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Can the Development of Renewable Energy Improve Total-Factor Carbon Emissions Efficiency? Evidence from 30 Provinces in China

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Abstract

The global temperature is exceeding 1.5°C above pre-industrial levels due to the increasing carbon emissions, and developing renewable energy is expected to be one of the most effective solutions. However, whether the development of renewable energy contributes to curbing the carbon emissions while maintaining economic development is still under investigation. Using the total-factor carbon emission efficiency (TFCEE), this paper first measures the carbon emission abatement and economic development of 30 provinces in China from 2005 to 2019. Then, based on the super-efficiency slacks-based measure (SE-SBM) model, the panel threshold models and spatial Durbin models are established to comprehensively investigate the impact of RED on TFCEE. The findings reveal that: (1) RED significantly improves TFCEE. For every 1% increase in RED, TFCEE experiences a rise ranging from 0.020% to 0.035%. (2) The beneficial effect of RED on TFCEE increases with economic restructuring and technological progress. (3) The indirect impact of RED on TFCEE through spatial spillover is significantly greater than its direct effect. Potential transmission mechanisms for this spatial spillover effect are the cross-regional mobilization of renewable electricity and the diffusion and absorption of low-carbon knowledge and technologies. The above conclusions provide empirical evidence for China and other developing countries to formulate appropriate energy transformation strategies.

Keywords: Renewable energy development; Total-factor carbon emissions efficiency; Transmission mechanism; Spatial spillover effect; Nonlinear effect.

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1. Introduction

The global temperature is temporarily exceeding 1.5°C above pre-industrial levels due to the increasing carbon emissions for at least one of the next five years according to WMO (World Meteorological Organization). The adverse effects of climate change are multifaceted, including causing sea-level rise, destroying agriculture and ecosystems, aggravating flooding, and drought, and increasing human disease risk and mortality. The primary drivers of climate change remain the significant rise in greenhouse gas emissions, particularly carbon dioxide (Manabe, 2019). Fossil fuel usage persists as the predominant contributor to these emissions. According to the World Resources Institute (WRI), fossil energy consumption produces about 90% of all carbon emissions in 2022. Therefore, countries around the world still need to achieve deep decarbonization of energy systems.

The modern economic-energy system is complicated. Linkages between energy consumption and economic development are often multi-folded and non-linear because of the unclear but surely complex interactions. To effectively decarbonize carbon emissions while maintaining sustainable economic development, the shift from a fossil-based energy system to a renewable energy system may trigger the pattern of transition of resource utilization, economic development, and behavioral changes. Specifically, the linkages may be influenced by structural changes in the economic system and technological advances. While the development of renewable energy development has been regarded as one of the most effective solutions to decarbonize carbon emission from energy systems, exploring how the relationship between RED and TFCEE changes with the structure of the economy and technological advances is important for emerging economies undergoing energy transitions. This can provide insights for these economies to choose appropriate economic restructuring strategies and technological progress paths. In addition, due to the development of renewable energy, resource redistribution in geographical space may occur, thereby influencing the distribution of carbon emissions, leading to a strong spatial correlation between the carbon emission efficiencies of different regions. This correlation is stronger between regions within a country.

Carbon emission efficiency, as a measure of the correlations between economy and energy, implies a balance between carbon emissions and economic development. However, many scholars (Zhang et al., 2022; Wang et al., 2022; Lee et al., 2023) point out that the carbon emission efficiency does not play an effective way to reflect the comprehensive relations between carbon investment and economic output because factors including economic quality, technology innovation are often neglected. Thus, Yao et al. (2015) include the carbon emissions in the Total-Factor Productivity (TFP) framework and propose the total-factor carbon emissions efficiency. In comparison, traditional single-factor carbon efficiency indicators such as carbon intensity take into account only one factor. The integration provides a more accurate assessment of whether the economic development mode aligns with the low-carbon growth objectives. Thus, TFCEE offers a superior means of evaluating the alignment of economic development with these objectives. Therefore, this paper concentrates on investigating the influence of RED on TFCEE. Therefore, it is imperative to analyze the comprehensive effect of RED on TFCEE based on the perspective of spatial spillovers.

The greatest carbon dioxide emitter in the world is now China. According to IEA, China's CO2 emissions in 2022 reached 12.1GT, representing 31.72% of the total global emissions. As a responsible major nation, China has set an ambitious target of peaking carbon by 2030 and becoming carbon neutral by 2060. One of China's biggest obstacles to lowering carbon emissions is wildly using fossil fuels like coal. Therefore, the energy transition has been an inevitable choice to achieve the goals. To advance the energy transition, Chinese government introduced a renewable energy bill in 2005 going for renewable energy. After ten years rapid development, China's installed capacity of wind power generation increased from more than 76 million kilowatts to more than 440 million kilowatts, an increase of nearly five times, and the installed capacity of photovoltaic power generation increased from more than 19 million kilowatts to more than 600 million kilowatts, an increase of more than 30 times. By 2023, more than half of the world's renewable energy power generation was installed, and the cumulative installed capacity accounted for nearly 40% of the world. Meanwhile, as the biggest developing nation in the world, China is also facing severe economic growth stress. Although in 2021 China has fully lifted itself out of poverty and its GDP per capita exceeds the world average, it still needs to make efforts to achieve SDG8. Therefore, it holds immense significance to study how to achieve carbon emission targets while ensuring economic growth.

This paper aims to make possible contributions in the following areas: (1) Considering the rapid economic structural changes and technological advancements occurring in China, this paper uncovers the dynamic nonlinear influence of renewable energy development on TFCEE from the viewpoints of structural changes and technological advances. (2) Considering the possible spillover influence of carbon emission efficiency between different regions, this paper adopts the spatial Durbin model (SDM) to study the spatial spillover effects of renewable energy development on TFCEE and further reveals its potential influence mechanism.

The remainder of this paper is structured as follows. The extant literature is reviewed succinctly in Section 2. The methods and data are introduced in Section 3. The empirical findings are reported and discussed in Section 4. The empirical findings are outlined in Section 5 along with specific policy suggestions.

