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Energy Policy Paradox on Environmental Performance: The Moderating Role of Renewable Energy Patents

Wasim Iqbal [1], Yuk Ming Tang [2,3], Ma Lijun [1,*], Ka Yin Chau [3], Wang Xuan [1], Arooj Fatima [2]

1. Department of Management Science, College of Management, Shenzhen University, Shenzhen, China
2. Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong
3. Faculty of Business, City University of Macau, Macau
4. College of Economics and Management Yanshan University, Qinhuangdao, China

wasimiqbal@szu.edu.cn; yukming.tang@polyu.edu.hk; ljma@szu.edu.cn; gavinchau@cityu.mo; wangx66@szu.edu.cn; aroojfatima132@yahoo.com

Corresponding Author: aroojfatima132@yahoo.com

Abstract

This study measures the association between resources and the atmosphere, social and environmental aspects of energy production have become critical. In this context, the aim of this research is to explore the mediating effect of renewable energy patents in developing potential frameworks for energy policy viewpoints on the climate. The study took panel data from 2010 to 2017 and used a non-radial data envelopment analysis (DEA) process and panel data model for 30 Chinese provinces. The findings indicate that between 2010 and 2017, the average environmental efficiency index (EPI) of Chinese areas increased by 9.88 percent. When firms' internal variables are proxied by their commodity (revenue), the relationship term's point approximate coefficient is about 0.05. This magnitude means that a 1% rise in a company's assets will result in a 5% increase is estimated to be about 0.157, implying that a 1% rise in firm leverage is correlated with a 15.7%. Finally, based on the study results, some policy implications were proposed.

1. Introduction

Significant research is being done to measure, investigate, and enhance energy efficiency as environmental degradation is a serious global concern. One of its leading causes is the

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greenhouse emissions involving carbon dioxide (CO_2), which is emitted as a result of burning fossil fuels (Liu et al., 2020a). Burning fossils fuels is a waste of natural resources and poses significant environmental risks (Taghizadeh-Hesary and Taghizadeh-Hesary, 2020; Zhang et al., 2020). Countries that consume the most energy are also the among the largest CO_2 emitters. National governments must, therefore, draft new policies to conserve natural resources, promote energy efficiency, defend territory, and attain environmental development. Some countries have already declared their commitment toward reducing CO_2 emissions per unit of GDP by 40% to 45%. Faced with significant environmental challenges, countries must carefully consider environmental restrictions to lower energy utilization and environmental pollution (Iqbal et al., 2020; Olusola, 2020).

Three types of indices—thermodynamic, physical-based, and currency-based indicators—are used to measure energy efficiency (Baloch et al., 2020; Chao et al., 2020; Mi et al., 2020; Zhang et al., 2016). The manufacturing process utilizes energy inputs such as natural gas, oil, and coal, along with labor and capital, to generate value, such as GDP, and polluting by-products, such as CO_2 and sulfur dioxide (SO_2) emissions. Environmental efficiency must not be neglected in efficiency marking protocols. Globally, industries account for more than one-third of total energy requirements, with analogously higher proportions of CO_2 emissions (Taghizadeh-Hesary and Yoshino, 2020). China's development model relies heavily on industries; local infrastructural development and manufacturing of export-oriented consumer products and heavy industrial equipment mostly entail energy-intensive production mechanisms. Therefore, China's share of carbon-based energy consumption is higher than the world average. The 2010 National Economic and Social Development statistical report states that the processing of raw materials of petroleum and chemical products, melting and crashing of metal, non-metal and ferrous metal products, and electricity generation and distribution are categorized as energy-intensive industries (Iqbal et al., 2019; Mohsin et al., 2021). Because of the rise of energy intensity and the subsequent carbon emissions, China faced massive international criticism, which led the government to initiate a low carbon emission policy under its 13th Five Year Plan (2016–2020) by setting a maximum carbon emission limit for all domestic energy-intensive companies (Taghizadeh-Hesary et al., 2019). It was determined in the program that the ferrous metal processing industry should decrease its energy use by a minimum of 10%, and the petrochemical and nonferrous metal industries, by 18% (Mohsin et al., 2018). As fossil fuels primarily drive global warming, an emphasis on energy-efficient production and distribution processes may be the key to mitigating this hazard. A nation's economic development is correlated with its energy intensity, carbon emissions, and global warming parameters. Businesses and governments should, therefore, consider human beings and wildlife, climate, and environmental aspects while designing their respective growth strategies (Taghizadeh-Hesary et al., 2021). In this regard, the initiation of the green movement by adopting green technology solutions for industrial production and distribution can be a useful undertaking. Robust energy and carbon management and control coupled with a strict regulatory framework and better energy policies can also improve environmental quality significantly.

In the past two decades, China's economy has undergone several transformations and achieved significant structural and economic progress, albeit at the cost of the environment. China's future growth trajectory must include a combination of economic enhancement and environmental safety. Decreasing the emission of pollutants, which severely affect public health and the environment, is one of the primary goals. The economy's environmental sustainability is generally measured by environmental efficiency. Environmentally efficient cities produce greater economic output and revenue along with fewer environmental pollutants such as greenhouse gases. Using a more ecologically efficient decision-making unit leads to better utilization of environmental resources and delivers the most acceptable ecological and economic returns to investments.

This study aims to investigate the impact of energy policies on China’s environmental performance (EP) and contributes to the existing literature in three ways: First, the non-radial data envelopment analysis (DEA) model (which minimizes environmental pollution and maximizes economic benefits) is used to evaluate and compare China's environmental performance indices (EPIs) at a provincial level. Second, energy policy, further divided into emission reduction and renewable energy policies, is used as a core variable. Finally, using the system generalized method of moments (GMM) estimation method, the study validates the effectiveness of various environmental regulations and assesses the nonlinear and heterogeneous effects of energy policy on provincial EP.

2. Literature review

The use of non-renewable energy inputs in the manufacturing process discharges higher amounts of point source pollutants, including gases such as CO_2 and SO_2, which harm the environment. To enhance energy efficiency and decrease pollutant emissions, non-renewable energy inputs must be efficiently distributed and conserved (He et al., 2021). Various DEA-type linear programming models use a dual output structure to calculate energy efficiency by using energy and non-energy inputs and undesirable output. In recent times, different DEA models have been projected to measure energy and resources instantaneously.

The hybrid power model attempts to consistently raise the individual output and decrease the low output to simultaneously estimate total efficiency. This is known as static analysis, and no change in efficiency is observed because only one year's production is measured. For several areas, only the annual efficiency is estimated; the measurement of production in different years overlooks technological progress, and efficiency is observed to be worse in multiple years. Energy plays a vital role in the rapid and comprehensive development of countries and also facilitates the survival and development of human civilization (Taghizadeh-Hesary et al., 2020). Coal burning generates 85% of CO_2 emissions, 73% of dust emissions, and 90% of SO_2 emissions (Zuo et al., 2020). Therefore, it is vital to manage energy consumption, climate change, and public health (Li et al., 2021). For an enhanced "Energy–Economy–Environment" structure, universal greenhouse gas emissions (Du et al., 2021) should be reduced. In this fast-paced globalized world, energy forms the core of strong economic growth, but it is also the root cause of global climate change. Decision-makers must, thus, formulate economic development strategies, keeping environmental sustainability in mind.

