes energy efficiency with a significant threshold effect across different R&D expenditure levels.

The relationship between variables and research hypotheses is shown in Figure 3.

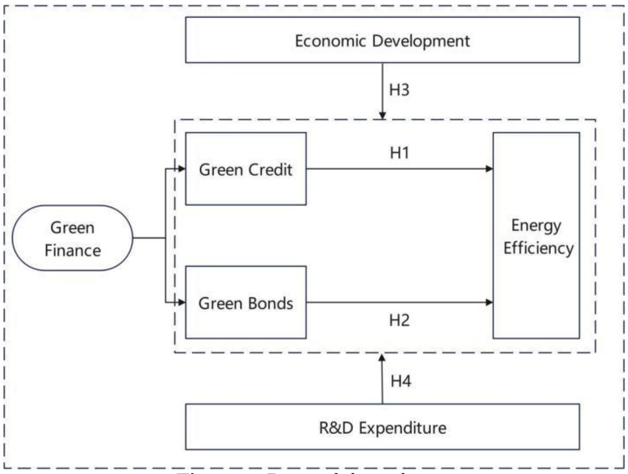

Figure 3. Research hypotheses.

3. METHODOLOGY AND DATA

3.1. Models

3.1.1. DK Standard Errors and FGLS Models

Considering the research hypothesis (H1 and H2), and according to the theory of resource allocation, green finance can expand the financing scale of energy-saving projects and technologies, providing financial support for improvements in energy efficiency (Chen, Sinha, Hu, & Shah, 2021). Therefore, we constructed an econometric model to evaluate the correlations between variables. The benchmark model is specified as follows.

Model 1: Green credit as the dependent variable.

$$EE_{it} = \alpha_0 + \beta_1 \ln GC_{it} + \beta_2 IND_{it} + \beta_3 ECS_{it} + \beta_4 FDI_{it} + \beta_5 TO_{it} + \mu_{it} \quad (1)$$

Model 2: Green bonds as the dependent variable.

$$EE_{it} = \alpha_0 + \gamma_1 \ln GB_{it} + \gamma_2 IND_{it} + \gamma_3 ECS_{it} + \gamma_4 FDI_{it} + \gamma_5 TO_{it} + \mu_{it} \quad (2)$$

In models 1 and 2, the subscripts i means the 30 provinces of China, and the subscripts t refers to the sample period of the research. α_0 stand for a constant term. Parameters $\beta_1, \cdots, \beta_5$ and $\gamma_1, \cdots, \gamma_5$ are the regression coefficients. The explained variable is energy efficiency (EE). The core explanatory variables are two indicators used to measure green finance, namely green credit (lnGC) and green bonds (lnGB). Furthermore, this paper also selects other influential factors as control variables, mainly including industrialization (IND), energy consumption structure (ECS), foreign direct investment (FDI), and trade openness (TO). And μ_{it} is the random error term.

3.1.2. Threshold Regression Models

The research hypothesis states that energy efficiency responds differently to green finance across levels of economic development and R&D expenditure (H3 and H4). Following the research methods of Wang, Zhu, and Yang (2020) and Jafary et al. (2024), we choose the Hansen (1999) panel threshold model to test the above hypotheses. This model is a classic method for panel data threshold estimation. The specific model is expressed as follows:

Model 3 Green credit as the dependent variable.

$$EE_{it} = \alpha_0 + \lambda_1 \ln GC_{it} \bullet I\,(Thr_{it} \le \eta_1) + \lambda_2 \ln GC_{it} \bullet I\,(\eta_1 < Thr_{it} \le \eta_2) + \lambda_3 \ln GC_{it} \bullet I\,(Thr_{it} > \eta_2) + \lambda_4 IND_{it} + \lambda_5 ECS_{it} + \lambda_6 FDI_{it} + \lambda_7 TO_{it} + \mu_{it} \quad (3)$$

Model 4 Green bonds as the dependent variable.

$$EE_{it} = \alpha_0 + \omega_1 \ln GB_{it} \bullet I\,(Thr_{it} \le \eta_1) + \omega_2 \ln GB_{it} \bullet I\,(\eta_1 < Thr_{it} \le \eta_2) + \omega_3 \ln GB_{it} \bullet I\,(Thr_{it} > \eta_2) + \omega_4 IND_{it} + \omega_5 ECS_{it} + \omega_6 FDI_{it} + \omega_7 TO_{it} + \mu_{it} \quad (4)$$

In model 3 and model 4, parameters $\lambda_1, \cdots, \lambda_7$ and $\omega_1, \cdots, \omega_7$ are the estimated coefficients. Thr_{it} is the threshold variable, including lnGDPP and lnRD, which represent economic development and R&D expenditure, respectively. Additionally, $I\,(\bullet)$ is the indicative function, and η_1, η_2 here is the threshold value.

3.2. Variables Explanation

3.2.1. Explained Variable

The explained variable is energy efficiency. It demonstrates the change between energy input and product output. This research calculates energy efficiency as GDP growth per unit of energy consumed, achieving maximum economic output with minimal energy use (Chien-Chiang Lee et al., 2023). The formula for calculation is

$$EE_{it} = \frac{GDP_{it}}{EC_{it}} \quad (5)$$

Where i and t respectively represent provinces and years ($i = 1, \cdots, 30; t = 1, \cdots, 13$). EE_{it} represents energy efficiency, GDP_{it} denotes economic output and EC_{it} refers to energy consumption.

3.2.2. Explanatory Variables

The measurement methods of green finance generally include two types: single variable and comprehensive indicators. However, both approaches have disadvantages. A single indicator cannot capture the effect of green financial tools on energy efficiency from multiple viewpoints; comprehensive indicators may affect the applicability and reliability of the empirical examination outcomes. Therefore, this article has selected the two most representative variables, green credit and green bonds.