2. Literature review

2.1 Impact of renewable energy development on economic growth

There is currently no consensus among available studies regarding the influence of renewable energy development (RED) on both economic growth and carbon emissions. Some scholars believe that RED can help economic growth. This enables industrial production to utilize renewable energy for electricity generation rather than relying on conventional fossil fuels. Moreover, the RED may assist energy-importing nations lessen their reliance on oil and natural gas and increase the capacity of their economies to withstand political threats. Inglesi-Lotz (2016) used a panel fixed effect model to investigate the effects of RED on economic growth in OECD nations and discovered that RED can promote economic growth. Koçak and Şarkgüneşi (2017) also observed the same results in 9 Black Sea and Balkan countries. Le et al. (2020) demonstrated that RED has a beneficial influence on the economic development of various income nations. However, some scholars argue that the expense associated with renewables surpasses that of traditional fossil fuels due to the substantial investment required for renewable energy infrastructure construction, potentially impeding economic growth. As Bhattacharya et al. (2016), RED exerts a negative impact on the economic growth of four out of the top 38 renewable energy consumers. In a similar study, Shahbaz et al. (2020) found that the economic development of seven nations is adversely affected by RED.

Moreover, the impact of RED on economic growth may also depend on the proportion of renewable energy in total energy. Bulut and Muratoglu (2018) discovered that RED has no substantial influence on Turkey's economic development, they attribute this to the low proportion of renewable energy in the total energy mix. Given these contradictory results, the linkage between economic growth and RED is likely to be nonlinear. Therefore, Chen et al. (2020) investigated the nonlinear influence of RED on economic growth using a panel threshold model. They discovered that in developing nations when RED falls below a certain threshold, it hinders economic development; when RED rises over the threshold, it fosters it. Wang et al. (2022) investigated the nonlinear impact of RED on economic growth in OECD countries. Their findings indicate that the beneficial effect of RED on economic growth intensifies when compound risk and political risk reach a certain threshold. Given the prevalence of economic linkages across regions, Li et al. (2022) applied the spatial Durbin model to explore the spatial spillover effects of RED on economic growth. They found that this spillover effect first shifts from positive to negative and then to positive as the RED increases.

2.2 Impact of renewable energy development on carbon emission reduction

Regarding the carbon emission reduction effect of RED, some scholars believe that RED can improve the energy structure, so RED can help reduce carbon emissions. Dong et al. (2018) discovered that RED lowers China's carbon emissions by utilizing the auto-regressive distribution lag (ARDL) model. Hasanov et al. (2021) also found the same evidence in BRICS countries. Khan et al. (2020) investigated the impact of RE usage on consumption-based carbon emissions in G7 countries. Their findings revealed that RED has an adverse effect on carbon emissions. By applying advanced panel estimation technology, Sun et al. (2022) affirmed that RED can constrain the rise of carbon emissions in 14 Middle Eastern and North African economies.

However, according to Dong et al. (2020), RED demonstrates no significant impact on carbon emissions in upper-middle income, lower-middle income, or low-income nations. In addition, Apergis et al. (2010) found that RED causes a long-term rise in the carbon emissions of selected 19 developed and developing countries. Their conclusion was corroborated in five North African countries (Ben Jebli and Ben Youssef, 2017) and Turkey (Yurtkuran, 2021). Recently, the potential nonlinear influence of RED on carbon emissions has attracted scholars' interest. The pooled mean group (PMG) estimator was used by Li et al. (2020) to determine the impact of RED on the carbon emissions of China. The findings unveiled an inverted "U" connection between RED and carbon emissions. Chen et al. (2022) emphasized that for developed countries, only when the consumption of RED exceeds the threshold can the increase of RED reduce the per capita carbon emissions.

In addition, some scholars have also directed their attention towards investigating the spatial spillover effect of RED on carbon emissions. Chen et al. (2022) argue that the fossil energy savings resulting from the utilization of renewable energy in the power generation sector within a local region are transferred to spatially related regions, indicating a CO2 transfer effect. Therefore, the spatial spillover effect of RED on reducing carbon emissions is negative. However, Liu et al. (2023) showed that RED has a positive spatial spillover effect on carbon emission reduction due to the presence of demonstration effects and cross-regional co-operation.

2.3 Combined impact of renewable energy development on economic growth and carbon reduction

Compared to a single economic growth indicator or carbon emission indicator, Total Factor Carbon Emission Efficiency (TFCEE) provides a more precise assessment of growth sustainability (Wu et al., 2020; Hao et al., 2022). Despite this, there is limited research on the effects of RED on TFCEE. Several studies have instead focused on exploring the impact of RED on energy intensity. The effect of RED on the energy intensity of 82 major nations was investigated by Yu et al. (2022). These studies revealed that the impact of RED) on energy intensity is notably negative, and this effect intensifies as RED surpasses a certain threshold. Liu et al. (2022) analyzed how RED affects China's energy intensity, and they found that this influence changes with the change in income level.

Some studies have also examined the influence of RED on the carbon intensity. Yu et al. (2020) utilized a panel quantile regression model to investigate the carbon reduction effect of RED. Their findings indicated that the negative influence of RED on carbon intensity is least pronounced in regions with moderate carbon intensity. Han et al. (2020) demonstrated the importance of technical innovation capability in the nonlinear influence of RED on carbon intensity. Lee et al. (2023) revealed the external mechanism that RED reduces carbon emission intensity. Their findings suggest that RED diminishes carbon emission intensity through enhancements in energy efficiency and optimization of industrial and energy structures.

In general, these studies have established a foundational theoretical framework for investigating the impact of RED on TFCEE, but the selected indicators only reflect one aspect of TFCEE. Lin and Li (2022) contend that RED serves as a mediating factor in the association between R&D and TFCEE. Dong et al. (2022) evaluated the non-linear effect of RED on TFCEE. They discovered that RED has a favorable influence on TFCEE in developed nations and that this impact diminishes when energy consumption intensity rises but improves as TFCEE and financial development levels improve. Based on a study of 114 countries, Wang et al. (2022) showed that the contribution of RED to TFCEE is negatively affected by income inequality and urbanization.

