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Nexus Between Energy Policy and Environmental Performance in China: the Moderating Role of Renewable Energy Patents.

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Abstract

The socioeconomic and environmental considerations of energy production have become crucial due to the increasing complexity of the relationship between energy and the environment. In this context, this study aims to develop possible mechanisms for perspectives of energy policy on environmental by exploring the mediating role of renewable energy patents. The study used a non-radial data envelopment analysis (DEA) model and panel data model for 30 Chinese provinces by taking the panel data from 2010 to 2017. The results show that the overall environmental performance index (EPI) of Chinese areas is improved by 9.88% from 2010 to 2017. Further, The econometric model findings offer evidence that provincial renewable energy policies and emission reduction policies positively impact the enhancement of EPI. The results also show that the P values of the single-threshold model and the double-threshold model both passed the 1% significance test, so it can be concluded that there is a double-threshold effect. Finally, the research findings posed several policy implications based on the research findings.

Keywords: energy policy; Environmental performance; Non-radial DEA

List of Abbreviations

Code	Variable Name
EPI	Environmental performance index
EmRP	Emission reduction policies
RePO	Renewable energy policies
GDP	GDP of secondary industry
CEXP	Consumption expenditure
EDU	Educational level
RePat	Renewable energy patents
Pop	Total number of Population
InvP	Investment in anti-pollution projects
DEA	Data envelopment analysis

1 Introduction

In the current ages, various researches are dedicated to measuring, investigating, and enhancing energy efficiency. At that time, the environmental problem is a severe issue in the world. Mainly the question of the world's environmental problems due to the greenhouse emissions in which carbon-dioxide (CO_2), which generally connected to the blazing of fossil fuels. However, this process also becomes the source of wasteful usage of natural resources and significant environmental issues. Today the country that consumes considerable energy will also become the source of highly intense carbon dioxide (Ozturk and Acaravci, 2010), (Abbas et al., 2020) and (Anser et al., 2020). The government must shape a new planned objective that helps save natural resources, develop a healthy environment for enhancing energy efficiency and defending territory, and attain environmental development. Some countries are already declared that they reduce their CO_2 releases per unit of GDP by 40% to 45% (Hou et al., 2019) and (Usman et al., 2021). At present, all nations are already facing enormous challenges of environmental issues. In this situation, these countries must enhance their energy efficiency and carefully think about environmental restrictions to lower their energy utilization and bring down environmental pollution (Iqbal et al., 2020), (Öztürk and Altınok, 2021). There are three types of index in which thermodynamic index, physical-based index, and currency-based indicators index. With index, we usually measure energy efficiency. The combined manufacturing procedure usually used energy such as natural gas, oil, and coal, etc. In this, labor and capital are also used to create unique productivity, e.g., GDP and unfortunate productivity, including emissions of pollutants (CO_2) and (SO_2) (Iqbal et al., 2019b). The environmental efficiency must not be unnoticed to deliver the more Similar type of Efficiency Mark.

Industries across the world consume more than one-third of the global energy. The proportion of CO_2 emission is slightly higher in this regard. China's development model relies heavily on the industry, so local infrastructure development, manufacturing of export-oriented

consumer products, and heavy industrial equipment are highly supported by energy-intensive production mechanisms. Therefore, the proportion of energy consumption concerning carbon emission is higher than the world average in China (Zhang et al., 2020) and (Iqbal et al., 2019a). The statistical report of 2010 from "the National Economic and Social Development states that processing the raw materials of petroleum and chemical products, melting and crashing of metal, non-metal and ferrous metal products, electricity generation and distribution are considered high energy-consuming activities. According to this report, all these sectors are segregated into sub-sector of Energy-intensive industries (Liu et al., 2019), (Iqbal et al., 2019c) and (Adedoyin et al., 2021). Due to the rise of energy intensity and subsequent carbon emission, China faced massive international criticism, and this led the government to initiate a low carbon emission policy in its 13th five-year plan from 2016 to 2020 by setting a maximum carbon emission limit for all the energy-intensive companies of the country. It is determined in the program that the ferrous metal processing industry should decrease its energy use by a minimum of 10%. In contrast, the petrochemical and nonferrous metal industries rate, in this regard, is 18% (Chen and Lin, 2020).

Since fossil energy is considered the main factor in global warming, emphasizing energy-efficient production and distribution processes may be the key to solving this hazardous issue (Meng et al., 2020). Economic developments across the nation are correlated with energy intensity, carbon emission, and global warming issues. Therefore, businesses and governments should care about the human and wildlife, climate, and environmental aspects while setting up their respective growth strategies. In this connection, the green movement initiation by adopting green technology solutions for industrial production and distribution can be a useful undertaking. A robust energy and carbon management and control, if possible, with a strict regulatory framework and better energy policy can also improve the environmental quality to a great extent.