- Green credit, represented by the credit amounts of environmental protection projects (taking the logarithm). China's financial system is primarily centered on banking institutions, where bank loans serve as the main method of external financing for companies. Among all green financial tools, green credit accounts for the largest proportion (Guo, Tan, & Xu, 2022; Song, Xie, & Shen, 2021).

- Green bonds are reflected by green bond issuances (taking the logarithm). The capital market is particularly critical in providing companies with R&D expenditure and green capital. In China, apart from loans, it is essential for enterprises to issue bonds in the capital market to obtain more financing, which encourages them to expand the scale of green investment (Chang et al., 2023; Rasoulinezhad & Taghizadeh-Hesary, 2022).

3.2.3. Threshold Variables

Threshold variables include economic development and R&D expenditure.

- Economic development, indicated by per capita GDP (taking the logarithm), has some influence on industry structure, the speed of technological progress, and the improvement of regulatory mechanisms; it also determines the allocation efficiency of financial resources (Cai & Zhang, 2024; Zhao, Zeng, Zhao, Zeng, & Jiang, 2024).
- R&D expenditure, indicated by research and development expenditures of large industrial enterprises (taking the logarithm). Green finance provides "green capital," but whether it can be truly transformed into efficient energy-saving equipment, clean technology, or low-carbon processes depends on whether the enterprise has sufficient R&D investment (Jafary et al., 2024; Yu, Wu, Zhang, Chen, & Zhao, 2021).

3.2.4. Control Variables

Referring to existing literature and in combination with this paper's research topic, the specific information of the main control variables is as follows.

- Industrialization, denoted by the share of secondary industry value added in GDP. Energy efficiency is closely related to the industrial sector, and the development of the industrialization level is accompanied by an increase in energy usage (Quang & Thao, 2022; Zhao et al., 2024).
- Energy consumption structure, defined as coal's weight in total energy consumption. Coal is classified as a low-grade fuel because of its inefficient energy conversion. Therefore, the energy consumption structure, primarily characterized by coal usage hinders energy efficiency (Cai & Zhang, 2024; Chi-Chuan Lee & Lee, 2022).
- Foreign direct investment, measured as the proportion of foreign investment in GDP. FDI can promote technology exchange, facilitate technology transfer and diffusion, and benefit technological innovation (Chien-Chiang Lee et al., 2023; Ye & Rasoulinezhad, 2023).
- Trade openness, evaluated by the proportion of imports and exports in GDP. Trade openness affects energy efficiency through trade product composition and technology absorption and transformation capacity (Tan et al., 2022; Zhao et al., 2020).

There are four main categories of data in this research. The first dataset focuses on energy efficiency performance. The data are obtained from the National Bureau of Statistics of China and the China Energy Statistical Yearbook. The second part is the green finance indicator; they are lnGC and lnGB. Data are derived from the CSMAR database. The third section of the research includes data on threshold variables and other variables. Most data are derived from the National Bureau of Statistics of China; only the data concerning energy consumption structure are sourced from the WIND database. Furthermore, due to the existence of measurement scale differences among the variables, to ensure analysis validity and stability, we applied a logarithmic transformation to green credit, green bonds, economic development, and R&D expenditure. The details are displayed in Table 1.

Table 1. Variables description.

Variables	Name of variables	Measurement	Time period	Expectation
Explained variable	Energy efficiency (EE)	GDP/Energy consumption	2010-2022	
Explanatory variables	Green credit (lnGC)	Environmental protection project credit (LN)	2010-2022	+
	Green bonds (lnGB)	Total green bond issuance (LN)	2010-2022	+
Threshold variables	Economic development (lnGDPP)	GDP per capita (LN)	2010-2022	
	R&D expenditure (lnRD)	Research and development expenditure (LN)	2010-2022	
Control variables	Industrialization level (IND)	Secondary industry value added/GDP	2010-2022	-
	Energy consumption structure (ECS)	Coal consumption/Energy cons umption	2010-2022	-
	Foreign direct investment (FDI)	Foreign direct investment inflo w/GDP	2010-2022	+
	Trade openness (TO)	Imports and exports/GDP	2010-2022	+/-

3.3. Estimation Methods

This research uses the kernel density estimation method to analyze the changes in energy efficiency in different regions of China. It is a non-parametric probability density function analysis method, which can construct a continuous smooth distribution curve through sample data (Węglarczyk, 2018). It is suitable for analyzing the development of energy efficiency in China and explaining the differences in energy efficiency across regions. In economic modeling, panel data often exhibits cross-sectional correlation, endogeneity, heteroscedasticity, and autocorrelation. Traditional regression analysis cannot address these issues, which affects the accuracy of results. Therefore, we use the Driscoll-Kraay standard error and FGLS method for empirical analysis (Jushan Bai, Choi, & Liao, 2021; Driscoll & Kraay, 1998). And choose the two-stage least squares (2SLS) method for the endogeneity test to verify the correctness of the results. This can effectively solve the problems of endogeneity, correlation, and heteroscedasticity common in economic models and guarantee the robustness of results with various model regressions. Additionally, this paper investigates the threshold effect, considering the roles of economic development and R&D expenditure. Hansen (1999) panel threshold model is well-suited for this objective. Threshold regression models adequately capture possible nonlinear associations among variables, and overlooking such relationships may result in biased regression estimates (Wang et al., 2020). The kernel density estimation method will be implemented using Matlab 2022b software, while the detailed regression analysis will be conducted with STATA 17.0 software.