2.4 Literature gap

To summarize, limited research has explored the impact of RED on TFCEE, revealing the following deficiencies: (1) China and many other developing countries around the world have been experiencing rapid economic restructuring and technological change. This dynamic environment may result in a non-linear impact of RED on TFCEE, which current studies have not adequately addressed. The evolving economic landscape and technological advancements introduce complexities that necessitate a more nuanced analysis to understand how RED influences TFCEE over time. (2) The majority of existing studies have overlooked the potential spatial dependence characteristic of TFCEE. This means they have failed to consider how changes in TFCEE in one region might be influenced by developments in neighboring regions. Consequently, these studies have not elucidated the role of RED in the trajectory of TFCEE evolution from the standpoint of spatial spillover effects. Spatial spillover effects refer to the impact that policy measures and technological advancements in one area can have on surrounding areas. Ignoring these effects limits the understanding of the full impact of RED on TFCEE, particularly how improvements in one region might propagate and influence other regions.

In conclusion, the current body of research on the impact of RED on TFCEE is deficient in addressing the dynamic non-linearity and spatial dependence aspects. These gaps highlight the need for more comprehensive studies that take into account the complex, evolving nature of economic and technological landscapes, as well as the interconnectedness of regions, to fully understand the implications of RED on TFCEE.

3. Methods and data

3.1 Model setting

In this study, an econometric model is formulated to investigate the effect of RED on TFCEE:

$$lnTFCEE_{it} = \alpha_0 + \alpha_1 lnRED_{it} + \alpha_k \sum_{k=2}^{7} lnX_{kit} + \mu_i + \nu_t + \varepsilon_{it} \tag{1}$$

Where i denotes the province, t denotes the year. $TFCEE_{it}$ is the independent variable and denotes the total factor carbon emission efficiency (TFCEE) of i province at time t, RED_{it} is the key explanatory variable that indicates the level of renewable energy development in province i at time t, X_{kit} refers to the other control variables, ln refers to the natural logarithm. α_0, α_1, and α_k represent coefficients to be estimated, μ_i represents individual fixed effect, ν_t represents time fixed effect, and ε_{it} represents residual terms.

Acknowledging the potential for a non-linear association between renewable energy development and TFCEE, following Hansen's methodology (1999), this study constructs a panel threshold regression model refer to Equation (1) in the following form:

$$lnTFCEE = \beta_0 + \beta_1 lnRED_{it} \bullet I(q_{it} \le \gamma) + \beta_2 lnRED_{it} \bullet I(q_{it} > \gamma) + \beta_k \sum_{k=3}^{8} lnX_{kit} + \mu_i + \nu_t + \varepsilon_{it} \tag{2}$$

Where, q_{it} represents the threshold variable, γ is the estimated threshold, and $I(\cdot)$ denotes an instruction function. When a double threshold exists, the above equation can be further extended to Equation (3):

$$lnTFCEE = \beta_0 + \beta_1 lnRED_{it} \bullet I(q_{it} \le \gamma_1) + \beta_2 lnRED_{it} \bullet I(\gamma_1 < q_{it} \le \gamma_2) + \beta_1 lnRED_{it} \bullet I(q_{it} > \gamma_2) + \beta_k \sum_{k=4}^{9} lnX_{kit} + \mu_i + \nu_t + \varepsilon_{it} \tag{3}$$

3.2 Variable definition

3.2.1 Explained variables

Most studies employ the DEA approach to measure TFCEE, which has emerged as the primary indicator for gauging the degree of coordination between the economy and the environment. Tone (2002) suggested a super-efficiency slacks-based measure (SE-SBM) model to address the drawbacks of the conventional DEA technique. Compared with the traditional DEA method, this method has three advantages: (1) It can deal with unexpected output. (2) Allowing input and output to change in different proportions is more realistic. (3) The decision-making unit's efficiency value is permitted to be greater than 1, ensuring that the efficiency values of all decision-making units may be compared. Nevertheless, the SE-SBM model is unsuitable for panel-type data due to the model constructs a different frontier in each period, resulting in a lack of comparability of measured efficiency in the temporal dimension. So this study introduces the global SE-SBM model using the global reference technique suggested by Pastor and Lovell (2005):

$$TFCEE = \min_{s_i^-, s_y^+, s_b^-, \lambda} \frac{1+\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}}{1-\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_y^+}{y_{ro}}+\sum_{k=1}^{s_2}\frac{s_b^-}{b_{ko}}\right)} \tag{4}$$

$$s.t.\begin{cases} \sum_{t=1}^{T}\sum_{j=1,j\neq o}^{n}\lambda_j^t x_{ij}^t - s_i^- \leq x_{io} \\ \sum_{t=1}^{T}\sum_{j=1,j\neq o}^{n}\lambda_j^t y_{rj}^t - s_y^+ \leq y_{ro} \\ \sum_{t=1}^{T}\sum_{j=1,j\neq o}^{n}\lambda_j^t b_{ij}^t - s_b^- \leq b_{ko} \\ \sum_{t=1}^{T}\sum_{j=1,j\neq o}^{n}\lambda_j^t = 1 \\ \lambda \geq 0, s_i^- \geq 0, s_y^+ \geq 0, s_b^- \geq 0 \end{cases} \tag{5}$$

Where *TFCEE* is the objective function and efficiency value; The vectors *x* ,*y* and *b* represent input, desirable output and undesirable output. *m, s1* and *s2* denote the amount of inputs, desirable and undesirable outputs of each DMU; s_i^-, s_y^+ and s_b^- are the slack variables of input, desirable output, and undesirable output. λ_j is the weight vector and *T, n* represents the year and province.

Based on previous scholars' studies (Zhang et al.,2022;Song et al.,2018), the input variables used in this study are capital, labor and energy, with carbon emissions as non-desired outputs and economic outputs as desired outputs.The base period in this research is 2000, and adoption of the perpetual inventory method for the calculation of capital stock. The labor force is measured by total employment, and total energy consumption serves as a measure of energy. In addition, consistent with most previous studies, this paper uses the variable returns to scale assumption in constructing the global SE-SBM model. Figure 1 illustrates the computed results of TFCEE.

From Figure 1, it can be seen that there are significant spatial disparities in TFCEE among provinces in China. TFCEE is generally higher in the eastern coastal provinces and lower in the western provinces, which is consistent with China's basic national conditions. While the eastern regions are experiencing rapid economic development, they are also undergoing a clean energy revolution, transitioning from the previous high-energy consumption, high-pollution, and high-emission development model. However, from a global perspective, most provinces remain in a stage of relatively low efficiency, with great potential and space for improvement. For example, Shanxi Province, as a typical resource-based province, relies mainly on coal as its primary energy source and economic pillar. Its industrial structure is dominated by heavy industry, with a focus on the secondary sector. Coupled with its relatively low level of technological development and a lack of advanced clean production technologies and equipment, it has fallen into a vortex of low carbon emission efficiency.