Researchers have adopted various energy efficiency measures to study the energy and environmental efficiency levels of many different countries and regions. DEA is one of the most popular and useful tools for measuring energy and EP. Despite its limitations, the application of DEA has some unique advantages in evaluating energy efficiency. This study reviews the DEA application used by previous studies on energy and environmental efficiency and the decomposition of the Malmquist index. For example, (Shao et al., 2014) applied DEA to measure energy efficiency within the metal sector, while Ma et al. (2019) studied both energy and pollution efficiency for China's mining industry. Lin and Jia (2019) evaluated the efficiency of environmental governance for China's energy industry.

Moreover, Zhang et al. (2021) measured the energy efficiency of the manufacturing industry by applying the Malmquist index decomposition, Stochastic frontier method (SFA), and meta frontier DEA method. Lin and Chen (2019) measured the ecological efficiency of Chinese regions' nonferrous metals industry by applying the non-radial DEA method. Du et al. (2020) explored the green total factor production efficiency and its determinants for China's metal industry using the sub-boundary and global DEA approaches. Several other studies were also conducted on the energy and environmental efficiency of the steel, construction, and chemical industries of Chinese provinces. The current literature is based mainly on EP; no prior studies have objectively measured China's ecological performance from the operational front. Also, the different industrial sub-sectors in different regions within China’s vast territory affect the EP of these regions. Therefore, by accounting for the heterogeneity of industries and areas, the total factor energy efficiency assessment of the six energy-intensive industries in the Chinese provinces can help policymakers develop sustainable strategies. Furthermore, the non-radial DEA approach toward efficiency measurement is more flexible than any other measurement technique as it satisfies the dual requirements of maximum economic growth and minimum pollution emissions. This study, thus, uses the non-radial DEA method for China’s EPI assessment at the provincial level. Due to the extensive acceleration of ecological degradation, governments have undertaken many corrective measures to promote sustainable development. Existing studies lack consensus on how different types of regional energy policies affect EP. Therefore, investigating the effect of other regional energy policies is a timely endeavor toward ensuring environmentally sustainable economic development in China.

3. Methodology

3.1. Model construction

DEA is considered a more effective efficiency measurement tool than conventional econometric approaches such as regression or ratio analysis. While efficiency has been defined by several scholars, in this study, we consider Farrell’s (1957) definition of efficiency, drawn from (Koopmann, 1951), to describe the measure of efficiency that constitutes multiple inputs. Farrell (Farrell, 1957) states that an organization's efficiency comprises two components: technical efficiency and allocative efficiency. In input-oriented efficiency measurement, technical efficiency refers to the ratio of the optimal input to the actual information. Output-oriented efficiency measurement relates the rate of real output to the optimal production.

On the other hand, allocative efficiency manifests in an organization's ability to utilize its inputs optimally with respect to its prices and technology. Based on the objective of decision-making units (DMU), production or cost frontiers are used to determine the optimal input and output. Two different methods are recommended in the literature in this regard: parametric and non-parametric approaches. In the parametric approach, a functional plan is assigned to the frontier, but no preceding specification is applied to the non-parametric approach's border. Charnes et al. (1978) first followed the non-parametric process to develop the DEA model for measuring a single DMU's efficiency.

Assume there are n DMUs, each signifying an administration zone. Separately, a DMU's non-energy input and L energy input produce the predictable cost output or low output, K. DMUs help attain desired production targets using fewer resources. By the usual method, a decrease in pollutants is not permissible. This can be resolved using different methods such as the opposite of worse output, bad behavior output, as the input, and statistically constructing the undesirable result into the desired outcome. In the study of energy and environmental efficiency, low production is mostly done using fossil fuels through manufacturing, which must be minimized if less energy is used.

$$\mathrm{EPI1} = \min \theta \tag{1}$$

$$\text{s.t. } \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{x-} = x_{ij0,}\ i = 1,\ldots,m, \sum_{j=1}^{n} \lambda_j e_{lj} + s_l^{e-} = \theta_l^{e} e_{lj0},\ \iota = 1,\ldots L, \sum_{j=1}^{n} \lambda j\, y_{rj} - s_r^{y+} = y_{rj0},\ r = 1,\ldots s, \sum_{j=1}^{n} \lambda_j\, b_{kj} = \theta_k^{b} b_{kj},\quad k = 1,\ldots,k\,, \lambda_{j,} S_i^{x-}, S_l^{e-}, S_r^{y+} \geq 0, \text{ for all j, i, l, r,}$$

Consider that a method decreases the unwanted output and possibly the level of ideal output and non-energy input. For sections between 0 and 1, the energy and environmental efficiency index takes a value of θ; the more superior the index, the better the region's performance in reducing pollutant discharges and saving energy. The corresponding part is measured to be energy and environmentally efficient. It cannot decrease its pollutant emissions and energy consumption if EPI1 = 1 (θ = 1) is zero; however, if the EPI1 < 1 (θ < 1) is not zero, then the corresponding region is considered environmentally inefficient and can further decrease energy utilization and pollutant discharges. This type of model is the radial efficiency model and may not yield strong energy efficiency assessments.

$$EPI_2 = \min \frac{1}{2}\left(\frac{1}{L}\sum_{l=1}^{L}\theta_l^e + \frac{1}{k}\sum_{K=1}^{k}\theta_k^b\right) \tag{2}$$

$$\sum_{j=1}^{n}\lambda_j x_{ij} + s_i^{x-} = x_{ij0},\ i = 1,\ldots,m, \sum_{j=1}^{n}\lambda_j e_{lj} + s_l^{e-} = \theta_l^e e_{lj0},\ \iota = 1,\ldots L, \sum_{j=1}^{n}\lambda j\, y_{rj} - s_r^{y+} = y_{rj0},\ r = 1,\ldots s, \sum_{j=1}^{n}\lambda_j b_{kj} = \theta_k^b b_{kj},\quad k = 1,\ldots,k, \lambda_j, S_i^{x-}, S_l^{e-}, S_r^{y+} \geq 0,\ \text{for all } j, i, l, r,$$

This model decreases the energy utilization and pollutant discharges by various methods to successfully attain the energy and environmental efficiency border. Energy and environmental efficiency consume altered non-proportional adjustments and assess constant efficiency by elected choice creators. The EP is integrated in the efficiency equation and shows various biases for an energy consumption presentation by decision-makers. We use this method to estimate the total-factor energy and environmental efficiency of the various areas because this model has a better-developed perceptive power than the first model. In this study, we design a strategy to compute the energy and environmental efficiency for various areas for 2000–2008 to obtain data about efficiency variations.

However, DEA window analysis is more important in increasing energy and environmental efficiency. It is used to develop time-varying and cross-sectional data to compute dynamic properties. This method works by altering medians to create efficiency measures, treating every DMU as an individual unit for various time periods. Therefore, the environmental efficiency of various areas over different periods is examined through overlapping windows using this technique.

The width of a window in efficiency measurement tends to yield three or four time periods. This study considers a window with three widths (w=3) for attaining a consistent environment and energy efficiency results. The period 2010–2012 has been utilized for the first window. This is followed by further one-year window changes by excluding the base year and adding the next one, until the last window. Thus, radial and non-radial environmental energy efficiency (EPI1 & EPI2) for each underlined country can be attained by applying DEA window analysis.