In the past two decades, China's economy has suffered several transformations and achieved significant economic structure progress. Though during this procedure, the environment of China has been seriously damaged. So, the combination of economic enhancement and environmental safety must be essential for China in the upcoming years. Decreasing the emission of pollutants, which creates terrible effects on public health and the environment, is one of China's primary goals. Environmental sustainability of the economy is generally measured with Environmental efficiency. Cities with environmentally efficient will also produce more economic output like revenues and less environmental output like greenhouse gasses. Using a more ecologically efficient decision-making unit will deliver us the most acceptable ecological and economic return for investment elements. Environmental resources will be used better with the help of an efficient decision-making unit.

This study aims to investigate the impact of energy policy on the environmental performance of China. This work contributes to the literature in the following three ways: First, the study used the non-radial DEA model to evaluate and compare China's EPIs at a provincial level (the non-radial DEA minimizes environmental pollution as it maximizes economic benefits). Second, the study used energy policy as a core variable and is further divided into emission reduction policies and renewable energy policies. Finally, with the help of the system GMM estimation method, the effectiveness of various environmental regulations is validated through our research; the nonlinear and heterogeneous effects of energy policy on provincial environmental performance are assessed.

The rest of the paper is structured as: section 2 review the relevant literature, section 3 explains the method and the indicators selected for the environmental performance index, 4th section discusses the results, and finally, 5th section presents the conclusion of the study and further provides the policy implications for decision-makers

2. Literature review

In the manufacturing method, gases such as carbon dioxide and Sulfur dioxide are discharged in higher amounts using energy, and these gases will destroy the healthy

environment. In real output productions, the point is used as the source of input, generally non-renewable. Still, the labor and capital are renewable in the process of other non-energy resources. To enhance energy efficiency and decrease pollutant releases, the non-renewable energy inputs must be divide and protected as well as possible. We study some DEA-based energy efficiency and environmental efficiency evaluation lessons in the later studies in which the pollutant emissions are examined. Some DEA methods were used to evaluate the environmental efficiency in 26 OECD countries from 1995-1997. In 2002 also assess the efficiency with the help of this model in eight world counties. (CO₂), sulfur oxides (SO_x), nitrogen oxides (NO_x), and carbon monoxide (CO) as poor output, and a non-radial DEA model are applied. Labor and main energy utilization as two inputs, and the one required result is GDP. In the end, it is essential to select total energy consumption, GDP, and CO₂ releases that are taken in the form of only input, individual output, and low output. Various DEA-type linear programming models used a dual output structure to calculate energy efficiency by using energy and non-energy inputs over the economy and besides individual and poor output.

In recent times, different DEA models projected to measure the energy and resource (energy) instantaneously. The hybrid power model tries to raise the individual output consistently and decrease the low output to simultaneously estimate the total efficiency. Therefore, the research is known as static analysis, so no alteration has been seen inefficiency because they only measure one year's production. In various areas, they just estimated the efficiency each year and easily measured production in different years where they overlooked the technological progress, and efficiency is worse in multiple years. For every country, energy plays a vital role in the rapid and complete development and the survival and development of human civilization. The burning of coal creates 85% of CO₂ emission, 73% of dust emission, and 90% of SO₂ emission. So, to handle energy consumption, climate change, maintain public healthiness have real great importance. To build a pleasantly enhanced "Energy–Economy–

Environment structure, we should reduce universal greenhouse gas emissions. In this way, a prosperous society can be made in these countries.

In this fast-paced globalized world, energy is the core of strong economic growth, but this energy is also the root cause of global climate change. In this case, decision-makers need to formulate economic development strategies, taking into account environmental sustainability issues. There is a mature argument that paying attention to energy-saving production technology may be a significant measure to solve the current climate problem. Some studies are supporting this claim. For example, Wang et al. (2017) studied the energy-saving potential of 17 of the 17 Asia-Pacific Economic Cooperation (APEC) countries. Nassiri and Singh (2009) evaluated the energy performance of 21 Organization for Economic Cooperation and Development (OECD) countries by adopting both parametric and non-parametric approaches. Khoshnevisan et al. (2013) also studied the energy efficiency of 23 developing economies and concluded that the role of a strict energy policy is the key to ensure energy-efficient production and the environment. Moreover, Geng et al.'s (2019) study on 15 EU countries revealed that creating alternative energy sources and popularizing their use among industries and households can reduce pressure on fossil energy and improve productivity comparatively. Meanwhile, (Song et al. (2013) and (Li and Lin, 2017) studied the provincial energy efficiency of China and concluded that technological advancement in the industry sector could lead to attaining energy-efficient economic growth.