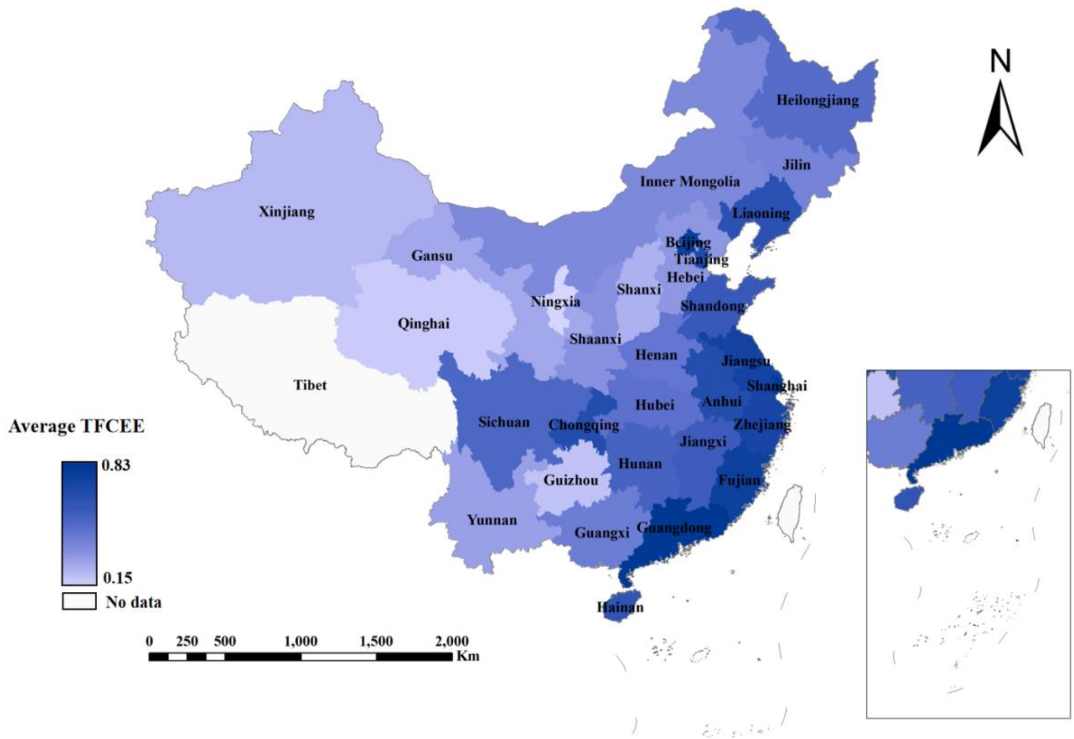

Figure 1: Average total factor carbon emissions efficiency of 30 provinces from 2005 to 2019

3.2.2 Key explanatory variables and control variables

In this study, renewable energy development (RED) serves as the main explanatory variable, measured by renewable energy generation concerning Yu et.al. (2020). Additionally, in the robustness testing phase, the paper substitutes the installed capacity of renewable energy (REI) for renewable energy generation to gauge renewable energy development.

Several control variables are further included to lower the deviation of missing variables: (1) Economic development level (PGDP), quantified by real GDP per capita. (2) Population (P), representing the population at the end of a year. (3) Research and Development input (RD), calculated as the proportion of R&D expenditure to GDP. (4) Environmental regulation intensity (ER), determined by the ratio of investment in industrial pollution prevention to GDP. (5) Economic openness (OPEN), assessed by the fraction of import and export volume in GDP. (6) Human capital level (HC), quantified as the average number of years of studying for workers.

3.2.3 Threshold variables

This study chooses seven threshold variables to examine the nonlinear impact of RED on TFCEE, containing five economic structure variables and three technological progress variables: (1) Industrial structure (IS) is defined as the contribution of tertiary value added to GDP. (2) Population structure (URB) is determined by the urbanization rate. (3) Energy consumption structure (ES) is determined by the share of coal usage in overall energy consumption. (4) Factor structure (KL) is quantified by the ratio of the real capital stock to the average annual number of workers. (5) Ownership structure (OS) is the proportion of non-state-owned fixed asset investment to total fixed investment. (6) Green technology (GT) is quantified by the amount of green patent grants and is log-transformed in regression. (7) Energy Technology (EE) is measured by GDP per unit of energy consumption. (8) Information and communication technology (ICT) is measured by the amount of internet users as a share of the total population.

3.3 Data

The majority of the data utilized in this paper is sourced from various authoritative publications including the China Statistical Yearbook, China Energy Statistical Yearbook, China Power Statistical Yearbook, China Water Resources Review Results, China Wind and Solar Energy Resources Annual Bulletin, Statistical Report on Internet Development in China, as well as databases such as the World Intellectual Property Organization (WIPO) and CEADS. Renewable energy generation data is derived by subtracting the electricity generated from thermal power and nuclear power from the total primary energy generation. Due to data limitations, Hong Kong, Macao, Taiwan, and Tibet are excluded from the study. We finally have gathered data from all 30 provinces in China spanning the years 2005 to 2019. All price-related data has been adjusted to constant prices in 2000. The descriptive statistical analysis of each variable is included in Appendix Table A1.

4. Empirical results

4.1 Basic regression results and robustness test

Columns (1)-(4) in Table 1 show the estimation outcomes for the pooled ordinary least squares (POLS), random effects (RE), fixed effects (FE) and two-way fixed effects (TWFE) models. On the key explanatory variable, the findings illustrated in Table 1 reveal that the coefficient of RED is notably positive at the 5% significance level. This suggests the advancement of renewable energy can foster low-carbon growth.