4. EMPIRICAL ANALYSIS AND DISCUSSION

4.1. Descriptive Statistics

Table 2 reports the descriptive statistics for the variables included in the regression analysis model. In the research sample data set, the mean and standard deviation of EE are 1.737 and 0.885, ranging from a minimum of 0.48 to a maximum of 6.033, which suggests that the data has relatively low volatility, but there are some significant differences in certain values. The mean lnGC is 6.775, accompanied by a standard deviation of 1.145, with the highest value being 8.733 and the lowest being 3.61. lnGB showed a mean of 4.184 and a standard deviation of 1.146, and its value range is from 0.967 to 6.229. According to the data, fluctuations in green finance figures are quite significant. This indicates substantial regional disparities in green finance development in China, especially green bonds, where some areas lag severely. Additionally, lnGDPP, IND, ECS, and TO are relatively stable, while lnRD and FDI data are more dispersed, especially FDI. Due to its geographical location and policies related to free trade ports, Hainan Province has attracted considerable foreign investment in recent years, resulting in relatively high figures.

Table 2. Descriptive statistics.

Variables	Meaning	Obs.	Mean	Std. Dev.	Min.	Max.
EE	GDP / Energy consumption	390	1.737	0.885	0.48	6.033
lnGC	Environmental protection project credit (LN)	390	6.775	1.145	3.61	8.733
lnGB	Total green bond issuance (LN)	390	4.184	1.146	0.967	6.229
lnGDPP	GDP per capita (LN)	390	10.860	0.478	9.482	12.156
lnRD	Research and development expenditure (LN)	390	5.117	1.404	0.451	8.076
IND	Secondary industry value added / GDP	390	0.395	0.085	0.159	0.601
ECS	Coal consumption / Energy consumption	390	0.378	0.151	0.006	0.687
FDI	Foreign direct investment inflow / GDP	390	0.783	4.009	0.047	55.938
TO	Imports and exports / GDP	390	0.27	0.295	0.008	1.548

4.2. Distribution Characteristics of Energy Efficiency

This research has plotted the kernel density of regional EE in China between 2010 and 2022. Further details are illustrated in Figure 4. Figure 4 (1) displays the kernel density estimation of EE at the national level. It can be observed that the distribution density of the curve shifts from concentration to dispersion. In the early stages, the curve's peak was relatively high, and the EE levels of most provinces were mainly concentrated below 2. In the later stages, the curve's peak continued to decline, the distribution width became wider, and the value above 4 had a certain density, but the EE levels of some provinces were still concentrated around 2. This shows that as energy-saving policies and technologies advance, China's overall EE has gradually improved from low to high, but significant regional differences exist. The EE of most provinces has improved rapidly, while the EE of some provinces remains low.

Figure 4 (2) shows the kernel density estimated results of EE in the eastern region. Its distribution curve is relatively close to the national distribution curve. However, in the later stage, the distribution curve tends to be flat, and the EE values of more provinces are concentrated around 4. This indicates that the overall EE of eastern provinces is relatively high, the improvement speed is relatively fast, and regional differences are relatively small.

Figure 4 (3) presents the kernel density estimated results of EE in the central region. During the research period, the EE value showed an overall upward trend. However, compared with the eastern provinces, the EE of the central provinces is lower, and most of the values are concentrated below 3 and exhibit a clear peak. This indicates that EE in most provinces continues to improve and develop in a balanced way, although the overall efficiency remains low.

Figure 4 (4) reports the kernel density estimate of EE in the western region. The distribution curve is highly concentrated in the inefficient range and shows a tendency to expand to the right. Similar to the central provinces, the EE of the western provinces has also improved. However, the difference is that only a few western provinces have significantly improved in EE, while most provinces' EE remains below 2, and the energy level continues to be low.

Overall, EE in China has shown a continuous upward trend, but development is uneven. The eastern region leads in both EE performance and growth rate; the central region ranks second in EE, with EE values being relatively concentrated and little difference between provinces; the western region lags behind, with most provinces exhibiting low EE, limited development, and significant internal disparities. This is related to regional differences in economic development, industrialization, and resource endowment in China. The high economic level and advanced technology in the eastern region have promoted the rapid improvement of EE; the central region has a high degree of industrialization, mainly heavy industry, resulting in large energy consumption. Its technical level also lags behind that of the eastern region, resulting in poor EE; although some western provinces have rapidly improved EE due to economic development and technological progress, most provinces are still economically underdeveloped. The industrial structure is mainly agriculture, the technology is backward, and the utilization rate of agricultural waste is poor, resulting in resource waste and continuous low EE.