4. Empirical results and discussions

4.1. Environmental performance

China continues to be the world's largest energy consumer, accounting for 24% of global energy consumption and 34% of global energy demand growth in 2018. Figure 1 presents the energy consumption profile of China. Energy consumption in China increased from the 10-year average of 3.3% in 2017 and 3.9% in 2017 to 4.3% in 2018. Fossil fuel consumption was led by natural gas (+18%) and oil (+5.0%), while coal usage increased for the second consecutive year. China's energy structure is continually evolving. Although coal was still the primary fuel, its share of total energy consumption in 2018 (58%) reached a historical low. China is the world's largest importer of oil and natural gas. The dependence on oil imports rose to 72% in 2018, the highest in the past half-century. By 2018, the reliance on natural gas imports increased to 43%. There were growing concerns about energy security. Among non-fossil fuels, solar energy consumption increased the fastest (51%), followed by wind energy (24%) and biomass and geothermal energy (14%). Hydropower increased by 3.2%, almost a third of the 10-year-average growth of 9.2%.

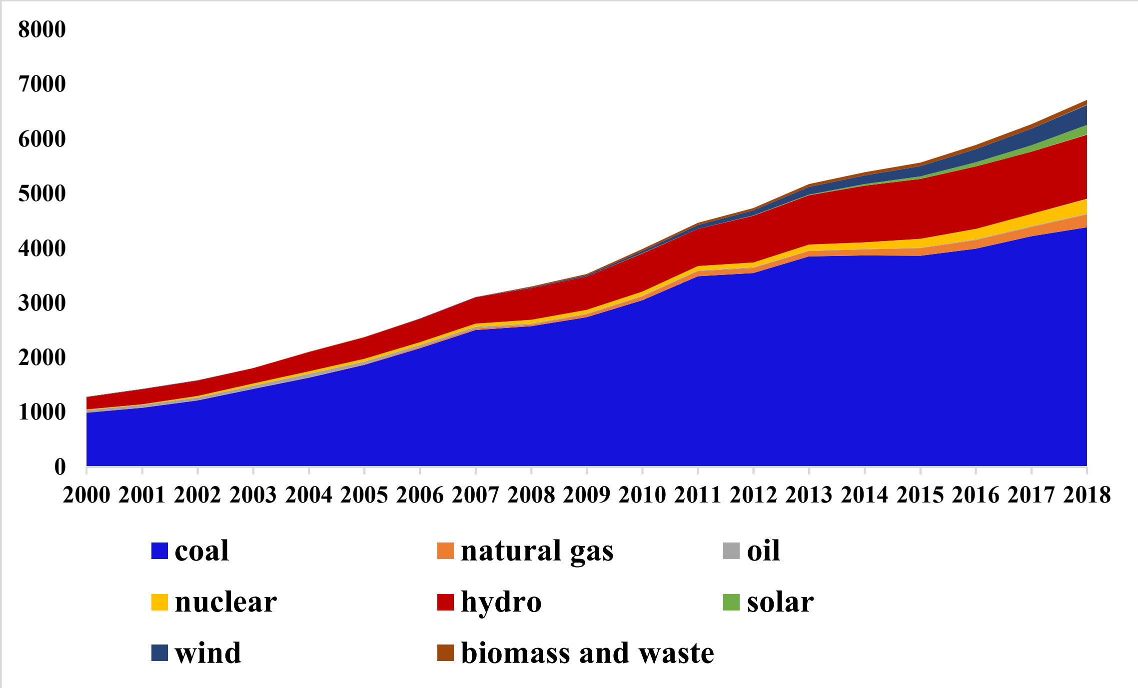

Fig. 1 Energy consumption by source

According to Table 1, the highest EPI is recorded in Hainan, Guangdong, Shanghai, Tianjin, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, and Sichuan. The lowest EPI is recorded in Shanxi, Qinghai, Heilongjiang, Yunnan, Gansu, Xinjiang, and Ningxia. Provinces in the central and eastern regions have high EPI, while those in the western and north-east areas have low EPI. Compared with the eastern and central provinces, China's western provinces have a lower EPI due to a poor economic foundation and backward technology. The low EPI is also because of highly energy-intensive industries located in north-eastern China. The old industrial base performs low on EPIs due to outdated equipment and severe environmental pollution.

Table 1. The EPI of China at the provincial level from 2010 to 2017

Province	2010	2011	2012	2013	2014	2015	2016	2017
Guangdong	0.9	0.891	0.9	0.9	0.882	0.9	0.855	0.882
Hainan	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Shanghai	0.9	0.9	0.9	0.9	0.81	0.9	0.9	0.9
Zhejiang	0.9	0.9	0.891	0.9	0.855	0.846	0.873	0.828
Jiangsu	0.891	0.891	0.882	0.873	0.873	0.891	0.9	0.9
Beijing	0.846	0.792	0.873	0.837	0.792	0.9	0.9	0.9
Fujian	0.774	0.693	0.621	0.693	0.648	0.594	0.666	0.684
Tianjin	0.756	0.702	0.711	0.828	0.702	0.774	0.738	0.801
Qinghai	0.657	0.765	0.684	0.675	0.522	0.54	0.531	0.531
Jiangxi	0.558	0.468	0.441	0.468	0.513	0.432	0.414	0.459

Gansu	0.549	0.405	0.234	0.234	0.189	0.216	0.171	0.198
Henan	0.531	0.549	0.423	0.45	0.396	0.387	0.342	0.378
Liaoning	0.504	0.531	0.495	0.495	0.495	0.54	0.477	0.351
Ningxia	0.495	0.468	0.378	0.342	0.279	0.333	0.288	0.387
Sichuan	0.459	0.351	0.279	0.315	0.243	0.243	0.198	0.288
Anhui	0.441	0.369	0.495	0.531	0.495	0.612	0.441	0.567
Hebei	0.432	0.522	0.45	0.468	0.504	0.468	0.468	0.486
Hubei	0.387	0.36	0.342	0.396	0.351	0.459	0.423	0.513
Chongqing	0.369	0.459	0.333	0.396	0.234	0.306	0.297	0.342
Guangxi	0.369	0.414	0.306	0.315	0.333	0.351	0.333	0.351
Jilin	0.369	0.486	0.468	0.477	0.459	0.495	0.324	0.477
Inner Mongolia	0.315	0.378	0.342	0.351	0.351	0.468	0.396	0.324
Hunan	0.27	0.225	0.27	0.315	0.27	0.306	0.279	0.612
Shaanxi	0.261	0.243	0.189	0.675	0.18	0.243	0.252	0.324
Guizhou	0.225	0.27	0.153	0.18	0.135	0.288	0.243	0.333
Yunnan	0.216	0.18	0.162	0.162	0.171	0.198	0.171	0.216
Xinjiang	0.162	0.387	0.171	0.108	0.108	0.153	0.081	0.207
Heilongjiang	0.144	0.162	0.117	0.117	0.36	0.108	0.081	0.108
Shanxi	0.135	0.135	0.126	0.108	0.099	0.099	0.072	0.09