Researchers have adopted various energy efficiency measures to study the energy and environmental efficiency levels of many different countries and regions. Data Envelopment Analysis (DEA) is one of the most popular and useful tools for measuring energy and environmental performance. Despite having some limitations, the DEA application has some 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) and (Chen and Lin, 2020) applied DEA to measure energy efficiency within the metal sector, and Ma et al. (2019) studied both energy and pollution efficiency for the mining industry of China. Besides, Lin and Jia (2019) evaluated the efficiency of environmental governance for China's energy industry.

Moreover, Yang et al. (2020) measured the energy efficiency of the manufacturing industry by applying Malmquist index decomposition, Stochastic Frontier Method (SFA), and meta frontier DEA method, and Lin and Chen (2019) measured the ecological efficiency of the nonferrous metals industry of Chinese regions by applying non-radial DEA method. Du et al. (2020) conducted another study to explore the green total factor production efficiency and its determinants for the metal industry case in China with the application of sub-boundary and global DEA approaches. Apart from these studies, several other studies were conducted on the energy and environmental coefficients for the steel, construction, and chemical industries of Chinese provinces. It is observed that current literature is based mainly on environmental performance. To the best of your knowledge, no prior studies objectively measured China's ecological performance from the operational front. Also, it is observed that China is a vast territory, and the different industrial sub-sectors that emerge along this territory affect the environmental performance (EP) of these regions. Therefore, by covering the heterogeneity of industries and areas, the total factor energy efficiency assessment of the six energy-intensive industries of Chinese provinces might help policymakers develop a sustainable strategy. It is further observed that the non-radial DEA approach of efficiency measure is more flexible than any other measurement technique as it can satisfy the requirements of maximized economic growth and minimized pollution emissions. This study uses the non-radial DEA method for the environmental performance index assessment of China at the provincial level. Due to the extensive acceleration of ecological degradation, governments have undertaken many corrective measures to tackle and promote sustainable development. It is currently unclear from

the existing studies how different types of regional-level energy policies affect environmental performance. Therefore, investigating the effect of other regional level energy policies a timely attempt for ensuring an environmentally sustainable developed economy in China.

3. Methodology

3.1. Model Construction

Data envelopment analysis (DEA) is considered a more effective efficiency measurement tool than the conventional econometric approaches like regression or ratio analysis (Inman and Anderson et al., 2006)(Inman et al., 2006). Efficiency, in this case, has been defined by several scholars. In this study, we consider Farrell's (1957)(Farrell, 1957) definition of efficiency, which was drawn from the study of (Koopmans 195) (Koopmann, 1951) to describe the measure of efficiency that constitutes multiple inputs. Farrell (1957)(Farrell, 1957) states that two components form an organization's efficiency: technical efficiency and allocative efficiency. In an input-oriented efficiency measurement, technical efficiency refers to the ratio of optimal input to the actual information. For an output-oriented efficiency measurement, it relates to the rate of real output to the optimal production.

On the other hand, allocative efficiency manifests an organization's ability to utilize its inputs optimally in respect to its prices and technology. Based on the objective of Decision-Making Units (DMU), production frontier or cost frontier is used to determine the optimal input and optimal output. Two different methods are recommended in the literature in this regard: parametric and non-parametric approaches. A functional plan is assigned for the frontier in the parametric approach, but no preceding specification is applied for the non-parametric approach's border. (Charnes et al., 1978) followed the non-parametric process to develop the DEA model for measuring the single DMU's efficiency for the first time. They designed an input-oriented DEA model assuming a constant return to scale. However, the following studies of the DEA model considered different assumptions set. For example,

(Banker, 1984) proposed variable returns to scale (VRS) and used mathematical programming in their DEA model to generate a linear best practice frontier that relies on experimental input-output data. This new DEA approach received wider acceptance for measuring the efficiency of different DMUs across industries or countries.