Table 1: Benchmark model regression results

	(1)	(2)	(3)	(4)
	POLS	RE	FE	TWFE
lnRED	0.002 (0.006)	0.018^{**} (0.008)	0.034^{***} (0.008)	0.035^{***} (0.008)
Control variables	Yes	Yes	Yes	Yes
Province fixed effect	NO	NO	Yes	Yes
Year fixed effect	NO	NO	NO	Yes
Cons	-2.751^{***} (0.307)	-2.955^{***} (0.423)	-6.150^{***} (0.943)	-5.538^{***} (1.253)
R^2	0.808	0.495	0.547	0.574

Notes: The figures in () are standard errors. *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

This paper performed several robustness tests to validate the robustness of the regression results of the benchmark model. First, we removed the control variables from the model. The results are shown in the column (1) of Table 2. This effect coefficient of RED on TFCEE remains significantly positive at the level of 1% after the control variables have been removed, which again proves that RED can improve TFCEE.

Second, we recalculated the standard errors using the Driscoll-Kraay approach (Driscoll and Kraay, 1998) to mitigate potential heteroscedasticity, autocorrelation, and cross-sectional dependency, thereby reducing the deviation. The outcomes are displayed in column (2) of Table 2. Despite employing the Driscoll-Kraay method, the impact of RED on TFCEE remains significantly positive at the 1% level. Consequently, there is no substantial evidence of autocorrelation or cross-sectional dependence in the basic model.

Thirdly, conducting indicator substitution. The installed capacity of renewable energy is utilized as a substitute for renewable energy generation to gauge the RED. The findings in Column (3) of Table 2 indicate that RED continues to significantly enhance TFCEE after the measurable indicator is replaced.

Table 2: Robustness test results.

	(1)	(2)	(3)	(4)	(5)
	lnTFCEE	*lnTFCEE*	*lnTFCEE*	*lnRED*	*lnTFCEE*
lnRED	0.026*** (0.008)	0.035*** (0.005)			0.020* (0.011)
lnREI			0.012** (0.005)		
IV				0.085*** (0.004)	
Control variables	No	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Cons	-1.301*** (0.035)	-5.538** (2.682)	-5.753*** (2.741)	-20.469*** (6.874)	-2.428 (1.507)
Kleibergen Paap rk Wald F statistic					414.919 {16.38}
Kleibergen Paap rk LM statistic					86.997 [0.0000]
R^2	0.518	0.574	0.558	0.980	0.529

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in () are standard errors, the figures in {} are 10% critical values at of Kleibergen-Paap rk Wald F test, and the figures in [] are P values of Kleibergen-Paap rk LM test.

Finally, to overcome potential endogeneity, a two-stage least squares (2SLS) approach is used to estimate the benchmark model. Drawing inspiration from Aragón and Rud (2016), this study incorporates renewable energy endowment, defined as the economically exploitable quantity of renewable energy, as an instrumental variable for assessing the development of renewable energy. This variable satisfies the exogeneity requirement, given that the endowment of renewable energy resources is solely determined by natural conditions. Moreover, it meets strong correlation and exclusivity criteria.On one hand, regions endowed with greater access to renewable energy resources are better positioned to advance renewable energy development and are more likely to establish comprehensive and scalable industrial chains. On the other hand, it is unlikely that renewable energy resources would impact economic and social development through channels other than RED.

It's worth noting that the original data of the chosen instrumental variable is cross-sectional, which cannot be directly utilized for panel data econometric analysis. Following the approach of Nunn and Qian (2014), a time-varying variable is introduced to create a panel instrumental variable. Specifically, a multiplication term is constructed by combining renewable energy generation from the previous year with the economically exploitable amount of renewable energy. This term serves as the instrumental variable for RED in that specific year.

The positive effect of the instrumental variable on RED is still positive at the 1% level of significance, as seen in column (4) of Table 2, which supports the idea that instrumental variable is strongly correlated. Furthermore, for testing the null hypothesis of "insufficient identification of instrumental variables," the p-value is 0.000, indicating strong evidence against the null hypothesis. Moreover, the Wald F-statistic of Kleibergen-Paap rk exceeds the critical value at the 10% level of the Stock-Yogo weak identification test, suggesting the absence of weak identification of IV. The experiments mentioned above show that the instrumental variables chosen were reasonable in general. After taking endogeneity into account, the outcomes in column (5) demonstrates the promotion effect of RED on TFCEE is still true.

4.2 Nonlinear effect analysis

4.2.1 Threshold effect test

This study utilizes the bootstrap approach to derive the F-statistic, for the threshold effect test through duplicate sampling (as shown in Appendix Table A2). The findings demonstrate a double threshold effect exists when using lnURB as a thresholding variable. Single and double thresholds in both significant at the 1% level. There is only single threshold effect when lnIS, lnGT, and lnEE are taken into consideration as threshold variables, and the threshold values are significant at the significance levels of 1% and 5%.

In addition, the validity of the estimated thresholds was examined using the LR test. The estimated threshold outcomes are shown in Appendix Table A3. The first threshold and second threshold are 4.129 and 4.456, respectively, when lnURB is set as the threshold variable. When lnIS, lnGTE and lnEE are used as threshold variables, the thresholds are 4.151, 7.573 and 0.168, respectively.

4.2.2 Threshold effect analysis

The outcomes of the threshold model are displayed in Table 3. According to column (1), when the share of the tertiary sector in GDP is less than 63.50%, the effect of RED on TFCEE is weak. Specifically, a 1% increase in RED raises TFCEE by only 0.02%. When the contribution of tertiary value added to GDP exceeds 63.50%, the impact of the RED on TFCEE expands nearly sevenfold. Due to the lower elasticity of energy demand in the third sector compared to the other sector, regions with a high share of the tertiary sector are more favorable for renewable energy to replace fossil energy. In these regions, it is less economically costly for firms to make the energy transition and easier to maintain an optimal scale of production. In addition, firms in the tertiary sector are more inclined to introduce or develop new low-carbon technologies to adapt to changes in the energy mix because of the lower cost of energy transition compared to firms in the secondary sector.