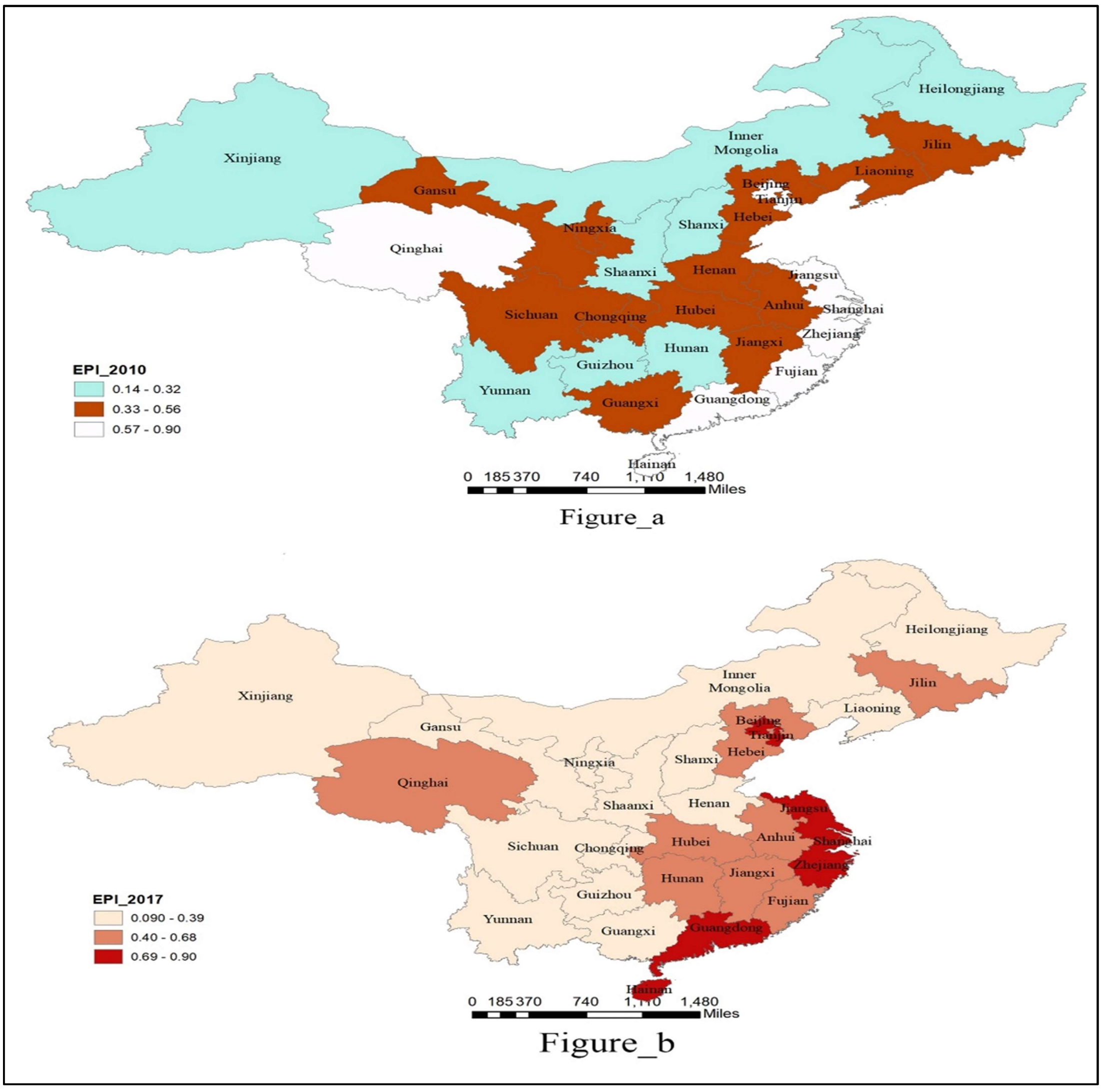

Figure 2 The spatial distribution of EPI in 2010 and 2017

According to Figure 2a, Beijing, Guangdong, Shanghai, Hainan, Qinghai, Guangxi, Shandong, Zhejiang, Jiangsu, and Liaoning have the highest EPI (0.82–1.00), whereas Guizhou, Henan, Inner Mongolia, Heilongjiang, Yunnan, and Shanxi have the lowest EP (0.07–0.20). According to Fig. 2b, an EPI score within the range of 0.74–1 is evident in Jiangsu, Shandong, Guangdong, Hainan, Zhejiang, Shanghai, and Fujian. In contrast, with a score of 0.07–0.26, Shanxi, Chongqing, Yunnan, Xinjiang, Heilongjiang, Sichuan, Hebei, Hubei, Hunan, Guangxi, and Guizhou show lower values. Beijing, Shanghai, Jiangsu, Guangdong, and Hainan are considered the most environmentally efficient provinces. With a particular focus on the western and north-eastern regions, China requires further improvement in EPI at the provincial level.

With better energy management and pollution control, Jiangxi and Sichuan show a relatively high EPI. The worst values are observed for the central region of Shanxi, the western part of Xinjiang, Yunnan, and Gansu. A significantly poor economic foundation, backward technological conditions, and low efficiency are evident in these provinces.

4.2. Average EPI values

Figure 3 shows the average EPI results from 2008 to 2017 based on the non-radial DEA model. From 2010 to 2017, the average EPI of China at the provincial level showed an upward trend. However, the average EPI was still weak, with an average value between 0.44 and 0.52, far below the optimal value of 1. Chinese industries consume large amounts of energy and emit large amounts of CO_2, resulting in low power and EPI, and thus, environmental inefficiency. However, the Chinese government has emphasized pollution control measures, and high emitting industries such as petrochemicals and metals have been subjected to severe environmental scrutiny. Because of this ecological regulatory initiative, the EPI for high carbon emission industries has dramatically increased. This finding is also in line with (Wu et al., 2020), who investigated the energy and environmental efficiency of Chinese provinces.

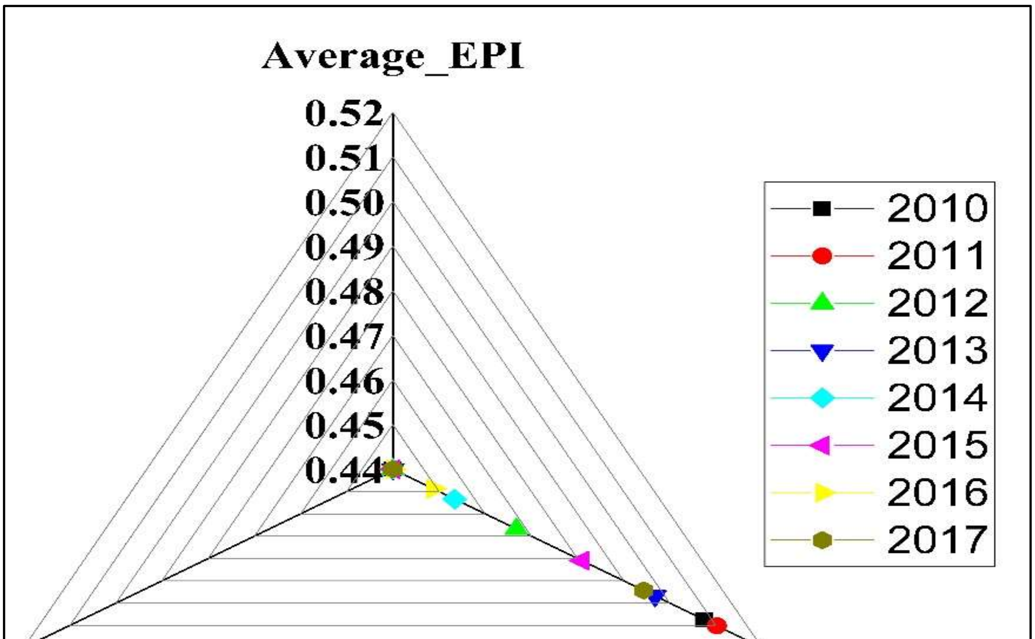

Figure 3. The average EPI of China's at the provincial level from 2010 to 2017

4.3. Econometric modelling and variable selection

4.3.1. The dynamic panel data model effect

The following equation examines the relationship between environmental regulation and total factor energy efficiency:

$$\mathrm{EPI}_{it} = \alpha + \beta \mathrm{EPI}_{i,t-1} + \gamma \mathrm{energy\_policy}_{it} + \theta X_{it} + u_t + v_i + \varepsilon_{it} \quad (3)$$