Assume there are n DMUs and individually signifies an administration zone. Separately, DMU's non-energy input and L energy input produce the predictable cost Output or low output of K . DMUs helps make as much wanted production as possible and spent the resources in less amount. Therefore, in the usual methods, the decreasing of pollutants is not allowable. This trouble can be resolved using different methods like using the opposite of worse output, bad behavior output as input, and statistically renovating the unwanted result into the desired outcome. In the study of energy and environmental efficiency, low production is mostly produced by fossil fuels through manufacture, which must be minimized if we use energy in less amount.

$$\begin{aligned} \text{EPI1} &= \min \theta & (1) \\ \text{s.t. } \sum_{j=1}^n \lambda_j x_{ij} + s_i^{x-} &= x_{ij0}, \quad i = 1, \dots, m, \sum_{j=1}^n \lambda_j e_{lj} + s_l^{e-} = \theta_l^e e_{lj0}, \quad l = \\ 1, \dots, L, \sum_{j=1}^n \lambda_j y_{rj} - s_r^{y+} &= y_{rj0}, \quad r = 1, \dots, s, \sum_{j=1}^n \lambda_j b_{kj} = \theta_k^b b_{kj}, \quad k = \\ 1, \dots, k, \lambda_j, s_i^{x-}, s_l^{e-}, s_r^{y+} &\geq 0, \quad \text{for all } j, i, l, r, \end{aligned}$$

Consider that method decreases the unwanted output and possible and a certain level of ideal output and non-energy input. For sections between 0 and 1, the energy and environmental efficiency index is θ , the superior the index, well the region's performance in terms of reducing pollutant discharges and energy saving. The corresponding part is measured to be energy and environmentally efficient. It cannot decrease its pollutant releases and energy consumption If $\text{EPI1} = 1$ ($\theta = 1$) is zero, but if the $\text{EPI1} < 1$ ($\theta < 1$) are not zero, then the corresponding region is environmentally inefficient, and can decrease energy utilization and pollutant discharges. This type of model is the radial efficiency model. They may not have strong perceptions in energy efficiency assessments.

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

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

This model decreases the energy utilization and pollutant discharges in various methods to attain top ideas with energy and environmental efficiency border. Energy efficiency and environmental efficiency consume altered non-proportional adjustments and investigate constant efficiency by elected choice creators. The environmental performance is unified in the efficiency equation and shows various partialities for an energy consumption presentation that decision-makers can give. We will use this method to estimate the total-factor energy and environmental efficiency of various areas because this model has a developed perceptive power than the 1st model.

In this research, years between 2000 to 2008, we make a strategy to compute the energy and environmental efficiency in various areas. This forceful assessment can give us data about efficiency variations. However, It is more important and significant to discovering energy and the environment by putting on DEA window analysis to increase efficiency. The DEA window analysis method is used to develop time-varying data and cross-section data to compute dynamic properties. This method works by affecting medians and creates efficiency measures after this, treating every DMU as an individual unit at various times. Therefore, we find the environmental efficiency of various areas of different ages through overlapping windows using this technology.

During possible measurement of efficiency, it has been seen that the width of the window has tended to yield 3or 4 periods of time. This paper considers (w=3) a window with three widths for attaining consistent environment and energy efficiency results. For such purpose, the first three years, 2010 to 2012, have been utilized for the first window. After that, we will

more for a further one-year window and release base year while adding the next one, and this procedure will continue till the last window is installed. Thus, radial and non-radial environmental energy efficiency (EPI1 &EPI2) of each underlined province can be attained by Applying DEA window analysis.

3.2 Data

In the above equation, we used three inputs labor, capital and energy use, one good output provincial Gross regional product which used as proxy for GDP and one bad output CO₂ emissions for environmental performance index over the period of 2010 to 2017. Table 1 shows the descriptive statistics for the input and output variables of this study. The data for input/output indicators is collected from National Bureau of Statistics of China and China database, (<http://www.stats.gov.cn/english/Statisticaldata/AnnualData/>) (<https://www.dccchina.org/services/china-data/>).

Table 1. Descriptive statistics of input/output indicator for environmental performance index

		CO₂ emission	Good output	Input 1	Input 2	Input 3
2010	Max	126.2	71.9	19.2	1435.1	24.4
	Min	3.7	1.6	1.3	0.7	0.3
	Mean	51.6	17.0	7.63	420.5	8.8
	SD	34.5	14.8	4.4	282.5	6.7
2012	Max	267.8	243.9	20.5	2371.5	37.3
	Min	7.5	6.2	1.6	43.2	0.8
	Mean	90.7	53.6	8.4	825.0	14.3
	SD	66.8	51.5	4.9	537.5	10.5
2015	Max	373.9	436.4	22.0	5825.9	58.0
	Min	9.8	11.2	1.2	252.3	0.2
	Mean	131.2	107.0	9.2	2441.1	18.8
	SD	93.3	95.2	5.4	1325.0	13.5
2017	Max	453.9	761.2	20.4	12831.4	60.7
	Min	14.0	24.9	1.2	850.4	1.1
	Mean	148.2	182.8	9.4	5559.4	18.2
	SD	112.9	166.7	5.1	2911.8	14.1