Column (2) indicates that the effect of RED on TFCEE is relatively small when the urbanization rate is less than 62.12%. When the urbanization rate is higher than 62.12% and lower than 86.14%, TFCEE is significantly benefited by the RED. TFCEE increases by 0.047% for each 1% rise in the level of RED. When the urbanization rate is higher than 86.14%, the beneficial effect of RED on TFCEE is significantly enhanced, and the increase of RED level by 1% leads to an increase of 0.203% in TFCEE. The following three aspects may be used to explain the findings above: First, with the improvement of urbanization level, many people migrate from rural areas to cities, which leads to the improvement of the electrification degree of the residential sector. Second, urbanization provides infrastructure for the usage of new energy vehicles, which increases the electrification of the transportation sector. Therefore, urbanization creates conditions for energy transition. Finally, the establishment of smart grids and smart energy communities in urban areas can enhance the integration of renewable electricity into the grid and optimize energy utilization efficiency.

Columns (3) and (4) show that both green technology advances and energy technology advances will enhance the contribution of RED to TFCEE. Green and energy technology advances will reduce the elasticity of firms' demand for fossil energy, thereby increasing their ability to optimize the allocation of factors of production. In addition, technological advances may have improved the innovative capacity of firms. Therefore, RED is better able to promote low-carbon technological advances to enhance TFCEE.

Table 3: Results of threshold model regression

	Threshold variable			
	(1)	(2)	(3)	(4)
	lnIS	*lnURB*	*lnGT*	*lnEE*
$lnRED \cdot I(q \leq \lambda_1)$	0.020** (0.008)	0.017** (0.007)	0.037*** (0.008)	0.047*** (0.007)
$lnRED \cdot I(\lambda_1 < q \leq \lambda_2)$	0.146*** (0.016)	0.047*** (0.007)	0.061*** (0.008)	0.077*** (0.008)
$lnRED \cdot I(q > \lambda_2)$		0.203*** (0.014)		
Cons	-5.038*** (1.163)	-2.466** (1.028)	-4.849*** (1.153)	-5.254*** (1.096)
Control variables	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
R^2	0.635	0.729	0.642	0.675

Notes: *** and ** indicate statistical significance at the 1% and 5% levels, respectively. The figures in () are standard errors.

4.3 Spatial spillover effects

There may be spatial correlations between TFCEE in different provinces due to economic and technological linkages. The Moran's I index is employed here to test whether a spatial correlation exists. Table 4 shows the test outcomes of Moran's I index with three different spatial weighting matrices (neighborhood matrix, geographic distance matrix and economic distance matrix). We can see that under all the spatial weighting matrices, the Moran's I index for TFCEE exhibits a positive value and achieves significance at the 1% level across all years. This suggests the provincial TFCEE exhibits a notable positive spatial correlation rather than being random. Consequently, the spatial econometric model can be employed for analyses.

Table 4: Testing results for the Moran's I Index

Year	W_1		W_2		W_3	
	Moran's I	Z-value	Moran's I	Z-value	Moran's I	Z-value
2005	0.386***	3.512	0.099***	3.807	0.201***	2.289
2006	0.386***	3.541	0.096***	3.737	0.205***	2.351
2007	0.379***	3.525	0.089***	3.590	0.202***	2.347
2008	0.390***	3.653	0.092***	3.710	0.223***	2.579
2009	0.388***	3.576	0.096***	3.753	0.254***	2.843
2010	0.395***	3.625	0.095***	3.722	0.261***	2.897
2011	0.370***	3.383	0.094***	3.660	0.284***	3.100
2012	0.384***	3.466	0.100***	3.790	0.309***	3.309
2013	0.363***	3.286	0.099***	3.747	0.320***	3.414
2014	0.401***	3.563	0.115***	4.175	0.362***	3.776
2015	0.384***	3.432	0.117***	4.215	0.371***	3.875
2016	0.408***	3.601	0.123***	4.361	0.357***	3.708
2017	0.400***	3.545	0.126***	4.450	0.356***	3.708
2018	0.384***	3.423	0.123***	4.370	0.363***	3.779
2019	0.373***	3.343	0.117***	4.229	0.381***	3.967

Notes: *** indicate statistical significance at the 1% level. W_1, W_2 and W_3 denote neighborhood matrix, geographic distance matrix and economic distance matrix, respectively.

Panel spatial econometric models have three forms: spatial autoregressive model (SAR), spatial error model (SEM), and spatial Durbin model (SDM). The LR test and the Wald test show that the SDM can not be decomposed into the other model (as shown in Appendix Table A4), so this paper constructs the following SDM with spatial-temporal fixed effects to continue further research.

$$lnTFCEE_{it} = \alpha_0 + \rho_1 \sum_i^n W_{ij} y_{jt} + \alpha_1 lnRED_{it} + \rho_2 \sum_i^n W_{ij} RED_{jt} + \alpha_k \sum_{k=2}^7 lnX_{kit} + \rho_k \sum_i^n W_{ij} \sum_{k=2}^7 lnX_{kit} + \mu_i + \nu_t + \varepsilon_{it} \quad (6)$$

Where, i and j denote different provinces, t denotes the year. W_{ij} represents spatial weighting matrices. ρ_1, ρ_2 and ρ_k are spatial correlation coefficients.

Table 5 shows the regression outcomes of RED on TFCEE under SDM. The spatial autoregressive coefficient (ρ) of the SDM is notably positive at the 1% significance level. This signifies the presence of not only an exogenous interaction effect among the explanatory variables but also an endogenous interaction effect among the explained variables in this model. Thus, the choice of SDM is more appropriate.

Table 5: Estimation results of SDM

Explanatory variable	(1)	(2)	(3)
	W_1	W_2	W_3
lnRED	-0.008 (0.008)	0.013 (0.009)	0.013^{*} (0.007)
*W*lnRED*	0.071^{***} (0.013)	0.176^{***} (0.045)	0.098^{***} (0.023)
ρ	0.472^{***} (0.048)	0.337^{**} (0.141)	0.390^{***} (0.066)
Control variables	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
R^2	0.599	0.454	0.557

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The figures in () are standard errors. W_1, W_2 and W_3 denote neighborhood matrix, geographic distance matrix and economic distance matrix, respectively.

LeSage and Pace (2009) pointed out that analyzing direct and spillover effects through simple point estimate results would lead to erroneous conclusions. Therefore, following his suggestion, using partial differential method to estimate direct and spillover effects. According to the outcomes in Table 6, the direct and spillover effect of RED are significantly positive, indicating that RED not only enhances TFCEE in local regions, but also contributes significantly to TFCEE in spatially related regions. Moreover, the spatial spillover effects of RED are significantly more than the direct effects. Consequently, neglecting the spatial spillover effects of RED would result in a substantial underestimation of the beneficial effect of RED on TFCEE.