In this equation, α represents the intercept, and β, γ and θ are the coefficients to be estimated. $\mathrm{energy\_policy}_{it}$ is the independent variable, that is, the vector that represents the energy policy. $\mathrm{EPI}_{i,t-1}$ is the first lag term of EPI_{it}. This lagged dependent variable $\mathrm{EPI}_{i,t-1}$ is added as the independent variable considering the impact of the lagged EPI on the current EPI. X_{it} matrix indicates the set of control variables. u_t is fixed time effect, v_i is a single fixed-effect, and ε_{it} is a random error term.

(a) Dependent variable: The dependent variable for this study is the EPI.

(b) Independent variables: By providing economic incentives, services, new legislation or laws, and public education, current energy policies are expected to affect EPI (Liu et al., 2020b). The Chinese government's energy policy has been classified as a reduction or a renewable energy policy. We used the current number of provincial laws, regulations, and detailed plans as key independent policy variables, based on information collected from the Law Star website. To check and classify the provincial policies belonging to each group, we used keywords such as "emission reduction" and "renewable energy." In addition to energy policy variables as experience variables, socioeconomic and environmental variables were also used as control variables to illustrate their EPI impact. These included secondary industry GDP, consumer spending, education level, and population density. Ecological variables included the emission levels of private cars, exhaust emissions, investment in treatment of departmental pollution sources, and investment in anti-pollution programs. Financial support in terms of investment in industrial waste source treatment and pollution prevention programs is necessary for environmental pollution management.

Table 2. Descriptive statistics

Variable	Mean	SD	Min	Max
EPI	4.579	0.338	2.708	5.72
EMRP	2.056	1.517	0	4.89
REPO	0.938	1.014	0	3.584
GDP	3.822	0.212	2.955	4.119
CEXP	9.382	0.459	8.5	10.59
EDU	8.026	0.257	7.021	8.503
REPAT	4.714	1.263	2	7
PopD	3.88	0.295	3.037	4.495
InvP	4.322	1.673	−2.303	7.256

4.3.2. The empirical results of the panel data model

The panel data model approach was applied to fix the issues in dynamic panel estimation as stated in Equation 3. System GMM assumes that there is no autocorrelation within the disturbance terms. This approach also resolves the endogeneity issue by taking lag variables. The results of the GMM test are presented in Table 5. Additionally, the study also included Arellano–Bond (AR), Sargan–Hansen, and Wald chi-square test results for a more robust estimation. The AR test comprises both first and second-order autocorrelation of residuals tests, known as AR (1) and AR (2), respectively. The equation's residuals are regarded to not be autocorrelated if AR (2) is accepted and AR (1) is not. The Sargan–Hansen test is applied to check for homogeneity among the variables. The Wald test is performed to check the level of significance of each regression.

Table 3. The results of the panel data regression

	Emission reduction policy	Renewable energy policy

Constant	1.0384(0.117)	1.0586***(0.1225)	1.1112***(0.0519)	1.1477***(0.0701)
EMRP	0.0286***(0.1551)			
EMRP_lag		0.0342***(0.1137)		
REPO			0.0304***(0.0052)	
REPO_lag1				0.0605***(0.0761)
GDP	-0.0342***(0.0011)	-0.0350***(0.0012)	-0.0294***(0.0203)	-0.0301***(0.0214)
CEXP	0.0151(0.0014)	0.0160*(0.0017)	0.0209(0.0159)	0.0241*(0.0022)
EDU	0.03251***(0.0445)	0.03607***(0.045)	0.04251***(0.0624)	0.04399***(0.0661)
REPAT	0.0009**(0.0006)	0.0011***(0.0008)	0.0010***(0.0009)	0.0012***(0.001)
Pop	-0.0120***(0.0038)	-0.0135***(0.004)	-0.0201***(0.0114)	-0.0263***(0.0118)
InvP	0.0293***(0.0046)	0.0311***(0.0053)	0.0413***(0.0058)	0.0438***(0.0059)
AR (1) test	−2.0632	−2.0841	−2.4149	−2.5243
	[0.023]	[0.023]	[0.019]	[0.013]
AR (2) test	−1.1591	−1.2374	−1.2580	−1.3001
	[0.171]	[0.138]	[0.166]	[0.154]
Sargan test	21.3797	19.9903	23.5612	18.5531
	[0.068]	[0.069]	[0.11]	[0.139]
Wald test	176396	280449	192133	305156
	[0]	[0]	[0]	[0]
N	240	240	240	240

Note: Standard errors are in parentheses (). ***= 1% level of significance; **= 5% level of significance, and *=10% level of significance

Table 3 shows the result of the Tobit regression analysis for the study variables for four different models. It is observed that the lagged EPI coefficients are positive and statistically significant at a 1% level of significance, showing that the present EPI performance is affected by the previous period's EPI's performance. It is further observed that the coefficients of emission reduction policy (EMRP) and renewable energy policy (REPO) are 0.0286 and 0.0304, respectively, indicating that both EMPR and REPO are statistically significant at the 1% level. The results confirm that provincial renewable energy policies and emission reduction have different effects on improving EPI. This shows that energy policy positively influences the improvement in the EPI. This is in line with the Porter effect for China. Meanwhile, the control variables' regression estimation shows that both GDP and population negatively affect the EPI at 1% level of significance in all cases.

A 1% increase each in GDP and population reduces the EPI by 3.42% and 1.2%, respectively. On the other hand, investment in education and investment in anti-pollution projects have a significantly positive effect at a 1% level of significance. A 1% increase in education investment and investment in anti-pollution projects improves EPI by 3.25% and 2.93%, respectively. This affirms that spending more on education and air pollution control can help in improving EPI. Renewable energy patents positively affect EPI. On the other hand, it is observed that consumption expenditure has no significant influence on EPI improvement. Considering the probable lag effect of energy policy, the estimation of emission reduction policy and renewable energy policy was performed taking the lagged values of EMRP and REPO.

The results were identical to those of the baseline regression, reflecting a statistically significant EMRP over EPI, and the control variables are also consistent with the estimated coefficients. However, for the case of REPO, the coefficients (0.0605) of lagged variables were found to be positive and statistically significant at a 1% level of significance, proving that EPI is affected by lag terms. For a rigorous REPO practice, the influence of the "innovation offset" is more powerful than that of the "compliance cost" effect in the long run. This result matches the findings of Guo and Yuan (2020) and (Xu and Chen, 2019), who argued that taking the lagged variables instead of current variables may increase the chances of a positive and significant effect on energy efficiency.