4. Empirical results and discussions

4.1 Environmental Performance

Energy consumption in China increased from the 10-year average of 3.3% in 2017 and 3.9% in 2018 to 4.3% in 2018. China is still the world's largest energy consumer, accounting for 24% of global energy consumption and 34% of global energy demand growth in 2018. Consuming fossil fuels 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 is still the primary fuel, its share of total energy consumption in 2018 (58%) has 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 level in the past half-century. By 2018, the reliance on natural gas imports has increased to 43%. Concerns about energy security are growing. Among non-fossil fuels, solar energy consumption increased the fastest (51% increase), followed by wind energy (24% increase) and biomass and geothermal (14% increase). 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 Tab. 2, the highest EP is recorded in Hainan, Guangdong, Shanghai, Tianjin, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, and Sichuan. The lowest EP is recorded in Shanxi, Qinghai, Heilongjiang, Yunnan, Gansu, Xinjiang, and Ningxia. Provinces in central and eastern regions have high EPI, and western and north-east areas have low EPI. Compared to the east and central provinces, China's western provinces have a lower EPI due to a poor economic foundation and backward technological level. The other reason behind low EPI is due to high energy-intensive industries located in north-eastern China. The old industrial base developed earlier with a soft EPI due to outdated equipment and severe environmental pollution.

Table 2. The environmental performance index 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 Fig. 2a, Beijing, Guangdong, Shanghai, Hainan, Qinghai, Guangxi, Shandong, Zhejiang, Jiangsu, and Liaoning are recorded to 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 to 1 is evident in Jiangsu, Shandong, Guangdong, Hainan, Zhejiang, Shanghai, and Fujian. In contrast, with the score 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 needs further improvement in environmental performance at the provincial level. With better energy and pollution control effect, Jiangxi and Sichuan show a relatively high EPI. EPI's worst value is recorded in 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 the provinces mentioned above.

4.2 Average Environmental Performance Index

Figure 3 shows the average environmental performance index (EP) results from 2008 to 2017 based on the non-radial DEA model. It can be seen that during the 2010 to 2017 study period, the average EPI of China at the provincial level showed an upward trend. The average EPI's overall story is still shallow, with an average value of 0.44 and 0.52, far below the optimal value of 1. China's industries consume large amounts of energy and emit large amounts of carbon dioxide, resulting in low power and environmental performance. This shows that China's industries are responsible for high levels of carbon dioxide emissions, which ultimately makes china environmentally inefficient. However, China's government has emphasized pollution control measures, and high emitting industries like petrochemical and metal will be under severe environmental scrutiny. For this ecological regulatory initiative, EPI for high carbon emission industries has dramatically increased. This finding also goes in line with (Wu et al., 2020), who investigated the efficiency of energy and Chinese provinces' environment.

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

4.3 Econometric modeling and variable selection

4.3.1 The Dynamic Panel Data Model Effect

The following equation is constructed to find the relationship between environmental regulation and total factor energy efficiency:

$$EPI_{it} = \alpha + \beta EPI_{i,t-1} + \gamma \text{energy_policy}_{it} + \theta X_{it} + u_t + v_i + \varepsilon_{it} \quad (3)$$

In this equation, α represents the intercept and β , γ and θ are coefficients to be estimated. $\text{energy_policy}_{it}$ is the independent variable, that is, the vector that represents the energy policy. $EPI_{i,t-1}$ is the first lag term of EPI_{it} . This lagged dependent variable $EPI_{i,t-1}$ is added as the independent variable in constructing the equation considering the impact of lagged environmental performance index on the current environmental performance index. X_{it} matrix indicates the control variables set. 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 in this paper is environmental performance index.

(b) Independent variable: By providing economic incentives, services, new legislation or laws, and public education, current energy policies are expected to affect environmental

performance. As mentioned earlier, the Chinese government's energy policy has been classified as a reduction policy or a renewable energy policy. We use the current number of provincial laws, regulations, and detailed plans as key independent policy variables. These steps are from information collected on 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 in experience variables, socioeconomic and environmental variables are also used as control variables to illustrate their environmental performance impact. Social and economic variables include secondary industry GDP, consumer spending, education level, and population density. Ecological variables include emission levels of private cars, exhaust emissions, Investment in treatment of departmental pollution sources, and Investment in anti-pollution programs. Investment in industrial waste source treatment and pollution prevention programs is necessary financial support for environmental pollution management. They are used as proxy variables to reflect the ecological governance of government work. The data for the above variables comes from the "China Environmental Statistical Yearbook" and "China Statistical Yearbook". All variables in the table are expressed in their natural logarithm form. For each variable, there are 240 observations. Table 3 provides descriptive statistics for all variables.