Table 6: Direct, indirect, and total effects of RED on TFCEE.

	(1)	(2)	(3)
	W_1	W_2	W_3
Direct effect	0.002 (0.008)	0.018^{*} (0.010)	0.023^{***} (0.008)
Indirect effect	0.117^{***} (0.020)	0.279^{***} (0.091)	0.161^{***} (0.037)
Total effects	0.119^{***} (0.020)	0.297^{**} (0.094)	0.184^{***} (0.043)

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The figures in () are standard errors. W_1, W_2 and W_3 denote neighborhood matrix, geographic distance matrix and economic distance matrix, respectively.

This paper argues that the spatial spillover effects of RED on TFCEE may occur through two channels: (1) Inter-provincial transmission of renewable electricity. (2) Spillover of advanced management experience and technology. To test the first channel, this paper constructs two spatial Durbin models based on Equation (6) with lnREC and lnPREC as explained variables, respectively. As China's renewable energy resources are mostly in the western provinces, while the electricity-using provinces are mainly located in eastern regions, China's renewable electricity is often transported across multiple provinces. Therefore, it is more appropriate to use a geographic distance spatial weighting matrix than a neighborhood matrix in estimating the spatial spillover effect of RED on renewable energy consumption. According to columns (1)-(2) of Table 7, RED not only increases the consumption of renewable energy in space-related regions, but also changes the energy consumption structure in space-related regions.

Then, based on Eq. (1), this paper constructs fixed effects models with lnREC and lnPREC being the key explanatory variables, and the estimation outcomes are shown in columns (3)-(4) of Table 7. This demonstrate an increase in the proportion of renewable energy can increase TFCEE. Therefore, through inter-provincial transmission of renewable electricity, the RED in the local regions can elevate the proportion of renewable energy in the spatially connected regions and thus increase the TFCEE in the spatially connected regions.

Table 7: Physical transmission mechanism test for the spatial spillover effect of RED on TFCEE

Independent variables	Dependent variables			
	(1)	(2)	(3)	(4)
	lnREC	*lnPREC*	*lnTFCEE*	*lnTFCEE*
lnRED	0.394*** (0.039)	0.377*** (0.041)		
*W*lnRED*	0.754*** (0.196)	0.870*** (0.203)		
lnREC			0.024 (0.020)	
lnPREC				0.057*** (0.019)
Control variables	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
R^2	0.330	0.387	0.523	0.538
Direct effect of *lnRED*	0.383*** (0.040)	0.365*** (0.042)		
Indirect effect of *lnRED*	0.387*** (0.138)	0.511*** (0.155)		
Total effects of *lnRED*	0.770*** (0.131)	0.876*** (0.148)		

Notes: *** indicate statistical significance at the 1% level. The figures in () are standard errors. *lnREC* and *lnPREC* denote the logarithm of renewable energy consumption and the share of renewable energy consumption in total primary energy consumption, respectively.

According to the mechanism analyzed in the previous section, RED in local regions contributes to the improvement of management level and technological progress of local enterprises. Due to the close economic linkages between provinces in China, advanced management experience and low-carbon technologies induced by RED in one province may spill over to other provinces, leading to a higher TFCEE in other provinces. The magnitude of this spillover effect depends mainly on two aspects: (1) the absorptive capacity of the technology and knowledge of the recipient, and (2) the degree of diffusion of technology and knowledge. Thus, if RED-induced low-carbon knowledge and technology in local regions can spill over to spatially relevant regions, this spillover effect increases as the absorptive capacity and diffusion of technology and knowledge increases.

The existing literature indicates that the absorptive capacity of a country or a region for technology and knowledge is significantly and positively correlated with its economic level, its level of workers and its R&D intensity (Teixeira and Fortuna, 2010; Huang and Chen, 2020; Lee and Lee, 2022). In addition, the level of development of technology markets is seen as a key influence on the diffusion of technology and knowledge (Han and Seo, 2023). Therefore, to test the spatial spillover effects, we incorporate the interaction terms of lnRED with lnPGDP, lnHC, lnRD, and lnLMTD and the spatial lag terms of these interaction terms into Eq. (6) to establish the new spatial Durbin models. The results presented in Table 8 demonstrate that both the direct and spatial spillover effects of RED on TFCEE escalate with higher levels of economic development, human capital, R&D intensity, and technological market development. These findings indirectly validate the economic transmission mechanism underlying the indirect effect of RED on TFCEE.

Table 8: Economic transmission mechanism test for the spatial spillover effect of RED on TFCEE

	(1)	(2)	(3)
	Direct effect	Indirect effect	Total effects
*lnRED*lnPGDP*	0.035^{***} (0.007)	0.091^{***} (0.027)	0.126^{***} (0.031)
*lnRED*lnHC*	0.076^{***} (0.042)	0.333^{**} (0.157)	0.409^{**} (0.186)
*lnRED*lnRD*	0.049^{***} (0.007)	0.113^{***} (0.020)	0.162^{***} (0.022)
*lnRED*lnLMTD*	0.020^{***} (0.003)	0.036^{***} (0.009)	0.056^{***} (0.011)

Notes: *** and ** indicate statistical significance at the 1% and 5% levels. The figures in () are standard errors. *lnLMTD* denotes the logarithm of technology market turnover as a share of GDP which is used to measure technology market maturity.

5. Discussion

Based on the above empirical results, five findings are highlighted.

First, the development of renewable energy has a significantly positive impact on the TFCEE in various provinces of China. Compared to traditional fossil fuels, renewable energy is cleaner, and its development reduces dependence on fossil fuels. Additionally, renewable energy technologies usually come with higher energy conversion efficiency. For instance, modern wind and solar power generation technologies incur less energy loss during the conversion process, whereas traditional thermal power generation involves considerable energy waste. With technological advancements and the realization of economies of scale, the cost of renewable energy has significantly decreased, enabling provinces to adopt renewable energy technologies more economically and efficiently. The widespread adoption and cost reduction of these technologies has prompted more provinces to transition to renewable energy, thereby improving carbon emission efficiency. In conclusion, the sustainable effects of developing renewable energy have already begun to manifest in China.