4.3.3. The moderating effect of renewable energy patents

Table 4 presents the results for the moderating effect of renewable energy patents on China's EPI. The findings indicate that all the moderating coefficients are positive and statistically significant at a 1% level of significance, validating the moderating effect of renewable energy patents (REPAT) for energy policy. The regression results show that a greater number of REPAT can boost the EPI. Porter argues that, by making a well-structured energy policy, a positive effect can be established based on renewable energy patents and technology empowerment. Therefore, the moderation effect of renewable energy patents and energy policy on the EPI must be studied further to enhance the EPI to the highest level possible.

Table 4. Regression results of the renewable energy patents' effect on the EPI

	EMRP	REPO	EMRP	REPO
EPI_lag1	0.3711***((0.0026)	0.3996***(0.0011)	0.4028***((0.0031)	0.4154***(0.0013)
Constant	1.1383***(0.0390)	1.1099***(0.0590)	1.2353***(0.0490)	1.0723***(0.0590)
EMRP	0.0293***(0.0556)			
EMRP_lag1	0.0415***(0.0603)			
REPO		0.0322**(0.0046)		
REPO_lag1		0.0519***(0.0054)		
EMRP* REPAT			0.0410***(0.0069)	
EMRP_lag1* REPAT			0.0466***(0.0072)	
REPO* REPAT				0.0912***(0.1120)
REPO_lag1* REPAT				0.1032***(0.0589)
GDP	-.0306***(0.0033)	-0.0375***(0.0046)	-0.0323***(0.0042)	-0.0391***(0.0051)
CEXP	0.0158(0.0020)	0.0162(0.0017)	0.0183*(0.0021)	0.0204(0.0018)
EDU	0.2491*(0.0248)	0.3466(0.0516)	0.3157(0.0346)	0.0112(0.1737)
REPAT	0.0006**(0.0002)	0.0010**(0.0001)	0.0009***(0.0003)	0.0013(0.0002)
Pop	-0.0122**(0.0046)	-0.0239***(0.0054)	-0.0126***(0.0051)	-0.0301**(0.0056)
InvP	0.0193***(0.0177)	0.0201***(0.0170)	0.0234***(0.0186)	0.0355***(0.0199)
AR(1) test	−2.2932	−2.1575	−2.3024	−2.1235
	[0.023]	[0.019]	[0.023]	[0.013]
AR(2) test	−1.3401	−1.2380	−1.2552	−1.1895
	[0.1749]	[0.1382]	[0.1411]	[0.1312]
Sargan test	21.3771	17.8685	20.1098	15.596
	[0.0752]	[0.1123]	[0.0706]	[0.1269]
Wald test	198472.3	232216	300239.2	291644.1
	[0]	[0]	[0]	[0]
N	240	240	240	240

4.3.4 The dynamic threshold model

The moderating effects model fails to identify the key areas and relevant environmental energy policy breaks. This study thus considered a single threshold model in line with the idea of (Hansen 1999) non-dynamic panel threshold model to explore the nonlinear causality between energy policy and the EPI and confirm the rationale of the sample interval segment in reducing the errors in model estimate. The following section addresses the energy policy variable as the threshold-dependent variable to construct a threshold effect model as follows:

$$EPI_{it} = \alpha + \beta_1 EPI_{it-1} + \beta_2 ER_{i,t} \circ I(Q_i \leq \mathrm{C}) + \delta_1 ER_{i,t} \circ I(Q_i > \mathrm{C}) + \sum_{k=1}^{5} \delta_k X_{kit} + \alpha_i + u_t + \varepsilon_{it} \quad (4)$$

C is the estimated threshold value, and $I(\cdot)$ is the symptomatic function, which holds true if the corresponding condition is equal to 1 and false if the value is 0. The test results may indicate the presence of multiple thresholds, allowing extensions from the base single threshold model to double and numerous threshold models.

4.3.5 Analysis of threshold regression test

We first checked the number of thresholds to perform threshold regression analysis. In this study, we used Hansen's threshold panel model with bootstrap technology and repeated it for 500 iterations to test the threshold. We found a major dual-threshold effect of pollution mitigation and clean energy policies on the environmental efficiency index, wherein energy policy is the threshold component. The results of the importance assessment are summarized in Table 5. The impact of agricultural systems on carbon emissions can be seen in Model 1, while the impact of urbanization on carbon emissions can be seen in Model 2. The single-value and dual-value p-value threshold models passed the 1% significance test (as shown in Model 1), confirming the dual-threshold effect. The estimated thresholds were 0.240 and 0.82, each within the 95% confidence intervals [0.225, 0.692] and [0.692, 0.817], respectively. The 1% significance test also showed a potent dual-threshold effect in Model 2. The estimated thresholds were 0.762 and 0.823 and [0.801, [2.863] and [0.762, 2.861] were the corresponding 95% confidence intervals (Table 6).

Table 5. Results of the threshold test

	Threshold test	F-value	P-value	Critical value		
				1%	5%	10%
Model 1	Single	52.589***	0.000	24.557	14.670	10.134
	Double	28.661***	0.008	24.734	15.678	10.940
Model 2	Single	57.481***	0.000	24.521	14.987	10.623
	Double	27.229***	0.000	2.893	−5.832	−11.843

Table 6. Estimated threshold variables

Threshold variables		Estimated thresholds	95% confidence interval
Model 1	$\gamma 1$	0.240	[0.220, 2.762]
	γ_2	0.821	[0.762, 2.823]
Model 2	γ_1	0.762	[0.801, 2.163]
	γ_2	0.823	[0.762, 2.361]

Table 7 presents the level of provincial EPI based on the threshold values. The number of provinces with an EPI of less than 0.301 increased from 62.3% to 85.2% between 2010 and 2017 and showed an upward trend throughout the period. Simultaneously, provinces with EPI levels between 0.301 and 0.438 increased from 3.2% to 22.6%, indicating improved provinces' EPI during the study period. Provinces with an EPI higher than 0.438 also showed a similar steady growth trend. This happened due to the increasing levels of regional economic and technological development (Xu and Chen, 2019; Zhao et al., 2020), from 9.7% to 16.1%, and the growth of the regional innovation system. However, after 2013, provinces' EPI with a regional economic development level higher than 0.438 changed. Between 2010 and 2017, the proportion of regions with a regional economic development level of less than 0.438 declined from approximately 90.3% to 83.9%. Regional technological innovation has different positive effects on regional sustainable development capabilities. During the study period, the proportion of areas where regional technological innovation contributed to sustainable development dropped from 87.1% to 61.3%. Also, the proportion of regions where technological innovation weakly affected sustainable development increased from 3.2% to 22.6%. Therefore, it can be concluded that the overall situation in China was optimistic for the study period. When the LR value is 0, the corresponding threshold parameters of the provincial EPI are 0.346 and 0.456, respectively. The threshold estimate is the interval of the provincial EPI. When the confidence interval is 95%, it is less than the LR = 6.503. Therefore, the confidence intervals of the threshold estimate of 0.324 and 0.447 are [0.030, 0.709] and [0.038, 0.539], respectively. The true threshold value, that is, the authenticity is used to test the two threshold estimates of the dual-threshold model.