Table 3. Descriptive statistics and data sources.

Variable	Mean	SD	Min	Max
EPI	4.579	0.338	2.708	5.72
EeRp	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
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4.3.2 The Empirical Results of Panel data Model

The panel data model approach is applied to fix the issues relevant to dynamic panel estimation stated in equation 3. System GMM takes into consideration that there is no auto-correlation within the disturbance terms. This approach also solves the endogeneity issue by taking lag variables. The result of the GMM test is presented in table 4. Apart from performing the GMM, the study also conducted Arellano-bond (AR) test, Sargan-Hansen, and Wald chi-square tests to attain a more robust estimation result. The Arellano-Bond (AR) test comprises both first and second-order auto-correlation of residuals tests which are known as AR (1) and AR (2), respectively. The equation's residuals are regarded as not autocorrelated if AR (2) is accepted and AR (1) is rejected. Meanwhile, to check the homogeneity among the variables, the Sargan-Hansen test is applied. Moreover, the Wald test is performed to check the level of significance of each regression.

Table 4. The result 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% significant level; **= 5% significant level and *=10% significant level

Table 4 shows the result of the panel data analysis for the variables under study with four different models. It is observed that lagged EPI coefficients are positive and statistically significant at a 1% significance level, showing that the present EPI performance is affected by the previous period's EPI's performance. It is further observed that the coefficient of both emission reduction (EmRP) and renewable energy policy (ReEP) is 0.0286 and 0.0304 respectively, the findings indicate that both EmPR and ReEP are statistically significant at 1% level. The results first confirmed that provincial renewable energy policies and emission reduction had different effects on improving environmental performance. Our results are in line with (Cariola et al., 2020), they reveals that energy policy positively influences the improvement of environmental performance. This goes in line with the Porter effect for the case of China. Our findings are also in line with majority of the existing literatures, for example, (Hodson et al., 2018),(Galeotti et al., 2020), (Wang et al., 2020), (Yu and Wang, 2021). Moreover, the results are in line with the conventional view that more investment in renewable energy and pollution reduction leads to more renewable energy consumption and hence contribute to environmental degradation.

Meanwhile, the control variables (see table 4) regression estimation shows that both GDP and Population negatively affect the EPI at 1% significant level in all cases. It means a 1% increase in GDP and Population reduces the environmental performance by 3.42% and 1.2%,

respectively. Our results in line with, (Yu and Wang, 2021), their findings indicate that a 1% increase in GDP and Population contributes to decrease environmental performance by 0.71%-0.59%. On the other hand, Investment in education and Investment in anti-pollution projects have a significant positive effect at 1% significant level. It indicates that a 1% increase in education investment and Investment in anti-pollution projects improves environmental performance by 3.25% and 2.93%, respectively. This affirms that spending more on education and air pollution control might help to improve environmental performance. On the other hand, renewable energy patents have a positive effect on environmental performance. Besides, it is observed that consumption expenditure has no significant influence on EPI improvement. These findings are also in line with (Alam et al., 2019) who found a 1% increase in education help decrease in firm environmental performance by 2.89%.

Considering the probable lag effect of energy policy, the estimation of emission reduction policy and renewable energy policy is performed taking the lagged value of EmRP and RePo. The results show the same scenario as the baseline regression as it is seen that there is the existence of statistically significant EmRP over EPI, and the control variables also consistent with the estimated coefficients. However, for the case of RePo, the coefficients (0.0605) of lagged variables are found to be positive and statistically significant at 1% level, proving that environmental performance is affected by the lag terms (table 4). It refers to the fact that in the case of a rigorous CCER practice, the influence of “innovation offset” is more powerful than the result of the “compliance cost” effect in the long run. This proposition matches with the findings of Guo and Yuan (2020). They argue that taking the lagged variables instead of current variables might increase to chances to generate a positive and significant effect on energy efficiency.

4.3.3 The Moderating Effect of Renewable Energy Patents

Table 5 presents results of the moderating effect of renewable energy patents on the environmental performance of China. The moderating impact's findings indicate that all the moderating coefficients are positive and statistically significant with a 1% level. This proposes that the moderating effect of renewable energy patents (RePat) existent for energy policy. The result of the regression estimation shows that a greater number of RePat can boost EPI. Porter argues that, by making a well-structured energy policy based on the renewable energy patents effect, a positive effect can be established on renewable energy patents and technology empowerment. Therefore, the moderation effect of renewable energy patents and energy policy on EPI needs to be studied further to enhance EPI to the highest level possible. The moderating factors of renewable energy patents and energy policy are included in this study's dynamic panel modeling. The results are in line with (Böhringer et al., 2017; Li and Lin, 2016; Miyamoto and Takeuchi, 2019), their findings conclude that renewable energy have significant negative impact on environmental pollution. The results of the study are also in line with the study of (Alam et al., 2019), they check heterogeneous impacts of environmental and renewable energy patents on CO₂ emission. They find environmental and renewable energy patents have negative impact on carbon emission which is ultimately environmental performance.