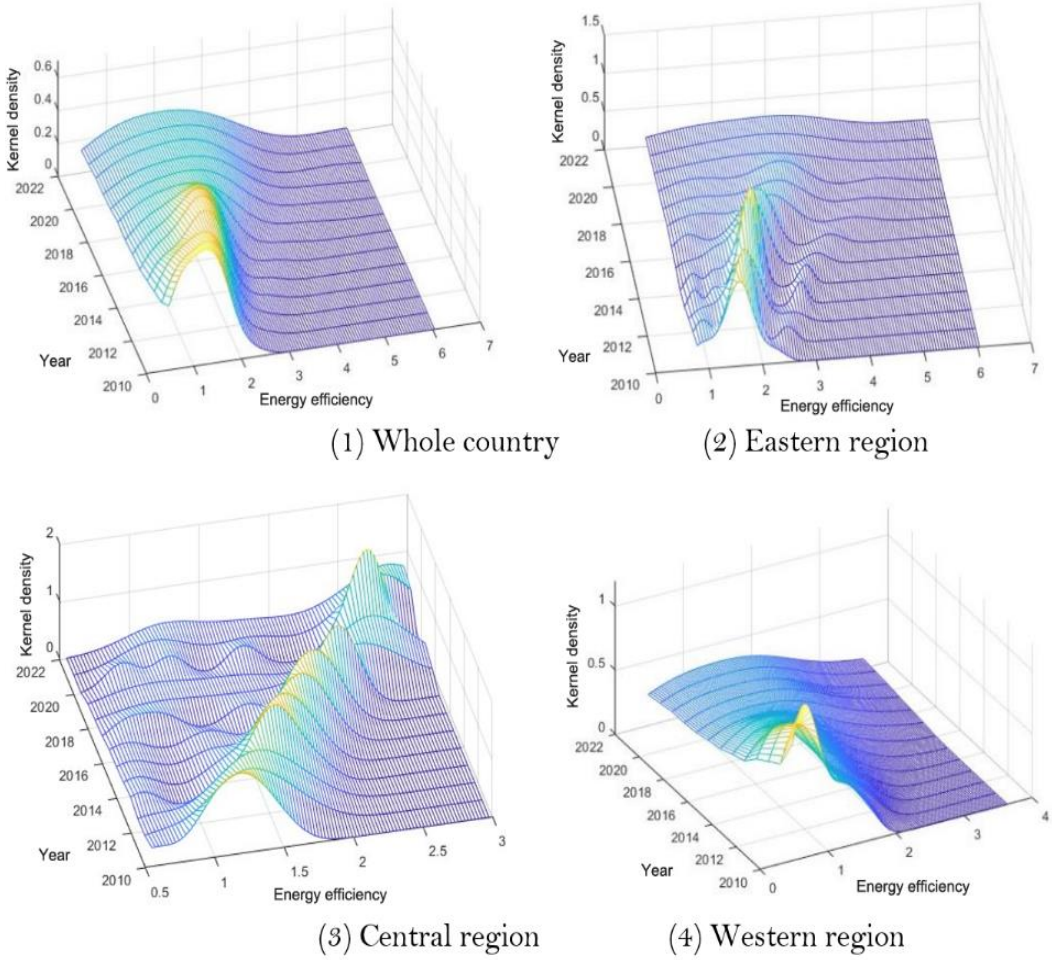

Figure 4. Kernel density estimation of energy efficiency.

4.3. DK Standard Errors and FGLS Regression Results

To guarantee the accuracy of the regression results and ensure a comprehensive evaluation, we conducted a systematic series of tests, including tests for multicollinearity, cross-sectional correlation, heteroskedasticity, and autocorrelation. Table 3 displays the multicollinearity test results. The VIF values for all variables were below 3.0, with an average VIF of 1.5, indicating no multicollinearity problem. Table 4 reports the findings of the cross-sectional correlation analysis. The test produced conflicting results; Frees' test and Pesaran's test both indicate the presence of cross-sectional dependence, whereas Friedman's test suggests its absence. Given this, to ensure accurate and robust regression results, we need to take the issue of cross-sectional correlation into account. Moreover, based on the results of heteroscedasticity and autocorrelation tests (Table 5), both models exhibit significant χ^2 statistics ($p<0.01$) and significant F-test statistics ($p < 0.01$). Therefore, heteroscedasticity and autocorrelation are concurrently observed in the models.

Table 3. Test results of multicollinearity.

Model 1			Model 2		
Variables	**VIF**	**1/VIF**	**Variable**	**VIF**	**1/VIF**
lnGC	1.26	0.795	lnGB	1.25	0.797
IND	1.32	0.755	IND	1.32	0.756
ECS	2.01	0.498	ECS	2.01	0.498
FDI	1.10	0.912	FDI	1.10	0.911
TO	1.83	0.547	TO	1.83	0.547
Mean VIF	1.50		Mean VIF	1.50	

Table 4. Test results of cross-sectional dependence.

	Frees' test			Friedman's test		Pesaran's test	
	Statistic	Critical values	P-value	Statistic	P-value	Statistic	P-value
Model 1	4.908	0.1984	0.10	30.242	0.4020	4.669	0.0000
		0.2620	0.05				
		0.3901	0.01				
Model 2	4.804	0.1984	0.10	29.938	0.4171	4.754	0.0000
		0.2620	0.05				
		0.3901	0.01				

Table 5. Test results of heteroskedasticity and autocorrelation.

Heteroskedasticity						Auto-correlation		
BP test			White's test			Wooldridge test		
	Model 1	Model 2		Model 1	Model 2		Model 1	Model 2
Chi2(1)	38.57	37.50	Chi2(20)	126.66	126.26	F(1,29)	69.382	68.556
P value	0.0000	0.0000	P value	0.0000	0.0000	P value	0.0000	0.0000

Given the cross-sectional correlation and issues of heteroscedasticity and autocorrelation, this research utilizes regression analysis incorporating Driscoll-Kraay standard errors and FGLS. We conducted Hausman tests, F-tests, and LM tests, and the results support the fixed effects (FE) specification; therefore, FE is primarily used to interpret the results. However, for comparison, Table 6 also presents the results from pooled OLS and FGLS estimations. In the empirical analysis, two models are estimated, with lnGC and lnGB as the main explanatory variables, respectively. The results obtained by all estimation methods are similar, indicating the stability of the empirical results.

The research results verify the important role of lnGC in improving EE. All lnGC estimation coefficients are significantly positive at the 1% level, indicating EE can be effectively improved through lnGC. Specifically, for every 1% increase in lnGC, EE increased by 0.381%, 0.333%, and 0.238%, respectively. Research hypothesis 1 of this article has been verified. These results are similar to the observations made by Yu et al. (2021) on developing and developed economies and Zhao, Zeng, Ke, and Jiang (2023) on China. The beneficial influence of lnGC on EE highlights the importance of expanding financing for environmental projects. By supporting advances in energy-efficient technologies and the deployment of clean energy, lnGC helps to optimize the scale and structure of EE. Under the condition that the bank's credit limit is fixed, increasing capital investment in green development will correspondingly reduce support for high energy consumption and traditional energy projects, thus improving EE.