Table 7. The level of provincial EPI with respect to the threshold value

	Low threshold	Medium threshold	High threshold
	EPI≤ 0.301	0.301 < EPI ≤ 0.438	EPI > 0.438
2010	Anhui, Chongqing, Chongqing, Fujian, Gansu, Guangxi, Guizhou, Hainan, Heilongjiang, Jiangxi, Jilin, Ningxia, Qinghai, Shanxi, Xinjiang, Xizang, Yunnan, Shanxi	Beijing, Zhejiang, Hebei,	Jiangsu, Shandong, Guangdong
2011	Anhui ,Chongqing ,Chongqing ,Fujian ,Gansu, Guangxi, Guizhou ,Hainan ,Heilongjiang, Inner Mongolia, Jiangxi, Jilin, Ningxia, Qinghai, Shanxi, Xinjiang, Xizang, Yunnan, Shanxi	Zhejiang, Henan	Jiangsu, Shandong, Guangdong
2012	Heilongjiang, Jiangxi, Hainan, Anhui, Shanxi, Chongqing, Chongqing, Guangxi, Jilin, Shanxi, Fujian, Inner Mongolia, Qinghai, Gansu, Xizang, Ningxia, Yunnan, Guizhou, Beijing, Xinjiang	Hebei, Liaoning, Henan	Jiangsu, Zhejiang, Shandong, Guangdong
2013	Heilongjiang, Fujian, Guangxi, Shanghai, Xizang, Jiangxi, Hainan, Chongqing, Jilin, Shanxi, Anhui, Inner Mongolia, Gansu, Shanxi, Yunnan, Qinghai, Guizhou, Chongqing, Beijing, Ningxia, Xinjiang	Hebei, Liaoning, Henan, Hubei, Sichuan	Jiangsu, Zhejiang, Shandong, Guangdong
2014	Heilongjiang, Fujian, Hunan, Shanghai, Yunnan, Jiangxi, Guangxi, Chongqing, Jilin, Shanxi, Anhui, Inner Mongolia, Shanxi, Xizang, Guizhou, Gansu, Chongqing, Hainan, Beijing, Qinghai, Ningxia, Xinjiang	Hebei, Liaoning, Hubei, Hunan, Sichuan	Jiangsu, Zhejiang, Shandong, Henan, Guangdong
2015	Heilongjiang, Fujian, Hubei, Shanghai, Sichuan, Jiangxi, Hunan, Chongqing, Jilin, Shanxi, Anhui, Inner Mongolia, Yunnan, Guizhou, Chongqing, Xizang, Hainan, Guangxi, Beijing, Shanxi, Gansu, Qinghai, Ningxia, Xinjiang	Hebei, Liaoning, Shanghai, Hubei, Hunan, Sichuan	Jiangsu, Zhejiang, Shandong, Henan, Guangdong
2016	Hainan, Heilongjiang, Fujian, Liaoning, Chongqing, Shanghai, Jiangxi, Anhui, Hunan, Shanxi, Jilin, Inner	Being, Hebei, Liaoning, Shanghai,	Jiangsu, Zhejiang,

	Mongolia, Guizhou, Sichuan, Hubei, Yunnan, Chongqing, Henan, Guangxi, Xizang, Shanxi, Gansu, Qinghai, Ningxia, Xinjiang	Hubei, Hunan, Sichuan	Shandong, Henan, Guangdong
2017	Liaoning, Shanghai, Jiangxi, Jilin, Hainan, Anhui, Chongqing, Fujian, Inner Mongolia, Hebei, Heilongjiang, Shanxi, Sichuan, Chongqing, Guangxi, Guizhou, Hunan, Hubei, Beijing, Yunnan, Xizang, Shanxi, Gansu, Qinghai, Ningxia, Xinjiang	Being, Hebei, Liaoning, Shanghai, Hubei, Hunan, Sichuan	Jiangsu, Zhejiang, Shandong, Henan, Guangdong

Table 8 presents the results of regression for the threshold model. As the values of emission reduction policies and renewable energy policies exceed the corresponding thresholds, the positive impact of energy policy on EPI gradually increases. The coefficient estimates for the threshold effect model are 0.0571 and 0.012, respectively, and there is an improvement in their corresponding level of significance from 5% to 1%. This indicates that when the energy policy's pull-out position improves by 1%, the EPI increases by 3.32% to 8.05%. It proves that the J-shaped curve has a marginal growth trend. These results depict how different regulations affect the causality between environmental regulations, the EPI, and the threshold or turning point in this relationship.

Table 8. Threshold regression results

	EMRP	REPO	EMRP	REPO
EPI_lag1	0.00499***(0.02)	0.0084***(0.016)	0.00502***(0.02)	0.0079***(0.017)
EMRP $< \gamma 1$	0.0332**(0.019)		0.0274**(0.018)	
EMRP$\geq \gamma 1$	0.0805***(0.108)		0.160***(0.069)	
REPO $< \gamma 2$		0.0202*(0.019)		0.0013**(0.04)
REPO $\geq \gamma 2$		0.0924***(0.025)		0.110***(0.045)
GDP	−0.707(0.844)	−0.422(1.018)	−0.716(0.848)	−0.363(1.032)
CEXP	0.0266(0.119)	0.0794(0.07)	0.0239(0.121)	0.0776(0.07)
EDU	0.542***(0.271)	0.201***(0.4)	0.543***(0.274)	0.248***(0.417)
REPAT	0.217(-0.259)	0.688***(0.208)	0.214(0.269)	0.690***(0.209)
Pop	−0.0169*(0.009)	−0.00538(0.01)	−0.0100(0.009)	−0.00683(0.01)
InvP	0.423(0.431)	0.423(0.439)	0.345(0.403)	0.494(0.444)
EMRP* REPAT	2.234***(0.845)	0.604**(0.53)	2.206***(0.848)	0.631***(0.534)
EMRP_lag1* REPAT	8.138**(2.778)	8.409***(3.796)	8.166***(2.764)	7.920***(3.771)
REPO* REPAT	1.217***(0.468)	0.0310(0.493)	1.133**(0.461)	0.0673(0.499)
REPO_lag1* REPAT	0.466***(0.168)	0.703**(0.278)	0.439***(0.166)	0.660**(0.291)
Observations	240	240	240	240

Constant	2.914(3.099)	0.832(3.56)	2.822(3.121)	0.553(3.607)
R-squared	0.441	0.109	0.439	0.101
Threshold Value	2.15	0.09	2.146	0.08
Threshold Test p-value	0.047	0.00	0.146	0,00

4.4 Robustness analysis

The robustness of the EPI analysis of Chinese provinces was measured using the newly developed data set having [±15] in DEA. Similar to mathematical composite indicators, robustness analysis can be measured by assigning equal weight to underlying indicators. One major concern is to evaluate the changing score of environment performance by adding [±15] shock to the existing data set.

We analyzed the EPI of Chinese provinces by putting the original simulations through the maximal multiplier, minimal multiplier, and a combination of both models without ignoring any variable. Table 9 shows little variation in the EPI (almost similar to the actual mean), indicating the robustness of our results.