Table 5. Regression results of renewable energy patents effect on 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

Note: ***/1% significant level; **/5 significant level and */10 significant level

4.3.4 The Dynamic Threshold Model

The study mentioned above carries some limitations as the moderating effects model fails to identify the key areas and relevant breaks of environmental regulation. This study considers 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 EPI, confirm the rationality of sample interval segment to reduce the errors in model estimate. The following section of this study addresses the energy policy variable as the threshold dependent variable to form a threshold effect model as below:

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

In this model above, C is the estimated threshold value, and $I(\cdot)$ is the symptomatic function, which will be true if the corresponding condition is equal to 1 and false if the value is 0. The test results might come up with the presence of multiple thresholds, which can further be stretched to double and numerous threshold models from the base single threshold model.

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, used bootstrap technology, and repeated it 500 times to test the threshold. We found that the impact of pollution mitigation policies and clean energy policies on the environmental efficiency index has a major dual-threshold effect, in which energy policy is the threshold component. The results of the importance assessment are summarized in Table 6. 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), so it can be inferred that there is a dual-threshold effect. The estimated thresholds are 0.240 and 0.82 and each estimated threshold falls within the 95% confidence interval [0.225, 0.692] and [0.692, 0.817] respectively, because the single threshold and dual-threshold models have passed. The 1% significance test also has a potent dual-threshold effect in Model 2. The estimated thresholds are 0.762 and 0.823 and [0.801, 2.163] and [0.762, 2.361] are the corresponding 95% confidence intervals (table 7).

Table 6. Results of 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 7. Estimated threshold variables.

Threshold variables		Estimated thresholds	95% confidence interval
Model 1	γ_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]

Figure 3 shows the result of the likelihood ratio (LR) function. The likelihood ratio (LR) function of the dual-threshold model is used to test the consistency of the threshold estimate to better understand the authenticity and confidence interval of the threshold estimate. When the LR value is 0, the regional environmental performance index is the threshold estimate. As shown in Figure 3, when the LR value is 0, the corresponding threshold parameters of the provincial environmental performance index are 0.346 and 0.456, respectively. The threshold estimate is the interval of the provincial environmental performance index. When the confidence interval is 95%, it is less than $LR = 6.503$. Therefore, the confidence intervals of the threshold estimates of 0.324 and 0.447 are $[0.030, 0.709]$, $[0.038, 0.539]$. Since the corresponding confidence interval contains two threshold estimates, the threshold estimate is consistent with the true value of the threshold. That is, the authenticity is used to test the two threshold estimates of the dual-threshold model. The specific distribution is shown in Table 3.

Figure 3. The likelihood ratio of Model 1 and Model 2

Table 8. The level of Provincial environmental performance with respect to the threshold value

	Low threshold	Medium threshold	High threshold
	$EPI \leq 0.301$	$0.301 < EPI \leq 0.438$	$EPI > 0.438$
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	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	Hunan, Sichuan	Jiangsu, Zhejiang, Shandong, Henan, Guangdong
2016	Hainan, Heilongjiang, Fujian, Liaoning, Chongqing, Shanghai, Jiangxi, Anhui, Hunan, Shanxi, Jilin, Inner Mongolia, Guizhou, Sichuan, Hubei, Yunnan, Chongqing, Henan, Guangxi, Xizang, Shanxi, Gansu, Qinghai, Ningxia, Xinjiang	Beijing, Hebei, Liaoning, Shanghai, Hubei, Hunan, Sichuan	Jiangsu, Zhejiang, 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	Beijing, Hebei, Liaoning, Shanghai, Hubei, Hunan, Sichuan	Jiangsu, Zhejiang, Shandong, Henan, Guangdong

Table 8 presents the level of provincial environmental performance concerning 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. At the same time, provinces with EPI levels between 0.301 and 0.438 increased from 3.2% to 22.6%, indicating that these provinces' environmental performance has improved during the study

period. Provinces with an EPI higher than 0.438 also showed a similar steady growth trend. This is happened due to the level of regional economic and technological development continued to increase (Zhang et al., 2020), from 9.7% to 16.1%, and the regional innovation system continued to shift to the best level. However, after 2013, provinces' environmental performance with a regional economic development level higher than 0.438 has changed. Between 2010 and 2017, the proportion of regions with a regional economic development level of less than 0.438 declined from approximately 90.3-83.9%. The story of regional technological innovation has different positive effects on these regions' regional sustainable development capabilities. During the study period, the proportion of areas where regional technological innovation contributed to promoting sustainable development dropped from 87.1% to 61.3%. Also, during the study period, the proportion of regions where regional technological innovation only had a weak impact on regional sustainable development increased from 3.2% to 22.6%. Therefore, it can be concluded that, overall, the situation in China is optimistic.