Similarly, lnGB is also a key financial instrument to improve EE, the estimation coefficient of lnGB is always positive. In different regression methods, its values are 0.387, 0.332, and 0.233, respectively, and $p<0.01$ for all estimates. Therefore, we can conclude that lnGB is significantly positively correlated with EE. Hypothesis 2 of this study is empirically supported. This conclusion is consistent with the viewpoints of Rasoulinezhad and Taghizadeh-Hesary (2022) and Devine and McCollum (2022). lnGB has a beneficial impact on EE, further confirming the importance and effectiveness of green finance in enhancing technological innovation and clean energy development. The transparency and evaluation mechanism of lnGB also reinforce its advantages in improving EE. Sample data and research show that although the financing scale of lnGB is smaller than that of lnGC in China, its impact on improving EE is comparable or even greater, which highlights the important contribution of lnGB to promoting energy conservation.

The analysis also found that the expansion of IND significantly reduced EE, with coefficients of -2.884, -2.837, -1.304, and -0.989, respectively, and all passed the significance test. This indicates that IND is a major obstacle to improving EE because it is associated with higher energy consumption, especially in heavy industry. Furthermore, there is a significant negative correlation between ECS and EE, suggesting that traditional fossil fuels, particularly coal consumption, exert considerable pressure on China's energy conservation efforts, leading to a decline in energy efficiency. This underscores the importance of promoting and adopting renewable energy. However, the FDI coefficients are positive and statistically significant, demonstrating that FDI inflow into China positively impacts EE improvement.

Table 6. Regression results with DK standard errors and FGLS.

Variables	(1) Fixed Effects	(2) Pool OLS	(3) Fixed Effects	(4) Pool OLS	(5) FGLS	(6) FGLS
lnGC	0.381*** (0.0598)	0.333*** (0.0232)			0.238*** (0.027)	
lnGB			0.387*** (0.0465)	0.332*** (0.0247)		0.233*** (0.027)
IND	-2.884*** (0.413)	-0.130 (0.276)	-2.837*** (0.433)	-0.110 (0.272)	-1.304*** (0.174)	-0.989*** (0.203)
ECS	-2.571*** (0.319)	-2.653*** (0.271)	-2.597*** (0.285)	-2.667*** (0.267)	-1.791*** (0.139)	-1.675*** (0.153)
FDI	0.00852*** (0.00154)	0.00894** (0.00436)	0.00868*** (0.00152)	0.00899** (0.00425)	0.009*** (0.001)	0.010*** (0.001)
TO	-1.710*** (0.266)	0.163 (0.233)	-1.703*** (0.265)	0.161 (0.229)	-0.143** (0.055)	-0.122 (0.079)
Constant	1.724*** (0.492)	0.486*** (0.0693)	2.671*** (0.329)	1.348*** (0.117)	1.116*** (0.150)	1.668*** (0.097)
Observations	390	390	390	390	390	390
F test	0.0000	0.0000	0.0000	0.0000		
LM test	0.0000	0.0000	0.0000	0.0000		
Hausman test	0.0000	0.0000	0.0000	0.0000		
R-squared	0.7635	0.5943	0.7668	0.5941		

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05.

4.4. Endogeneity Test

Considering the potential endogeneity problem, this research utilizes 2SLS regression analysis, with the lagged values of lnGC and lnGB (L.lnGC and L.lnGB) as instrumental variables. The analysis results are reported in Table 7. The F-statistics are 273.09 and 156.91 (both greater than 10), indicating a statistical correlation between the endogenous and instrumental variables and confirming the instrument's strong explanatory power. Meanwhile, the 2SLS regression results demonstrate that lnGC and lnGB are both significantly positively correlated with EE ($p < 0.01$), with coefficients of 0.954 and 1.030, respectively.

This suggests that endogeneity issues are effectively controlled, and the regression results with DK standard errors and FGLS exhibit high robustness.

Table 7. Endogeneity test results.

Variables	Two-Stage Least Squares			
	(1)	(2)	(3)	(4)
	PhaseI	Phase II	PhaseI	Phase II
	lnGC	EE	lnGB	EE
lnGC		0.954*** (0.361)		
L.lnGC	0.414*** (0.081)			
lnGB				1.030*** (0.323)
L.lnGB			0.350*** (0.059)	
IND	-0.047 (0.221)	-2.927*** (0.769)	-0.075 (0.282)	-2.810*** (0.769)
ECS	-1.477*** (0.221)	-1.022 (0.846)	-1.575*** (0.174)	-0.954 (0.732)

Variables	Two-Stage Least Squares			
	(1)	(2)	(3)	(4)
	PhaseI	Phase II	PhaseI	Phase II
	lnGC	EE	lnGB	EE
FDI	0.002*** (0.000)	0.005*** (0.002)	0.002*** (0.000)	0.005*** (0.002)
TO	-0.196** (0.090)	-1.536*** (0.273)	-0.210* (0.112)	-1.495*** (0.286)
Constant	4.632*** (0.627)	-2.777 (2.693)	3.431*** (0.331)	-0.707 (1.582)
Observations	330	360	330	360
R^2	0.7055	0.7197	0.6151	0.7044
F Statistics (PhaseI)	273.09		156.91	

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

4.5. Robustness Test

To further confirm the validity of the results, we select the logarithm of the total loan amount of listed environmental protection enterprises (lnGF) to replace lnGC and lnGB. Its regression coefficient was 0.053, consistent with the results of DK standard errors and FGLS (Table 8).