Second, economic transformation and energy transformation are complementary and collectively promote the achievement of a low-carbon development model. An increase in the proportion of the tertiary sector can enhance the positive impact of RED on TFCEE. The tertiary sector (services) typically has lower carbon emissions compared to the primary (agriculture) and secondary (industry) sectors. The service industry primarily relies on human labor and technology, with less dependence on energy-intensive and high-emission production processes. The tertiary sector includes a large number of technology- and knowledge-intensive industries, such as information technology, financial services, education, and scientific research. These industries generally have a higher acceptance of new technologies and stronger innovation capabilities, allowing them to better adopt and optimize renewable energy technologies. The service sector has strong adaptability and flexibility, enabling it to respond more quickly to and implement government environmental and renewable energy promotion policies. For example, service industry enterprises can more easily adopt measures such as green offices and energy management systems, which help promote energy transformation at a broader level. As the tertiary sector grows, especially with the rise of financial and commercial services, consumer environmental awareness also increases. More consumers will choose green energy products and services, thereby driving the development of renewable energy and further improving carbon emission efficiency.

Third, The advancement of urbanization is conducive to achieving carbon neutrality, as a higher urbanization rate can enhance the positive impact of RED on TFCEE. During the urbanization process, large-scale infrastructure construction and modernization provide a solid foundation for the development of renewable energy. For instance, newly constructed urban buildings and energy networks can incorporate the latest energy-saving technologies and renewable energy systems, thereby improving overall energy efficiency and reducing carbon emissions.

Urbanization is often accompanied by the development and improvement of public transportation systems. The widespread use of urban public transport systems such as subways, light rail, and electric buses can significantly reduce the use of private cars, thereby lowering carbon emissions in the transportation sector. Urbanization means a higher concentration of the population in urban areas, which facilitates more effective management and distribution of energy resources. The centralized energy demand makes large-scale renewable energy projects (such as large solar power stations and wind farms) more economically viable and feasible. Cities are typically the focal points for the implementation and regulation of national and local government policies. As urbanization progresses, governments at all levels find it easier to implement and enforce strict environmental policies and renewable energy development policies in urban areas. The effective implementation of these policies can further promote the achievement of a clean development model.

Fourth, technological advancements drive renewable energy development to further improve TFCEE. Progress in technology continually enhances the energy conversion efficiency of renewable energy technologies. For example, the conversion efficiency of solar panels has increased from around 10% in the early stages to over 20% today, with some technologies even surpassing 30%. Advances in wind power technology have also significantly improved wind energy utilization efficiency. These efficiency improvements mean that more clean energy can be generated per unit of resource, reducing the reliance on fossil fuels and promoting further energy transformation. Technological progress has significantly lowered the production and installation costs of renewable energy. For instance, the cost of generating solar and wind power has dramatically decreased over the past decade, achieving cost parity with, or even becoming cheaper than, traditional fossil fuel power generation in many regions. The reduction in costs has made renewable energy more economically competitive, driving its large-scale adoption. Technological advancements extend beyond the power generation equipment itself, encompassing the optimization of the entire industry chain, including raw material supply, manufacturing processes, logistics, and installation and maintenance. This comprehensive industry-wide technological progress further reduces the overall cost of renewable energy, promoting its widespread application and improving carbon emission efficiency.

Fifth, renewable energy development not only enhances the TFCEE of local areas but also makes a significant positive contribution to the TFCEE of spatially related regions. This spatial spillover effect is achieved through the interprovincial flow of electricity and the spillover of technology. With technological advancements and improvements in grid infrastructure, the electricity generated from renewable energy can be transmitted and shared through cross-regional grids. For example, when there is an excess of solar power generation in one area, it can be efficiently transmitted via the grid to other areas that need energy. This cross-regional energy-sharing mechanism allows different regions to better utilize renewable energy, optimize overall energy allocation, and improve carbon emission efficiency across regions. The successful application of renewable energy technologies can also drive technological progress in surrounding areas. Through technology diffusion and knowledge dissemination, advanced renewable energy technologies and management experiences can spread from one region to another. This diffusion of technology and knowledge not only helps to improve the carbon emission efficiency of the local area but also enhances the energy utilization efficiency of related regions, collectively boosting overall carbon emission efficiency.

6. Conclusions and policy implications

This study first uses the global super-efficiency slacks-based measure model to assess total factor carbon emissions efficiency (TFCEE) using data collected at the province level in China between 2005 and 2019. On this basis, the linear and non-linear effects of renewable energy development (RED) on TFCEE are explored using the two-way fixed effects model and the threshold effects model. Furthermore, utilizing the spatial Durbin model, the paper delves into the spatial spillover effect of RED on TFCEE and discusses potential transmission mechanisms associated with these spatial spillover effects. The key findings are listed below:

(1) RED significantly improves TFCEE, and this effect is still there following several robustness tests that include endogenous treatment. TFCEE rises by 0.020% to 0.035% for every 1% increase in RED. (2) China's RED complements its economic structural transformation and technological progress. Upgrading the industrial structure, promoting urbanization, and developing green technologies and energy technologies can help to enhance the positive impact of RED on TFCEE. (3) The neighborhood effect of RED on TFCEE is much larger than the local effect. When spatial spillovers are considered, a 1% increase in RED leads to an 0.12%-0.30% increase in TFCEE. Inter-provincial transmission of renewable electricity and spatial spillovers of new knowledge and technologies are potential transmission mechanisms for the spatial spillover effects of RED on TFCEE.

The conclusions of this study have the following clear policy recommendations: (1) China should maintain its commitment to the energy transformation strategy and actively promote the advancement of renewable energy. To achieve this, the Chinese government should allocate resources towards developing supportive infrastructure and offer financial subsidies and tax incentives to encourage private investment in renewable energy initiatives. (2) To maximize the impact of RED on TFCEE, the Chinese government should persist in promoting industrial structure upgrades and fostering new urbanization. Additionally, increased investment in research and development of green and energy technologies is crucial. (3) The facilitating effect of RED on TFCEE depends on its spatial spillover effect. Therefore, the central government should co-ordinate the planning of electricity infrastructure and technology trading market construction. Local governments should strengthen co-operation in renewable energy power production and consumption, increase investment in education and R&D, and introduce talents.

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