Table 9. 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 < γ_1	0.0332** (0.019)		0.0274** (0.018)	
EmRP $\geq \gamma_1$	0.0805*** (0.108)		0.160*** (0.069)	
RePO < γ_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

Table 9 presents the results of regression for the threshold model. As, the values of emission reduction policies and renewable energy policies exceed the levels of corresponding thresholds, the positive impact of energy policy on environmental performance gradually increases. It is observed that the coefficient estimates for the threshold effect model are 0.0571, 0.012, respectively, and there is an upbound of their corresponding level of significance from 5% to 1%. This proposes that when the energy policy's pull-out position improves by 1%, the environmental performance increases by 3.32% to 8.05%. It proves that the “J-shape” has a marginal Growth trend. These investigation results depict how different regulations affect the causality between the surrounded position of environmental regulations, the EP, and the threshold or turning point in this relationship.

5. Discussion and Policy Implication

This study used no radial Data Envelopment Analysis (DEA) and panel data model for the case of 30 Chinese provinces by taking the panel data from 2010 to 2017. The results show that economic development can lead to environmental degradation by affecting energy policy and industrial structure but in different directions. Also, the P-values of the single and double threshold models passed the 1% significant test, so it can be concluded that there is a double threshold effect. The estimated thresholds are 1.240 and 2.821. Environmental performance index (EPI) score within the range of 0.74 to 1 is evident in Jiangsu, Shandong, Guangdong, Hainan, Zhejiang, Shanghai, and Fujian. In contrast, with the score 0.07-0.26, Shanxi, Chongqing, Yunnan, Xinjiang, Heilongjiang, Sichuan, Hebei, Hubei, Hunan, Guangxi, and Guizhou show lower values. Comparative analysis of the causality and communication mechanism in different situations. Economic development will significantly increase carbon

emissions, confirmed through data envelopment analysis and econometric estimation. Second. Also, they have become an indirect source of increased carbon emissions by influencing environmental regulations and upgrading the industrial structure. Therefore, the environment is deteriorating, but these two mechanisms are entirely different. It limits the strength of ecological regulations and increases carbon emissions in the context of environmental regulations. On the other hand, it promotes the upgrading of the industrial structure, thereby increasing carbon emissions in the industrial system.

Secondly, the impact of energy consumption on carbon dioxide emissions coefficient estimates for the threshold effect model is 0.0571, 0.012, respectively. There is an upbound of their corresponding level of significance from 5% to 1%. This proposes 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 is higher in level and scale than the eastern and western regions. Also, the mechanism has apparent heterogeneity in the east of, west and central regions. Regardless of the environmental regulations or industrial structure, the central area's transmission path is much more important and more extensive than that in the eastern and western regions. This phenomenon may affect environmental regulations and industrial structure. However, this insignificant impact hinders the transmission path in the region of the west.

The study pointed out that revenue 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 the environmental governance and public service capabilities of local governments is another thing that needs to be done to stimulate the enthusiasm and efficiency of local governments in protecting the environment.

Next, policymakers should pay close attention to the distorting effects of energy consumption on local government behavior and are optimistic that they will maintain close supervision to improve environmental governance efficiency. Therefore, it is necessary to reduce pollution through coexistence and flexible government expenditure in environmental protection and monitoring environmental protection.

An increase in environmental protection expenditures will help formulate pollution transmission in underdeveloped areas and financial self-sufficiency areas. In contrast, developed areas with strong economic capacity need to improve environmental supervision further. This will help prevent the government's production expenditures from squeezing out fiscal expenses related to technological innovation.

This is also conducive to changing the phenomenon that the upgrading of the industrial structure leads to an increase in pollution emissions, which weakens the second stage of the transmission path (related to media effects) and reduces the negative impact on the environment.

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Figures

Figure 1

Energy consumption by source

Figure_a

Figure_b

Figure 2

The spatial distribution of EPI in 2010 and 2017 Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Average_EPI

Figure 3

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

Figure 4

The likelihood ratio of Model 1 and Model 2