Next, the EE index and regression model are replaced. This research utilized fixed capital, employment, and total energy consumption as input indicators; selected GDP as the expected output variable; and adopted a comprehensive environmental pollution index as the non-expected output variable to re-estimate EE through the DEA-ML index and replace the estimation method with Tobit regression. The estimation results indicate that the relationship between lnGC, lnGB, and EE remains strong and significant.

Finally, the sample is changed to remove the data from 2021-2022. Affected by the COVID-19 pandemic, China's economic and financial development during this period exhibited significant volatility. To improve the consistency and trustworthiness of the estimated results, we deleted data from those two years. The results remain robust.

Table 8. Robustness test results.

Variables	Substituting the explanatory variable	Substituting the explained variable and method		Substituting sample	
	(1)	(2)	(3)	(4)	(5)
	FE	Tobit	Tobit	FE	FE
lnGF	0.053*** (0.019)				
lnGB		0.021** (0.010)		0.323** (0.127)	
lnGC			0.379*** (0.054)		0.350*** (0.106)
IND	-2.765*** (0.738)	0.031 (0.103)	-2.939*** (0.264)	-2.691*** (0.783)	-2.609*** (0.788)
ECS	-2.937*** (0.418)	-0.175*** (0.067)	-2.380*** (0.197)	-2.363*** (0.487)	-2.360*** (0.461)
FDI	0.008*** (0.001)	-0.001 (0.001)	0.009*** (0.003)	0.003 (0.002)	0.001 (0.002)
TO	-1.653*** (0.302)	-0.054** (0.027)	-0.941*** (0.148)	-1.543*** (0.230)	-1.533*** (0.227)
Constant	3.728*** (0.391)	0.921*** (0.083)	2.428*** (0.326)	1.884* (0.951)	2.579*** (0.588)
Observations	390	390	390	390	390
F test	0.0000			0.0000	0.0000
LM test	0.0000			0.0000	0.0000
Hausman test	0.0000			0.0000	0.0000
R-squared	0.7657			0.7735	0.7775
P-value		0.141	0.000		

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

4.6. Threshold Regression Results

4.6.1. Threshold Existence Test

Tables 9 and 10 report the threshold existence test results. The results show that with lnGDPP as the threshold variable, there are two threshold values at the 5% significance level, which are 11.1581, 11.9614, 11.1581, and 11.9614, respectively. The corresponding 95% confidence intervals for model 3 are [11.1451, 11.1608] and [11.9561, 12.0110], while for model 4, they are [11.6814, 11.7055] and [11.9587, 12.0130]. Using lnRD as the threshold variable, one threshold is identified at the 5% significance level, with all threshold values being 5.6132, and the corresponding 95% confidence interval is [5.5962, 5.6157]. Overall, as regional economies evolve and investments in science, technology, and R&D expenditure shift, a notable threshold relationship emerges between lnGC, lnGB, and EE.

Table 9. Tests of thresholds.

Threshold variable	Green finance indicator	Threshold model	F-value	P-value	The critical value		
					1%	5%	10%
lnGDPP	lnGC	Single	114.25	0.0000	71.5138	48.4198	40.8004
		Double	42.15	0.0133	44.6183	28.0352	24.5959
	lnGB	Single	113.55	0.0000	70.2716	50.6903	39.5657
		Double	45.85	0.0100	43.8089	27.0366	23.8974
lnRD	lnGC	Single	58.00	0.0333	76.0267	53.4038	42.0574
	lnGB	Single	60.33	0.0200	78.8863	51.0430	40.2189

Table 10. Threshold estimates and confidence intervals.

		lnGDPP		lnRD	
Green finance indicator	Order of thresholds	Threshold estimate	95% confidence interval	Threshold estimate	95% confidence interval
lnGC	1^{st} threshold value	11.1581	[11.1451,11.1608]	5.6132	[5.5962,5.6157]
	2^{nd} threshold value	11.9614	[11.9561,12.0110]		
lnGB	1^{st} threshold value	11.6889	[11.6814,11.7055]	5.6132	[5.5962,5.6157]
	2^{nd} threshold value	12.0110	[11.9587,12.0130]		

4.6.2. Empirical Analysis

Taking lnGDPP as the threshold variable (Table 11). The impact of lnGC on EE in Model 3 unfolds through three distinct stages, reflecting resource allocation efficiency and policy support strength across different economic conditions. When lnGDPP $\leq$ 11.1581, the coefficient of lnGC is 0.284; when 11.1581< lnGDPP $\leq$ 11.9614, the coefficient increases to 0.319; when 11.9614< lnGDPP, it reaches 0.456. All coefficients are significant (p<0.01). After calculation, we can observe that the threshold values for annual GDP per capita in Model 3 are RMB 70,204.264 and RMB 86,800.256, respectively. Data show that 14 Chinese provinces have low GDP per capita (Gansu, Heilongjiang, Guizhou, etc.), 14 provinces are at a medium level (Anhui, Hunan, Zhejiang, etc.), and only Beijing and Shanghai reach the third stage.

Besides, the effect of lnGB is also increasing. When lnGDPP $\leq$ 11.6889, the coefficient of lnGB is 0.331; when 11.6889< lnGDPP $\leq$ 12.0110, it rises to 0.424; when 12.0110< lnGDPP, it reaches 0.573. All coefficients are significant (p<0.01). And the calculated threshold values for annual GDP per capita in Model 4 are RMB 120,485.096 and RMB 163,780.291, respectively. According to provincial GDP per capita, the majority of provinces remain in the first stage, while Tianjin, Jiangsu, and Fujian have advanced to the second stage, and Beijing and Shanghai have reached the third stage. lnGC and lnGB positively influence EE, and this effect is more pronounced at higher lnGDPP. This conclusion aligns with that of Cai and Zhang (2024). Research hypothesis 3 of this paper is established.