Table 9. Robustness analysis of the EPI

Province	2010	2011	2012	2013	2014	2015	2016	2017
Guangdong	0.91	0.88	0.92	0.91	0.89	0.92	0.91	0.89
Hainan	0.90	0.92	0.94	0.90	0.90	0.94	0.95	0.91
Shanghai	0.92	0.92	0.90	0.92	0.88	0.93	0.90	0.92
Zhejiang	0.90	0.91	0.89	0.92	0.86	0.85	0.87	0.87
Jiangsu	0.91	0.89	0.88	0.87	0.87	0.89	0.92	0.92
Beijing	0.88	0.79	0.87	0.84	0.79	0.92	0.91	0.92
Fujian	0.78	0.69	0.62	0.69	0.65	0.59	0.67	0.65
Tianjin	0.78	0.70	0.71	0.83	0.70	0.77	0.74	0.82
Qinghai	0.69	0.77	0.68	0.68	0.52	0.54	0.53	0.55
Jiangxi	0.62	0.47	0.44	0.47	0.51	0.43	0.41	0.46
Gansu	0.59	0.41	0.23	0.23	0.19	0.22	0.17	0.21
Henan	0.59	0.55	0.42	0.45	0.40	0.39	0.34	0.39
Liaoning	0.56	0.53	0.50	0.50	0.50	0.54	0.48	0.42
Ningxia	0.49	0.47	0.38	0.34	0.29	0.35	0.33	0.41
Sichuan	0.45	0.35	0.28	0.32	0.24	0.24	0.20	0.31
Anhui	0.49	0.37	0.50	0.53	0.50	0.61	0.44	0.58
Hebei	0.47	0.52	0.45	0.47	0.50	0.47	0.47	0.43
Hubei	0.40	0.36	0.34	0.40	0.35	0.46	0.42	0.53
Chongqing	0.39	0.46	0.33	0.40	0.23	0.31	0.30	0.38
Guangxi	0.39	0.41	0.31	0.32	0.33	0.35	0.33	0.32

Jilin	0.39	0.49	0.47	0.48	0.46	0.50	0.32	0.49
Inner Mongolia	0.37	0.38	0.34	0.35	0.35	0.47	0.40	0.39
Hunan	0.28	0.23	0.27	0.32	0.27	0.31	0.28	0.63
Shaanxi	0.26	0.24	0.19	0.68	0.18	0.24	0.25	0.33
Guizhou	0.22	0.27	0.15	0.18	0.14	0.29	0.24	0.34
Yunnan	0.25	0.18	0.16	0.16	0.17	0.20	0.17	0.29
Xinjiang	0.15	0.28	0.17	0.11	0.11	0.15	0.08	0.22
Heilongjiang	0.14	0.16	0.12	0.12	0.36	0.11	0.08	0.12

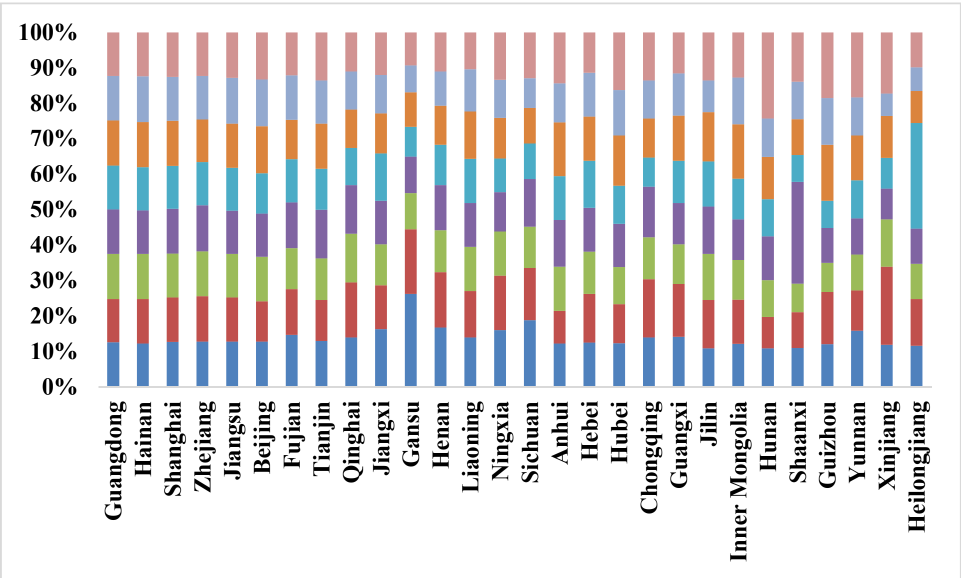

Figure 3. **Environmental performance trend**

The robustness analysis score shows that energy consumption in China increased from 3.3% in 2017 and 3.9% in 2018 to 4.3% in 2018. The total energy consumption in 2017 (57%) reached a historical low. Beijing, Guangdong, Shanghai, Hainan, Qinghai, Guangxi, Shandong, Zhejiang, Jiangsu, and Liaoning showed the maximum EPI (0.83–1.00), whereas Guizhou, Henan, Inner Mongolia, Heilongjiang, Yunnan, and Shanxi had the lowest EPI (0.07–0.20). Therefore, China requires further development in terms of EPI at the provincial level.

5. Discussion and policy implications

This study used non-radial DEA and panel data models for 30 Chinese provinces using panel data from 2010 to 2017. The results showed that economic development affects energy policies and industrial structure, but in different directions, leading to environmental degradation. The p-values of the single and double threshold models passed the 1% significance test, implying the existence of a double threshold effect, with estimated thresholds of 1.240 and 2.821. EPI scores were within the range of 0.74 to 1 Jiangsu, Shandong, Guangdong, Hainan, Zhejiang, Shanghai, and Fujian. With scores of 0.07–0.26, Shanxi, Chongqing, Yunnan, Xinjiang, Heilongjiang, Sichuan, Hebei, Hubei, Hunan, Guangxi, and Guizhou showed lower values. This study performed a comparative analysis of the causality and communication mechanisms in different situations. Economic development significantly increases carbon emissions, as confirmed through DEA and econometric estimation. Furthermore, it is an indirect source of increased carbon emissions by limiting the strength of environmental regulations and requiring upgradation of the industrial structure. The two mechanisms leading to environmental deterioration are entirely different.

The coefficient estimates for the threshold effect model are 0.0571 and 0.012, respectively, with an improved level of significance from 5% to 1%. This implies that when the pull-out position of the environmental regulations improves by 1%, the high emitting industries' total factor energy efficiency increases by 1.2% to 5.7%. The central region exhibits higher level and scale than the eastern and western regions, with apparent heterogeneity in the east, west, and central regions. Regardless of the environmental regulations or industrial structure, the central area's transmission path is much more important and extensive than that of the eastern and western regions. The insignificant impact of environmental regulations and industrial structure hinders the transmission path in the western region.

The study highlights that revenues must match responsibilities so that local governments have both financial resources and corresponding environmental management rights and obligations to improve environmental quality. Also, making full use of transfer payments, tax rebates, and other support systems to enhance environmental governance and public service capabilities of local governments is necessary to stimulate their enthusiasm and efficiency toward protecting the environment.

Furthermore, policymakers should pay close attention to the distortionary effects of energy consumption on local government behavior and maintain close supervision to improve environmental governance efficiency. It is necessary to reduce pollution through cooperation and flexible government expenditure in environmental protection and monitoring.

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