Based on the research findings, we can suggest that the effects of lnGC and lnGB on EE exhibit a non-linear characteristic in response to lnGDPP. Overall, lnGB has a stronger facilitating effect compared to lnGC, and the implementation of lnGB requires a higher degree of lnGDPP, as evidenced by the larger threshold value observed in Model 4. lnGB can attract new social capital into the green investment field, expanding green funding. Their flexible investment terms facilitate long-term EE improvement projects. The market-based pricing mechanism of lnGB incentivizes companies to improve EE and better financing, while the transparent disclosure also strengthens oversight of fund usage. Furthermore, high lnGDPP regions have more comprehensive EE assessment systems and stronger green certification and information disclosure mechanisms. Green finance can significantly improve EE by encouraging enterprises to undertake green upgrades through financial support. Conversely, low lnGDPP regions lack mature green financing systems, restricting green finance's impact on improving EE.

Table 11. Threshold regression results.

lnGC as the dependent variable				**lnGB as the dependent variable**			
lnGDPP is a threshold variable		**lnRD is a threshold variable**		**lnGDPP is a threshold variable**		**lnRD is a threshold variable**	
IND	-2.805*** (0.283)	IND	-2.425*** (0.322)	IND	-2.784*** (0.280)	IND	-2.387*** (0.319)
ECS	-2.331*** (0.249)	ECS	-2.099*** (0.281)	ECS	-2.605*** (0.223)	ECS	-2.137*** (0.257)
FDI	0.009*** (0.003)	FDI	0.010*** (0.003)	FDI	0.009*** (0.003)	FDI	0.010*** (0.003)
TO	-1.127*** (0.132)	TO	-1.706*** (0.138)	TO	-0.903*** (0.141)	TO	-1.689*** (0.137)
Constant	2.015*** (0.618)	Constant	1.585** (0.691)	Constant	2.638*** (0.377)	Constant	2.477*** (0.423)
lnGC(PGDP ≤ 11.1581)	0.284*** (0.077)	lnGC(SCI ≤ 5.6132)	0.328*** (0.086)	lnGB(PGDP ≤ 11.6889)	0.331*** (0.068)	lnGB(SCI ≤ 5.6132)	0.316*** (0.077)
lnGC(11.1581<PGDP ≤ 11.9614)	0.319*** (0.077)	lnGC(5.6132<SCI)	0.371*** (0.086)	lnGB(11.6889< PGDP ≤ 12.0110)	0.424*** (0.069)	lnGB(5.6132<SCI)	0.384*** (0.076)
lnGC(11.9614<PGDP)	0.456*** (0.077)			lnGB(12.0110< PGDP)	0.573*** (0.069)		

Note: Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$.

With lnRD as the threshold variable (Table 11). The effect of lnGC on EE in Model 3 can be categorized into two different stages. When lnRD ≤ 5.6132, the coefficient of lnGC is 0.328; when5.6132< lnRD, it increases to 0.371. Both coefficients are significant ($p < 0.01$). Moreover, the effect of lnGB on EE is also slightly different. When lnRD ≤ 5.6132, the coefficient of lnGB is 0.316; when5.6132< lnRD, it rises to 0.384. Both estimated values are significant ($p<0.01$). Calculations show that the threshold for annual R&D expenditure in Model 3 and Model 4 is RMB 27.415 billion. According to data, 19 provinces in China have reached the R&D expenditure threshold, while 11 provinces, including Qinghai, Hainan, and Xinjiang, remain relatively low. lnGC and lnGB are positively correlated with EE, and their effect on EE improvement grows with higher lnRD. This finding corresponds to the research conclusions reported by Jafary et al. (2024). Hypothesis 4 in this paper is established.

The results imply that the positive impacts of lnGC and lnGB on EE demonstrate a threshold effect as lnRD increases. When lnRD is low, lnGC has a marginally stronger effect; when lnRD is high, lnGB exhibits a slightly greater impact. Both lnGC and lnGB require substantial lnRD to be effective, particularly lnGB. Because R&D activities are the core component in transforming green financing into EE improvements, they reflect a company's ability to absorb and utilize green funds. Higher lnRD means greater financial availability for equipment upgrades and technological innovation, enabling more effective investments in EE. However, in areas where lnRD is inadequate, the conversion efficiency of green finance remains poor, resulting in high input costs with limited output and insignificant impact on EE improvement. Therefore, lnRD notably and effectively modifies the impact of lnGC and lnGB on EE.

4.7. Heterogeneity Analysis

To explore the regional heterogeneity, this paper adopts the approach of Xiong and Zhao (2024) and integrates the criteria of the National Bureau of Statistics of China to establish the classification of eastern, central, and western regions (Table A), carrying out corresponding analyses and evaluations based on sample data. Moreover, since all the samples are long panel data, FGLS is used for the regression analysis. The findings are summarized in Table 12.

Table 12 reports the regional analysis results, revealing that both lnGC and lnGB have a positive advancing effect on EE, but the influence varies by region. lnGC and lnGB have the greatest impact on EE in eastern China, with coefficients of 0.684 and 0.659, followed by the central region, with coefficients of 0.172 and 0.171; the western region has the smallest coefficients, with 0.148 and 0.117. In eastern China, economic development, technological proficiency, green finance, and legal regulations are all superior to those in other regions. Therefore, green finance plays a more significant role. In contrast, the industrial structure in central China is dominated by heavy industries, resulting in high energy consumption and limited technological innovation. Western China has a less developed economy, with industries mainly composed of agriculture, and fewer channels for accessing green finance. These factors have restricted the effects of green finance.

Table 12. Regional heterogeneity results.

Variables	Eastern region		Central region		Western region	
	(1)	(2)	(3)	(4)	(5)	(6)
	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS
lnGC	0.684*** (0.029)		0.172*** (0.051)		0.148*** (0.009)	
lnGB		0.659*** (0.022)		0.171*** (0.042)		0.117*** (0.008)
IND	-2.301*** (0.200)	-1.849*** (0.138)	-0.715*** (0.231)	-0.740*** (0.234)	-0.351*** (0.045)	-0.285*** (0.046)
ECS	-2.618*** (0.141)	-3.139*** (0.092)	-1.110*** (0.209)	-1.121*** (0.213)	-0.743*** (0.035)	-0.717*** (0.028)
FDI	0.005*** (0.002)	0.007*** (0.002)	-0.164** (0.071)	-0.149** (0.072)	0.024** (0.010)	0.020** (0.009)
TO	-0.654*** (0.053)	-0.630*** (0.033)	-1.212*** (0.386)	-1.240*** (0.380)	0.495*** (0.057)	0.406*** (0.047)
Constant	-0.901*** (0.210)	0.954*** (0.130)	1.229*** (0.428)	1.692*** (0.280)	0.415*** (0.034)	0.788*** (0.018)
Observations	143	143	104	104	143	143

Note: Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$.

The results of the impact of the IND and ECS correspond with the national sample. However, the influence of FDI and TO differs. (1) The influence of FDI in the east and west areas aligns with the national econometric results. In the central region, FDI exhibits an inverse association with EE because FDI not only drives technological exchange and innovation among enterprises but also results in the transfer of energy-intensive industries. Considering China's regional development characteristics, industrial enterprises have relatively backward technologies.

The technological innovation brought by FDI is unable to offset the increase in energy consumption, which hinders EE. (2) TO is not beneficial for the development of EE in the eastern and central areas, but it has a favorable impact on EE in the western area.

This is mainly because western China has limited commodity exports and low production capacity. Commodity imports can bring about technological innovation and exchange, boosting EE.

5. CONCLUSIONS AND POLICY IMPLICATIONS

5.1. Conclusions

This research uses sample data from China covering 2010 to 2022 and employs the kernel density estimation method to examine the change in EE. Additionally, the impact of lnGC and lnGB on EE, as well as their threshold effects and regional heterogeneity, was verified using DK standard error, FGLS, and threshold regression methods. The main research findings are presented below. (1) During the research period, China's EE has improved steadily, but the national average remains low, and there is an imbalance between regions. The eastern region has high EE and rapid growth; the central region ranks second, with small differences between provinces; the western region has the lowest EE and is lagging behind in development. (2) lnGC and lnGB can significantly promote EE. Sample data shows that the scale of lnGC is far larger than that of lnGB. However, according to model estimates, the positive impact of lnGB on EE is comparable to or even better than that of lnGC. This highlights the function of lnGB in promoting green development. (3) This article confirms the presence of a threshold phenomenon. With the increase of economic development and R&D expenditure, the contribution of lnGC and lnGB in promoting EE is increasing, especially lnGB. This shows that it is necessary to develop the technology trading market to promote technology diffusion and transfer and to strengthen the supporting infrastructure for green finance. (4) From a regional perspective, lnGC and lnGB still help to improve EE, but there is regional heterogeneity. The effect was highest in the east, moderate in the center, and lowest in the west.

5.2. Policy Implications

According to the research findings, regional resources must be combined with the improvement in energy efficiency. Green financial initiatives and targeted energy intensity management must be effectively promoted. First, we must actively promote green credit and green bonds and extend the access channels of green financial products and encourage social capital for backing renewable energy and technological progress initiatives. Moreover, green bonds are conducive to enhancing energy efficiency, but they are smaller than green credit. It is necessary to actively promote the innovation of green bond products, improve market standardization and transparency, and attract continuous capital investment. Second, economic development is crucial to green finance. Under the condition that the level of economic development is established, it is crucial to strengthen the construction of green financial infrastructure, including institutional security, market mechanisms, and service support. Similarly, technological innovation will also affect the performance of green finance. As a result, green finance must be strengthened to support technological innovation in manufacturing companies and increase R&D investment. Third, strengthen inter-regional cooperation and resource flow. Build and enhance the green technology trade market, increase the diffusion of technology between enterprises, make full use of the technological advantages of the eastern region, and promote the transfer and spillover of technological achievements to the west and center of China. Meanwhile, we will support the construction of green energy demonstration parks and renewable energy bases in the western area, strengthen the storage systems for energy and transportation-related infrastructure, improve energy distribution and transmission capabilities, deliver more clean energy to the eastern provinces, and improve the efficiency of energy utilization.

6. LIMITATION AND FUTURE RESEARCH IMPLICATIONS

Enterprise-level variables, including management systems, production operations, human capital, and information technology levels, may also exert a notable influence on energy efficiency. However, this analysis primarily focuses on macro factors that enhance energy efficiency, such as financial development, industrialization level, energy consumption structure, foreign direct investment, and trade. To gain a more comprehensive understanding of the elements contributing to energy efficiency development, future research should explore the impact of internal enterprise factors from a micro-variable perspective. Investigating how internal firm-level factors influence energy efficiency at the micro level is essential for a complete analysis.

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Appendix

Table A. The provinces and regions of China.

Region	Province
Eastern	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Central	Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan
Western	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang