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Directed Technical Change and Pollution Emission: Evidence From Fossil and Renewable Energy Technologies in China

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In this paper, we provide a study of the effect of directed technical change in the energy sector on pollution emission. We make an empirical analysis under the framework of the extended stochastic impacts by regression on population, affluence, and technology model and the environmental Kuznets curve hypothesis and employ the patent data onto fossil energy and renewable energy technologies from 2000 to 2015 to match the economic and environmental data of 30 provinces in China. We show that the prerequisite of restraining pollution emission is to transform the direction of energy technical change rather than only increase the magnitude of energy technical change. Furthermore, the direction of energy technical change will set up dissimilar purification effects on different pollutants, which indicates that the path of emission reduction of renewable energy technology is different. Moreover, promoting energy technology cooperation in adjacent provinces can further intensify the effect of directed energy technical change in restraining pollution emission according to the regional features of each area, and formulating targeted environmental policies to change the energy technology from dirty to clean can effectively curb environmental degradation, which is the mechanism to realize the rationalization and transformation of the energy structure.

Keywords: directed technical change, fossil energy, renewable energy, pollution emission, energy technology

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INTRODUCTION

The rapid evolution of China's economy has been mainly based on extensive growth patterns since the reform and opening up, which has led to high energy consumption (EC). It may be effective in the short term to decrease the burden on the environment by reducing the total EC by improving energy efficiency, but it is difficult in the long term. To find a solution to this fact, some scholars focus on the innovation of energy technology and analyze how to reduce the negative effect of the employment of energy on the environment through the energy technical change (Lin and Li, 2014; Buonocore et al., 2016). It is important to note that in the energy sector, technical change is not only showing the magnitude but also the direction. It is a potential fact that there is also a directed technical change in the energy sector since energy is a crucial input factor for modern economic growth, which can be divided into two kinds: dirty-type fossil energy and clean-type renewable energy due to various application technologies (Yang et al., 2019). Fossil energy has a long history, its technology is relatively robust and leading, and its application cost is low; renewable energy belongs to the emerging industry, its requirements on technology are higher than fossil energy, and its application cost is high. Consequently, there are two kinds of directed energy technical change (DETC), dirty and clean, respectively.

However, the energy structure in China always presents the style fact that the proportion of fossil energy (coal, oil, and gas) is relatively in the height for a long time. In that case, if we only pay attention to the magnitude of energy technical change and ignore the direction of energy technical change, under the condition of the free market, the energy technology is likely to be affected by the features of the lock-in effect or path dependence on technology (Acemoglu et al., 2012; Aghion et al., 2016), which forced the energy technology to develop in the direction of the fossil energy, thus forming the dirty direction of energy technical change. Although this kind of DETC can also improve China's energy efficiency, under the rebound effect of energy, fossil EC may increase accordingly, and the increase in fossil EC is bound to cause continuous pollution. Finally, it is hard to overcome the dilemma of both economic growth and environmental pollution through the energy technical change. Consequently, both the direction and magnitude of energy technical change should be given high attention. DETC, in particular, may be a prerequisite for restraining pollution emission through energy technologies.

In addition, there are great gaps in economic growth, population, and technology among different areas in China, which might make the pollution emission have a spatial effect. The potential fact is that the more pollution emissions, the worse the environmental quality. Therefore, according to the hypothesis of the environmental Kuznets curve (EKC), there is a nonlinear correlation between the economy and the environment (Grossman and Krueger, 1995). When economic growth and environmental quality are not decoupled, the requirements of environmental quality in developed areas are commonly higher than in underdeveloped areas (Al-Mulali et al., 2015; Pata and Caglar, 2021). It is not only easy to form the pollution haven, that is, the transfer of pollution industries from developed areas to underdeveloped areas, but it also further causes significant regional gaps in energy technical change, that is, there may be spatial effects in energy technology. The DETC reflects the relative intensity between renewable energy and fossil energy technology, which is an expressive way of energy technical change, so the DETC may also have a spatial correlation. If we ignore the potential spatial effect between pollution emissions and the DETC, we will not be able to obtain the correlation accurately. To solve this problem, we make the empirical analysis based on an extended STIRPAT model and the hypothesis of EKC (Dietz and Rosa, 1994; Grossman and Krueger, 1995; York et al., 2003), in the form of spatial panel data. Furthermore, some studies have shown that China's environmental degradation is becoming more and more serious (Pata and Isik, 2021), and the contribution of renewable energy and its technology to the environment remains to be investigated (Pata and Caglar, 2021).

In general, to more effectively alleviate the contradictory problems of environmental pollution and economic development facing China, it is urgent to increase investment and support for the innovation of energy technology. Combined with environmental policies, the energy technology in China will be promoted to show the clean direction, to complete the substitution of fossil energy by renewable energy, and to realize the coordinated growth of the economy and environment in finality.

This paper is organized as follows: a literature review is presented in *Literature Review*. The methodology shown in *Methodology*. *Data and Variables* is data and variables. *Empirical Results* includes the results and discussion. The conclusions are in the final section.

LITERATURE REVIEW

Acemoglu (2002) creatively altered the research of technical change from neutral to directed, that is, there is a specific direction in technical change for all sectors. With the continuous improvement in the theory of directed technical change, it has been more and more applied to the study of energy and environmental issues. These studies can be divided into two categories.

The first category of research starts from the factors of economic growth to explore the directed technical change between the capital (K), labor (L), energy (E), and its environmental performances, focusing on empirical analysis. Otto et al. (2007) related the use of energy with pollution emission and establishes a Computable General Equilibrium (CGE) model to discuss the directed technical change on specific productive factors. The research shows that the substitution elasticity between different factors has an important impact on which factors the technical change tends to. Karanfil and Yeddir-tamsamani (2010) used the trans-log cost function to consider the energy factor into the study scope of directed technical change and found that the energy price is the important factor affecting the directed technical change. Zha et al. (2017) employed the Constant Elasticity of Substitution (CES) production function to measure the direction of technical change of 11 energy-intensive industries in China from 1990 to 2012. The results show that more than half of the industries in technical change are directed toward energy, while the rest of industries are directed toward capital and labor, which means that recent environmental policies have failed to promote the advancement of green technology in China. Yang et al. (2018) and Cheng et al. (2019) also discussed the DETC of China's industry and divided the energy factors into fossil and non-fossil energy. The research shows that optimizing the technical change in labor, capital, and non-fossil energy can alterat the energy structure, which can promote the green transformation of economic growth.

The second category of research is based on the theory of endogenous economic growth, discussing how policies affect the directed technical change and the continuous impact on pollution emission after the transformations in directed technical change, focusing on theoretical analysis. Acemoglu et al. (2012) constructed the analysis framework of directed technical change and environment under the theory of endogenous economic growth[1]. It is found that the directed technical

[1]This framework is called AABH model in general (Wiskich, 2021).

change depends on the three effects of price, market size, and productivity, and the government can transform the directed technical change through temporary environmental policies, to avoid environmental disasters. Energy is a crucial factor of the economy, and the energy factor market is forward looking. André and Smulders (2014) established a theoretical model on this basis, which links the growth speed and direction of technical change with energy employment and exploitation, and proposed that energy factors should be considered in the analysis framework of directed technical change, to better explore the long-term and short-term effects of environmental policies on the directed technical change and environment. Mattauch et al. (2015) introduced the spillover effect of learning by doing it into the framework of directed technical change and believed that an important reason hindering the transformation of low-carbon economy is the lock-in effect in technology caused by the high stock of fossil energy technology, which indicates that we need to pay attention to the issue of directed technical change within energy sectors and that this is the key to solve environmental pollution. Some scholars further extended this framework to the open economy model to explore the impact of unilateral environmental policy on directed technical change and environment (Hemous, 2016; Bijgaart, 2017). Recently, Wiskich (2021) has summarized the relevant theoretical research and supplemented and improved the study of Acemoglu et al. (2012), to achieve a more stable equilibrium.

Compared with previous studies, this paper focuses on the empirical analysis of the impact of the DETC on pollution emission, and the potential contributions are as follows: first, the technical change in the STIRPAT model is decomposed into energy efficiency and DETC, to examine the prerequisites for restraining pollution emission through energy technology. Second, three different types of pollutants are employed to reflect the industrial pollution emission, to explore the emission reduction path of renewable energy technology, and to realize the balanced growth of renewable energy technology. Third, combined with the EKC hypothesis, the STIRPAT model is extended to a spatial panel, and the spatial econometrics method is employed to make up for the lack of considering the spatial effect of pollutants in the existing study.

METHODOLOGY

This section shows how the STIRPAT model is extended and explains how the model fits the EKC hypothesis. The STIRPAT model is a way of an extensible environmental effect assessment, and it is also a classical method to investigate the impact factors of pollution emission (Dietz and Rosa 1994; Lin, Zhao, and Marinova 2009). The STIRPAT model is as follows:

$$I_t = aP_t^{\beta_1} A_t^{\beta_2} T_t^{\beta_3} \varepsilon_t \tag{1}$$

where I is the emission of pollutants in time t. Population (P), affluence (A), and technology (T) are considered to be important factors affecting pollution emissions (I). Next, the model of STIRPAT is expanded to meet the application requirements of econometrics.

Baseline Model

The power of the STIRPAT model is not only can it expand the estimation form of the model, but it also allows to improve the factors affecting pollution emissions. Therefore, we take the logarithm based on **Eq. 1** to get the baseline model of panel data, as follows:

$$\ln I_{it} = \alpha + \beta_1 \ln P_{it} + \beta_2 \ln A_{it} + \beta_3 \ln T_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{2}$$

γ_i and μ_t are areas and time-fixed effects, respectively. ε is the residual term, and α is the constant term. The population density per unit area of each area is used to represent the population ($P \rightarrow POP$). Affluence (A) is expressed as the real Gross Domestic Product (GDP) per capita ($pGDP$).

It must be noted that we decompose the technology (T) in the STIRPAT model into two parts: energy efficiency (EE) and $DETC$, to examine the impact from the magnitude and the direction of energy technical change on pollution emissions. The larger the magnitude of energy technical change, the higher the energy efficiency, generally.

In addition, the EKC hypothesis illustrates that there is a high-order nonlinear correlation between economic growth and environment (Grossman and Krueger, 1995; Shao et al., 2011). The quadratic and cubic terms of $pGDP$ are included in **Eq. 2**, and the model is as follows:

$$\begin{aligned}\ln I_{it} = \alpha &+ \beta_1 \ln POP_{it} \\ &+ \beta_2 \ln pGDP_{it} + \beta_3 (\ln pGDP_{it})^2 + \beta_4 (\ln pGDP_{it})^3 \\ &+ \beta_5 \ln EE_{it} + \beta_6 \ln DETC_{it} + \sum X_{it} + \gamma_i + \mu_t + \varepsilon_{it}\end{aligned} \tag{3}$$

X_{it} is the control variables affecting the pollution emissions, including the energy consumption (EC), environmental regulation (ER), industrial structure (IS), and foreign direct investment (FDI), which can be used to reduce the endogenous issue.

Spatial Econometric Model

Next, we further extend **Eq. 3** to the panel form of the spatial econometric model. In the expansion of the spatial econometric model, we need to analyze the potential features of variables spatially, to find the suitable model.

The first fact is that most pollutants (SO_2, WW, SW) have the features of spatial diffusion and transfer, so the spatial correlation of pollution emissions (I) is existent. Consequently, this paper divides the sources of spatial correlation between different areas into 1) the spillover effect of neighboring pollution emissions on local areas and 2) the leakage effect of local pollution emissions on neighboring areas. The difference of "spillover effect" and "leakage effect" between different areas reflects the spatial correlation of pollution emissions, that is, $\rho W \ln I_{it}$, where ρ is the coefficient of spatial lag and W is the spatial weight matrix.

The second fact is that other independent variables in **Eq. 3** may also have a spatial correlation. For example, technical change

TABLE 1 | Descriptive statistics of variables.

Variables	Average	Std.dev	Min	Max	Skew	Kurt	Obs
SO2	0.016	0.011	0.001	0.061	1.930	7.303	480
WW	16.309	8.652	3.252	47.631	1.159	3.841	480
SW	1.821	2.633	0.094	25.267	5.414	39.870	480
DETC	0.477	0.133	0.053	0.952	0.198	3.711	480
EE	0.939	0.547	0.159	3.245	0.966	3.882	480
POP	418.196	583.643	7.161	3,825.690	3.892	20.112	480
pGDP	27,478.760	21,678.910	2,661.557	108,000	1.355	4.648	480
EC	2.691	1.488	0.556	8.093	1.114	4.169	480
ER	0.179	0.142	0.007	0.992	2.315	10.333	480
IS	46.426	7.936	19.738	66.42	–1.152	4.677	480
FDI	733.132	1,206.192	5.772	7,821.536	3.017	13.094	480

in a local area will not only affect the pollution emissions of a local area but also the pollution emissions of its neighboring areas (Xie et al., 2016).

The third fact is that environmental regulation (*ER*) may alter pollution emissions by influencing technical change or innovation, which may be one of the mechanisms of environmental regulation affecting pollution emissions (Lanoie et al., 2008; Li and Du, 2021). Thus, we construct two groups of interactive variables in the way of a regulatory effect (ln*DETC* × ln*ER*, ln*EE* × ln*ER*), to control the indirect impact of environmental regulation on pollution emissions.

To sum up, the extended STIRPAT model belongs to the spatial Durbin model (SDM), which contains both the spatial lag of the dependent variable and independent variables. The SDM model is as follows:

$$\begin{aligned}\ln I_{it} = {} & \alpha + \rho W \ln I_{it} + \sum\nolimits_{j=1}^{7} \beta_j C_{it} + \sum\nolimits_{k=1}^{7} \theta_j W C_{it} \\ & + \beta_8 (\ln DETC \times \ln ER) + \beta_9 (\ln EE \times \ln ER) \\ & + \theta_8 W (\ln DETC \times \ln ER) + \theta_9 W (\ln EE \times \ln ER) \\ & + \gamma_i + \mu_t + \varepsilon_{it} \end{aligned} \tag{4}$$

where C_{it} shows the variable collection of $\ln POP_{it}$, $\ln pGDP_{it}$, $(\ln pGDP_{it})^2$, $(\ln pGDP_{it})^3$, $\ln EE_{it}$, $\ln DETC_{it}$, and X_{it}. The interaction between the DETC and environmental regulation is expressed by ln*DETC* × ln*ER*. The interaction between energy efficiency and environmental regulation is expressed by ln*EE* × ln*ER*.

Spatial Weight Matrix

In the spatial econometric model, the geographical distance and economic distance are considered, to build a composite spatial weight matrix (Case, Rosen, and Hines 1993). This is because pollutants not only have the features of diffusion due to geographical distance but are also generated by the employment of energy factors and economic activities. First, we employ the square of the inverse distance matrix to represent the geographical distance weight matrix (W^{GEO}). Second, the economic distance weight matrix (W^{GDP}) is represented by the square of the reciprocal of the absolute value of the difference between the GDP per capita of each area. Third, the composite space weight matrix (W^{BOTH}) is represented by the weight of the W^{GEO} and W^{GDP}, which is as follows:

$$W^{BOTH} = \phi W^{GEO} + (1 - \phi) W^{GDP} \tag{5}$$

ϕ represents the weight of W^{GEO} and W^{GDP} in W^{BOTH} and $\phi \in (0, 1)$. We assume that $\phi = 0.5$, which shows that the impact of geographical distance and economic distance on spatial effect is similar, to relax the analysis.

DATA AND VARIABLES

This paper employs the annual panel data of the 30 areas of provinces in China as the research sample and the period of 2000–2015. A total of 480 observations constitute the panel data. Due to the missing details on EC, pollutant emission, and so on, Tibet, Hong Kong, Macao, and Taiwan are not included.

Pollution Emissions

The potential fact is that the more pollution emissions, the worse the environmental quality. Consequently, the emission of sulfur dioxide (SO_2), wastewater (*WW*), and solid waste (*SW*) from the industrial sector (*I*) is employed to measure the pollution emission from the *I*. These pollutants are closely related to the application of energy factors and energy technology (Buonocore et al., 2016). We also use the *per capita* form of the above variables to eliminate the impact of the scale effect. The data of *SW* are missing due to the alteration of the statistical scale in 2011 (Zhao et al., 2021). Consequently, the production of industrial solid waste is used instead of the emission.

The Magnitude of Energy Technical Change

The magnitude of energy technical change is measured by energy efficiency (*EE*). Specifically, this paper uses the GDP per unit of EC to measure energy efficiency[2]. The improvement of energy efficiency is, of course, not only determined by energy technology. The advancement of the application, management, and transformation of energy structures will also affect energy efficiency. However, as an external reflection of energy technical change and Research and Development (R&D) investment in energy technology, the higher the scope of energy efficiency, the lower the EC at the same economic output, indicating the improvement of energy technology (Shao et al., 2011).

[2]All kinds of EC are converted to standard coal unit.

The Direction of Energy Technical Change

The employment of patent application data to reflect technical change or innovation has been widely applied (Popp, 2002). So, the energy technical change is represented by the count of patents by the application on energy technology (Yang et al., 2019) in the China National Intellectual Property Administration (CNIPA). Second, energy technology in this paper consists of fossil energy and renewable energy technology patents (Johnstone et al., 2010; Lanzi and Sue Wing, 2011; Albino et al., 2014; Noailly and Shestalova, 2017; Cho and Sohn 2018). Third, referring to the researches of Noailly and Smeets (2015) and Aghion et al. (2016), the *DETC* is voiced by the proportion of renewable energy technology patents in energy technology patents. For the international patent classification code of fossil and renewable energy technology patents, please refer to **Supplementary Appendix Tables SA1, SA2**.

Control Variables

Other essential factors affecting energy technical change need to be controlled, as follows: 1) *EC* is expressed by the ratio of the total EC and the total population of the corresponding region at the end of the year. 2) For each area, environmental regulation (*ER*) is shown by the proportion of industrial pollution investment in GDP. 3) Industrial structure (*IS*) is reflected by the proportion of the added value of the secondary industry in GDP. 4) The proportion of foreign direct investment in GDP is used as the proxy variable of *FDI*. Control variables are based on the relevant studies, such as Lin et al. (2009), Shao et al. (2011), Al-Mulali et al. (2015), Yin et al. (2015), Zhao et al. (2021), and Qu et al. (2021). Refer to *Baseline Model* for the definition of population and affluence.

Descriptive Statistics

Datasets are collected from the China Environmental Statistical Yearbook, China Energy Statistical Yearbook, and CNIPA. The economic and environmental data mainly come from statistical yearbooks. The data on energy technical change come from the CNIPA, and they are indicated by the patent application data. For empirical analysis, we employed the zip code and patent address for matching the economic data and patent data. **Table 1** shows the results of descriptive statistics.

EMPIRICAL RESULTS

The empirical analysis needs first to test the spatial correlation contained in the proxy variables of pollution emissions. The index of Moran's I and Geary's C is widely employed in spatial correlation tests[3]. The test results of the spatial correlation are shown in **Supplementary Appendix B Table SB1**. The Moran's I scatter diagram is presented in **Supplementary Appendix B Figure SB1**.

The spatial correlation test shows that Moran's I is greater than 0, and Geary's C is less than 1 most times under the spatial weight matrices of W^{GEO}. The results show that the three pollutants ($SO2$, WW, SW) have the features of positive aggregation, that is, high (low) pollution areas and high (low) pollution areas together, which means the leakage effect of pollutants gradually worsens. **Supplementary Appendix Figure SB1** reveals that under the spatial weight matrices of W^{GEO} and W^{BOTH}, the feature of positive aggregation is supported with the province as the spatial unit. Thus, it is feasible to employ a spatial econometric model.

The Results of the Baseline Model

An analysis with the baseline model is performed based on **Eq. 3**. The Lagrange multiplier (LMLAG, LMERR) and their robustness tests (Robust-LMLAG, Robust-LMERR) are employed to explore whether the baseline model ignores the potential spatial correlation of the research objects. The Hausman test shows that the fixed effect (FE) model is more suitable for estimation than the random effect (RE) model, and the results are reported in **Table 2**.

We find that the estimated coefficient of directed energy technical change (*lnDETC*) is significantly negative at least at the 10% level, which means that increasing the DETC can reduce pollution emissions (*lnSO2*, $lnWW$, *lnSW*). The empirical results in columns (2), (4), and (6) further control the impact of energy efficiency (*lnEE*) on pollution emission. It should be noted that the effect of energy efficiency on pollution emission is uncertain; in other words, the magnitude of energy technical change is not the prerequisite for restraining pollution emission. It is important to note that the DETC tends to show inconsistency in the purification capacity of different pollutants. Specifically, it has the highest improvement effect on solid waste (*lnSW*), followed by wastewater ($lnWW$), and a weak purification effect on sulfur dioxide ($lnSO_2$). Taking the coefficients in columns (2) and (6) as an example, for a 1% increase in the DETC, sulfur dioxide emissions will be reduced by about 0.09%, while solid waste emissions will be reduced by 0.17%. The estimated coefficients of other variables rarely deviate from economic intuition.

For different pollutants (*lnSO2*, $lnWW$, *lnSW*), moreover, the estimated coefficients of affluence (*lnpGDP*) and its high-order terms ($lnpGDP^2$, $lnpGDP^3$) show a trend of "negative, positive, and negative," that is, the correlation between pollution emission and economic growth will show an inverted N-type in EKC hypothesis. The results show that in the future, pollution emissions and economic output will gradually achieve decoupling in China, and economic growth will not be at the expense of the environment.

Finally, the results of the LM test and robust LM test are significant at least at the level of 10%, indicating that there is a spatial correlation between pollution emission and independent variables such as the DETC. Therefore, the further employment of a spatial econometric model can improve the effectiveness of the empirical results.

[3]Calculation methods of Moran's I and Geary's C are common, so they are not shown in this paper.

TABLE 2 | Results of *SO2*, *WW*, and *SW* in the baseline model.

Variables	*lnSO2*		*lnWW*		*lnSW*	
	(1)	(2)	(3)	(4)	(5)	(6)
lnDETC	−0.085* (−1.95)	−0.087** (−2.00)	−0.122*** (−3.00)	−0.112*** (−2.73)	−0.173*** (−3.48)	−0.172*** (−3.42)
lnEE	—	0.032 (0.39)	—	−0.119 (−1.58)	—	−0.012 (−0.13)
lnPOP	0.212 (0.84)	0.229 (0.90)	0.193 (0.82)	0.130 (0.54)	0.816*** (2.83)	0.810*** (2.76)
lnpGDP	−15.64*** (−3.18)	−15.76*** (−3.19)	−18.77*** (−4.06)	−18.31*** (−3.96)	−36.36*** (−6.44)	−36.32*** (−6.41)
lnpGDP^2	1.733*** (3.40)	1.745*** (3.41)	2.006*** (4.19)	1.959*** (4.09)	3.850*** (6.58)	3.846*** (6.55)
lnpGDP^3	−0.064*** (−3.67)	−0.065*** (−3.69)	−0.071*** (−4.34)	−0.070*** (−4.22)	−0.134*** (−6.64)	−0.133*** (−6.61)
lnEC	0.805*** (8.38)	0.833*** (6.91)	0.386*** (4.28)	0.278** (2.47)	0.671*** (6.09)	0.660*** (4.77)
lnIS	0.229* (1.88)	0.242* (1.91)	0.058 (0.50)	0.009 (0.08)	0.017 (0.12)	0.012 (0.08)
lnFDI	−0.086** (−2.35)	−0.090** (−2.38)	−0.096*** (−2.78)	−0.084** (−2.40)	−0.120*** (−2.85)	−0.119*** (−2.76)
lnER	0.053*** (2.67)	0.054*** (2.69)	0.062*** (3.32)	0.060*** (3.22)	0.079*** (3.47)	0.079*** (3.45)
Cons	41.90*** (2.72)	42.26*** (2.74)	61.06*** (4.23)	59.70*** (4.13)	109.20*** (6.19)	109.10*** (6.16)
Hausman test	20.07** (0.018)	20.35** (0.022)	24.46*** (0.004)	28.10*** (0.002)	24.13*** (0.004)	23.43*** (0.009)
F test	47.05*** (0.000)	42.28*** (0.000)	30.20*** (0.000)	28.50*** (0.000)	226.02*** (0.000)	202.96*** (0.000)
Obs	480	480	480	480	480	480
R^2	0.489	0.490	0.392	0.396	0.821	0.822
LM(lag)	11.454***	13.228***	74.688***	68.177***	5.344**	5.611**
Robust LM(lag)	9.818***	11.575***	72.355***	65.897***	6.622**	6.298**
LM(error)	19.456***	28.316***	6.301**	3.251*	140.667***	112.531***
Robust LM(error)	18.288***	27.186***	3.911*	3.412*	136.478***	156.866***

*Notes: *, **, and *** represent significance at the 10%, 5%, and 1% level. T statistics in parentheses. FE report the within* R^2. Cons *is the constant.*

TABLE 3 | Results of SO2, WW, and SW in spatial econometric model.

Variables	lnSO2		lnWW		lnSW	
	(1)	(2)	(3)	(4)	(5)	(6)
rho (ρ)	0.217*** (3.02)	0.171** (2.41)	0.095 (1.12)	0.179* (1.89)	0.173*** (4.19)	0.156*** (4.13)
lnDETC	−0.125** (−2.51)	−0.133*** (−2.89)	−0.131** (−2.50)	−0.129** (−2.56)	−0.171* (−1.89)	−0.173* (−1.85)
lnEE	0.139 (1.13)	0.309** (2.11)	−0.024 (−0.16)	0.062 (0.33)	0.060 (0.30)	0.134 (0.65)
lnPOP	0.859 (1.01)	0.871 (1.07)	1.204* (1.78)	1.241* (1.89)	1.235 (0.89)	1.284 (0.94)
lnpGDP	−15.530* (−1.68)	−11.63 (−1.32)	−23.89*** (−3.14)	−21.42*** (−3.00)	−15.98 (−1.45)	−13.01 (−1.13)
lnpGDP^2	1.754* (1.88)	1.311 (1.46)	2.680*** (3.37)	2.394*** (3.22)	1.801 (1.57)	1.487 (1.25)
lnpGDP^3	−0.064* (−2.07)	−0.048 (−1.58)	−0.097** (−3.57)	−0.087*** (−3.40)	−0.066* (−1.67)	−0.055 (−1.35)
lnEC	0.738*** (2.66)	0.702*** (2.81)	0.543** (2.08)	0.537** (2.10)	0.969** (1.96)	1.025** (1.98)
lnIS	−0.169 (−0.66)	−0.078 (−0.35)	−0.485 (−1.57)	−0.389 (−1.36)	−0.143 (−0.68)	−0.068 (−0.34)
lnFDI	−0.016 (−0.28)	−0.008 (−0.13)	−0.049 (−0.63)	−0.040 (−0.56)	−0.053 (−0.98)	−0.057 (−1.03)
lnER	0.062** (2.19)	0.117** (2.00)	0.056** (2.08)	0.131*** (2.69)	0.073*** (2.59)	0.088** (2.45)
lnDETC×lnER	—	0.018* (1.91)	—	0.028* (1.80)	—	0.006 (0.36)
lnEE×lnER	—	0.086** (2.01)	—	0.039 (0.90)	—	0.023 (0.89)
*W*lnDETC*	−0.104 (−0.70)	−0.183 (−1.16)	−0.107 (−1.03)	−0.133 (−1.31)	−0.288 (−1.07)	−0.317 (−1.18)
*W*lnEE*	−0.550* (−1.80)	−0.721** (−2.41)	−0.430** (−1.98)	−0.193 (−0.69)	−0.669 (−1.53)	−0.435 (−0.80)
*W*lnPOP*	−0.404 (−0.32)	−1.205 (−0.94)	−0.726 (−0.65)	−0.992 (−0.89)	0.523 (0.40)	0.568 (0.48)
*W*lnpGDP*	−13.33 (−0.70)	−6.828 (−0.40)	1.015 (0.06)	5.075 (0.32)	−51.45** (−2.10)	−52.33* (−1.91)
*W*lnpGDP*^{2}	1.364 (0.72)	0.652 (0.39)	−0.321 (−0.18)	−0.758 (−0.48)	5.420** (2.13)	5.498* (1.93)
*W*lnpGDP*^{3}	−0.047 (−0.75)	−0.021 (−0.38)	0.016 (0.27)	0.032 (0.59)	−0.187** (−2.13)	−0.189* (−1.92)
*W*lnEC*	0.265 (0.60)	0.406 (1.05)	0.154 (0.46)	0.247 (0.73)	−0.850*** (−2.60)	−0.910*** (−2.80)
*W*lnIS*	−1.18*** (−3.33)	−0.83** (−2.31)	−0.269 (−0.69)	−0.007 (−0.02)	−1.517*** (−4.70)	−1.371*** (−3.79)
*W*lnFDI*	−0.31*** (−2.62)	−0.26** (−2.23)	−0.103 (−1.09)	−0.088 (−0.90)	−0.209 (−1.51)	−0.184 (−1.41)
*W*lnER*	−0.079** (−2.12)	0.018 (0.27)	−0.062 (−1.33)	−0.058 (−0.86)	−0.103* (−1.68)	−0.051 (−1.06)
*W*lnDETC×lnER*	—	0.055 (1.61)	—	−0.003 (−0.14)	—	0.012 (0.55)
*W*lnEE×lnER*	—	−0.147* (−1.66)	—	0.068 (1.03)	—	0.102 (0.90)
Obs	480	480	480	480	480	480
R^2	0.563	0.604	0.395	0.420	0.854	0.856

*Notes: *, **, *** represent significance at the 10%, 5%, and 1% level. T statistics in parentheses.* Cons *is the constant.* W *is the spatial weight matrix.*

TABLE 4 | The direct and indirect effects of the spatial econometric model.

Variables	*lnSO2*		*lnWW*		*lnSW*	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
lnDETC	−0.141*** (−3.09)	−0.229 (−1.16)	−0.122** (−2.41)	−0.103 (−1.07)	−0.188* (−1.92)	−0.392 (−1.16)
lnEE	0.289* (1.94)	−0.779** (−2.15)	0.079 (0.41)	−0.195 (−0.76)	0.127 (0.55)	−0.480 (−0.71)
lnPOP	0.858 (1.06)	−1.241 (−0.89)	1.316* (1.89)	−1.086 (−1.10)	1.358 (0.97)	0.868 (0.77)
lnpGDP	−12.35 (−1.48)	−10.28 (−0.52)	−22.26*** (−3.06)	7.93 (0.52)	−15.39 (−1.44)	−63.03* (−1.94)
lnpGDP^2	1.388 (1.63)	1.013 (0.52)	2.496*** (3.28)	−1.065 (−0.68)	1.746 (1.56)	6.635* (1.95)
lnpGDP^3	−0.051* (−1.76)	−0.034 (−0.51)	−0.090*** (−3.46)	0.043 (0.80)	−0.064* (−1.66)	−0.229* (−1.93)
lnEC	0.722*** (2.74)	0.625 (1.39)	0.533** (1.98)	0.167 (0.56)	1.005* (1.74)	−0.850** (−2.14)
lnIS	−0.125 (−0.57)	−0.982** (−2.27)	−0.415 (−1.39)	0.068 (0.17)	−0.126 (−0.61)	−1.607*** (−3.59)
lnFDI	−0.014 (−0.25)	−0.304** (−2.37)	−0.032 (−0.45)	−0.079 (−0.88)	−0.061 (−1.06)	−0.230 (−1.40)
lnER	0.120** (2.14)	0.043 (0.61)	0.135*** (2.75)	−0.068 (−1.05)	0.085** (2.34)	−0.044 (−0.86)

*Notes: *, **, *** represent significance at the 10%, 5%, and 1% level. T statistics in parentheses.*

TABLE 5 | Robustness test with POLS method.

Variables	*lnSO2*		*lnWW*		*lnSW*	
	(1)	(2)	(3)	(4)	(5)	(6)
lnDETC	−0.100** (−2.02)	−0.105** (−2.07)	−0.125** (−2.35)	−0.122** (−2.31)	−0.137** (−2.33)	−0.145** (−2.35)
lnEE	—	0.060 (0.77)	—	−0.042 (−0.53)	—	0.111 (1.03)
lnPOP	0.523 (1.48)	0.582 (1.59)	0.888*** (2.74)	0.847*** (2.60)	1.258*** (3.17)	1.367*** (3.05)
lnpGDP	−22.82*** (−4.62)	−22.93*** (−4.63)	−19.03*** (−4.02)	−18.96*** (−4.01)	−30.02*** (−4.84)	−30.21*** (−4.78)
lnpGDP^2	2.501*** (4.88)	2.514*** (4.90)	2.092*** (4.25)	2.083*** (4.24)	3.241*** (5.07)	3.265*** (5.00)
lnpGDP^3	−0.090*** (−5.14)	−0.091*** (−5.17)	−0.075*** (−4.47)	−0.074*** (−4.46)	−0.114*** (−5.23)	−0.115*** (−5.15)
lnEC	0.600*** (4.01)	0.662*** (3.52)	0.456*** (3.36)	0.414** (2.45)	0.946*** (5.63)	1.059*** (4.57)
lnIS	−0.067 (−0.37)	−0.057 (−0.32)	−0.250 (−1.15)	−0.257 (−1.17)	−0.134 (−0.85)	−0.116 (−0.74)
lnFDI	−0.067* (−1.83)	−0.072* (−1.95)	−0.079* (−1.88)	−0.076* (−1.84)	−0.081* (−1.89)	−0.090** (−2.07)
lnER	0.045** (2.03)	0.046** (2.09)	0.067*** (3.21)	0.066*** (3.16)	0.108*** (4.21)	0.111*** (4.21)
Cons	60.21*** (3.85)	60.15*** (3.84)	53.61*** (3.76)	53.65*** (3.75)	82.17*** (4.31)	82.06*** (4.26)
Time-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Area-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Obs	480	480	480	480	480	480
R^2	0.9091	0.9092	0.8787	0.8788	0.9334	0.9336

*Notes: *, **, *** represent significance at the 10%, 5%, and 1% level. T statistics in parentheses.* Cons *is the constant.* R^2 *is adjusted.*

The Results of the Spatial Econometric Model

The estimation of the spatial econometric model is based on **Eq. 4** with the spatial weight matrix of W^{BOTH}, and the results are shown in **Table 3**.

We can find that after controlling the environmental regulation (*lnER*) and their interaction terms (*lnDETC* × *lnER*, *lnEE* × *lnER*) in columns (2), (4), and (6), the coefficient of spatial lag ρ is significantly positive at the level of 10%, which confirms that all of the pollutants (*lnSO2*, *lnWW*, *lnSW*) have spatial correlation once again. Subsequently, the local DETC can reduce local pollutant emissions. Although the directed energy technical change of neighboring areas (*W*lnDETC*) has a restraining effect on the local pollution emission, the results are not significant. The results show that the *W*lnDETC* will not improve the local pollution emission, and the cooperation in energy technology in various areas is inadequate. In addition, energy efficiency (*lnEE*) still cannot have a significant impact on pollution emission, which is consistent with the results of the baseline model.

Combined with the empirical results of **Tables 2**, **3**, we believe that the prerequisite for restraining pollution emission through energy technology innovation is to focus on the direction of energy technical change, not just to improve the magnitude of energy technical change. Secondly, pollution emissions and economic growth are still showing signs of decoupling, especially in wastewater and sulfur dioxide. This result can be found from the inverted N-type in EKC hypothesis. Thirdly, the *lnEC* is bound to cause environmental deterioration, which mainly depends on the fact that China's energy structure is still dominated by fossil energy.

Moreover, referring to LeSage and Pace (2009) and Zhao et al. (2021), we decompose the spatial correlation into the direct effects and the indirect effects based on the results in columns (2), (4), and (6) of **Table 3**. The direct and indirect effects are shown in **Table 4**.

Except for population (*lnPOP*) and technology (*lnDETC*, *lnEE*), similar factors have a similar impact on pollution emission, but for different pollutants, the level of direct and indirect effects is different. Specifically, the effect of *lnDETC* on pollution emission is determined by the direct effect, that is,

TABLE 6 | Robustness test with different spatial weight matrixes.

Variables	*lnSO2*	*lnWW*	*lnSW*
	(1)	(2)	(3)
rho (ρ)	0.352*** (3.87)	0.142* (1.79)	0.248*** (3.55)
lnDETC	−0.117** (−2.31)	−0.139*** (−2.74)	−0.170* (−1.78)
lnEE	0.087 (0.69)	−0.021 (−0.14)	0.008 (0.04)
lnPOP	0.863 (1.10)	0.987 (1.47)	0.878 (0.97)
lnpGDP	−17.88* (−1.75)	−27.93*** (−3.56)	−21.93* (−1.73)
$lnpGDP^2$	2.002* (1.92)	3.079*** (3.81)	2.364* (1.80)
$lnpGDP^3$	−0.074** (−2.08)	−0.110*** (−4.01)	−0.084* (−1.86)
lnEC	0.777*** (2.81)	0.474* (1.92)	0.771** (2.42)
lnIS	−0.026 (−0.10)	−0.560* (−1.82)	−0.127 (−0.60)
lnFDI	−0.049 (−0.91)	−0.059 (−0.81)	−0.035 (−0.61)
lnER	0.056** (1.99)	0.045* (1.69)	0.081*** (2.80)
*W*lnDETC*	−0.131 (−0.80)	−0.230** (−2.00)	−0.301 (−1.11)
*W*lnEE*	0.124 (0.22)	−0.556** (−2.03)	−0.814** (−1.99)
*W*lnPOP*	0.650 (0.57)	0.695 (0.62)	1.435 (1.46)
*W*lnpGDP*	−6.259 (−0.23)	−1.587 (−0.09)	−32.20* (−1.81)
$W*lnpGDP^2$	0.769 (0.29)	0.077 (0.04)	3.716* (1.91)
$W*lnpGDP^3$	−0.031 (−0.36)	−0.002 (−0.02)	−0.136* (−1.94)
*W*lnEC*	−0.104 (−0.16)	0.100 (0.25)	−1.541*** (−2.96)
*W*lnIS*	−0.877 (−1.53)	−0.648 (−1.32)	−1.824*** (−3.46)
*W*lnFDI*	−0.288* (−1.86)	−0.169 (−1.46)	−0.335 (−1.50)
*W*lnER*	−0.046 (−0.73)	−0.037 (−0.67)	−0.115* (−1.82)
Obs	480	480	480
R^2	0.529	0.406	0.857

*Notes: *, **, *** represent significance at the 10%, 5%, and 1% level. T statistics in parentheses.* Cons *is the constant.* W *is the spatial weight matrix.*

the DETC can play an important role in restraining local pollution emission, while the impact on the pollution emission of neighboring areas is weak. For SO_2, the direct effect of energy efficiency (*lnEE*) on pollution emission is positive, but its indirect effect is negative, which can be explained as follows: 1) the advancement of energy efficiency will lead to the increase of local EC, which is not conducive to the improvement of local pollution emission. 2) The increase of local EC has a crowding-out effect on the EC of neighboring areas, to improve the pollution emission of neighboring areas.

Robustness Tests

This paper has carried out robustness tests as follows: first, the results of the baseline model are compared and examined by employing the Pooled Ordinary Least Square (POLS) method. Second, considering the spatial weight matrix of W^{GEO}, the results of the spatial econometric model are verified again. Third, the substitution variable is employed to remeasure the direction of energy technical change.

Robustness Test With POLS Method

Compared with **Table 2**, the estimated coefficients of the central independent variables in **Table 5** have no reverse in direction and significance. For example, the *lnDETC* is negative, and energy efficiency (*lnEE*) is still not significant. The estimated coefficient of affluence (*lnpGDP*, $lnpGDP^2$, $lnpGDP^3$) still shows the trend of "negative, positive, and negative," correlation of an inverted N-type, which is consistent with the results of **Table 2**. The purification effect of directed energy technical change on solid waste (*lnSW*) is still the highest.

Robustness Test With Different Spatial Weight Matrixes

The geographical distance weight matrix (W^{GEO}) is employed to replace the composite space weight matrix (W^{BOTH}) to estimate **Eq. 4** again, as shown in **Table 6**. The directed energy technical change will still purify the pollutants, and the pollution emission will be restrained. The coefficient of spatial lag (ρ) is still significantly positive. The connection between pollution emission and economic growth also presents an inverted N-type. The above results prove the relative robustness and effectiveness of the spatial econometric model.

TABLE 7 | Robustness test with an alternative variable in baseline model (FE).

Variables	*lnSO2*		*lnWW*		*lnSW*	
	(1)	(2)	(3)	(4)	(5)	(6)
lnpRETP	−0.118*** (−4.68)	−0.120*** (−4.72)	−0.102*** (−4.27)	−0.098*** (−4.06)	−0.196*** (−3.25)	−0.195*** (−3.19)
lnEE	—	0.051 (0.64)	—	−0.115 (−1.56)	—	−0.026 (−0.29)
lnPOP	0.278 (1.13)	0.305 (1.22)	0.221 (0.95)	0.162 (0.68)	0.808*** (2.80)	0.795*** (2.71)
lnpGDP	−15.80*** (−3.27)	−15.99*** (−3.31)	−18.83*** (−4.12)	−18.39*** (−4.02)	−36.34*** (−6.42)	−36.24*** (−6.39)
$lnpGDP^2$	1.761*** (3.52)	1.780*** (3.55)	2.018*** (4.26)	1.973*** (4.17)	3.847*** (6.57)	3.837*** (6.53)
$lnpGDP^3$	−0.065*** (−3.80)	−0.066*** (−3.83)	−0.072*** (−4.40)	−0.070*** (−4.29)	−0.133*** (−6.61)	−0.133*** (−6.56)
lnEC	0.809*** (8.60)	0.854*** (7.27)	0.383*** (4.29)	0.279** (2.51)	0.659*** (5.98)	0.636*** (4.61)
lnIS	0.162 (1.35)	0.181 (1.46)	−0.005 (−0.04)	−0.049 (−0.41)	−0.047 (−0.33)	−0.057 (−0.39)
lnFDI	−0.080** (−2.24)	−0.085** (−2.32)	−0.086** (−2.52)	−0.075** (−2.18)	−0.105** (−2.49)	−0.102** (−2.39)
lnER	0.044** (2.22)	0.045** (2.26)	0.058*** (3.12)	0.056*** (3.01)	0.080*** (3.49)	0.080*** (3.46)
Cons	41.32*** (2.74)	41.89*** (2.77)	60.65*** (4.24)	59.34*** (4.15)	109.0*** (6.16)	108.7*** (6.12)
Hausman test	23.21*** (0.006)	23.58*** (0.009)	31.16*** (0.000)	32.51*** (0.000)	28.79*** (0.001)	27.22*** (0.002)
F test	50.96*** (0.000)	45.84*** (0.000)	21.62*** (0.000)	19.76*** (0.000)	225.08*** (0.000)	202.16*** (0.000)
Obs	480	480	480	480	480	480
R^2	0.509	0.510	0.306	0.310	0.821	0.822

*Notes: *, **, *** represent significance at the 10%, 5%, and 1% level. T statistics in parentheses. FE report the within* R^2. Cons *is the constant.*

TABLE 8 | Robustness test with alternative variable in spatial econometric model (SDM).

Variables	*lnSO2*	*lnWW*	*lnSW*	*lnSO2*	*lnWW*	*lnSW*
	Spatial weight matrix: W^{BOTH}			Spatial weight matrix: W^{GEO}		
rho (ρ)	0.165** (2.51)	0.094 (1.08)	0.208*** (4.06)	0.281*** (3.45)	0.028*** (6.20)	0.289*** (3.52)
lnpRETP	−0.113*** (−3.53)	−0.088*** (−2.79)	−0.095** (−2.12)	−0.091** (−2.36)	−0.087*** (−2.70)	−0.096** (−1.98)
lnEE	0.120 (1.07)	−0.044 (−0.29)	0.033 (0.17)	0.063 (0.51)	−0.055 (−0.34)	−0.026 (−0.15)
lnPOP	0.814 (1.01)	1.123 (1.60)	1.072 (0.82)	0.838 (1.12)	0.920 (1.32)	0.766 (0.88)
lnpGDP	−13.58 (−1.50)	−22.48*** (−2.90)	−14.36 (−1.21)	−16.18 (−1.58)	−26.67*** (−3.36)	−20.75 (−1.53)
lnpGDP^2	1.548* (1.68)	2.528*** (3.14)	1.619 (1.31)	1.817* (1.74)	2.942*** (3.59)	2.233 (1.59)
lnpGDP^3	−0.057* (−1.85)	−0.092*** (−3.33)	−0.059 (−1.38)	−0.067* (−1.88)	−0.105*** (−3.78)	−0.078 (−1.64)
lnEC	0.749*** (2.84)	0.532** (2.05)	0.940** (1.98)	0.781*** (2.94)	0.463* (1.85)	0.761** (2.46)
lnIS	−0.205 (−0.83)	−0.495 (−1.61)	−0.143 (−0.68)	−0.071 (−0.29)	−0.586* (−1.90)	−0.139 (−0.63)
lnFDI	−0.003 (−0.05)	−0.038 (−0.51)	−0.053 (−0.98)	−0.034 (−0.67)	−0.047 (−0.68)	−0.024 (−0.44)
lnER	0.055* (1.90)	0.056** (2.05)	0.078** (2.34)	0.048* (1.73)	0.046* (1.67)	0.088** (2.32)
*W*lnpRETP*	−0.127* (−1.90)	−0.030 (−0.67)	−0.044 (−0.62)	−0.204*** (−3.50)	−0.054 (−1.14)	0.044 (0.49)
*W*lnEE*	−0.584* (−1.87)	−0.472** (−2.11)	−0.744* (−1.82)	0.062 (0.11)	−0.722** (−2.54)	−1.036*** (−2.65)
*W*lnPOP*	−0.515 (−0.40)	−0.982 (−0.91)	−0.052 (−0.03)	0.180 (0.15)	0.053 (0.05)	0.624 (0.62)
*W*lnpGDP*	−17.49 (−0.96)	0.289 (0.02)	−47.87** (−2.14)	−6.822 (−0.26)	0.976 (0.06)	−26.40* (−1.67)
*W*lnpGDP*^{2}	1.793 (0.98)	−0.271 (−0.16)	4.997** (2.17)	0.812 (0.31)	−0.245 (−0.14)	3.032* (1.79)
*W*lnpGDP*^{3}	−0.061 (−1.00)	0.016 (0.28)	−0.171** (−2.16)	−0.031 (−0.37)	0.012 (0.20)	−0.110* (−1.83)
*W*lnEC*	0.307 (0.67)	0.102 (0.28)	−0.994*** (−2.92)	0.038 (0.06)	−0.033 (−0.08)	−1.812*** (−2.90)
*W*lnIS*	−1.184*** (−3.88)	−0.252 (−0.70)	−1.484*** (−4.14)	−0.901* (−1.74)	−0.699 (−1.53)	−1.880*** (−3.13)
*W*lnFDI*	−0.277** (−2.40)	−0.067 (−0.67)	−0.137 (−1.22)	−0.238 (−1.56)	−0.112 (−0.92)	−0.278 (−1.34)
*W*lnER*	−0.104*** (−2.85)	−0.064 (−1.33)	−0.089* (−1.76)	−0.096 (−1.62)	−0.032 (−0.60)	−0.075 (−1.63)
Obs	480	480	480	480	480	480
R^2	0.589	0.400	0.850	0.562	0.406	0.853

*Notes: *, **, and *** represent significance at the 10%, 5%, and 1% level. T statistics in parentheses.* Cons *is the constant.* W *is the spatial weight matrix.*

Robustness Test With Alternative Variable

This paper employs the count of applications with renewable energy technology patent per 10,000 researchers (*pRETP*) to describe the output capacity of renewable energy technology. The stronger the output capacity of renewable energy patents, the higher the DETC, so this alternative variable can be employed to reflect the direction of energy technical change. **Tables 7**, **8** show the estimated results of the baseline model and spatial econometric model after employing the alternative variable of *DETC*, respectively.

The estimated coefficients of *lnpRETP*, *lnEE*, and affluence (*lnpGDP*, *lnpGDP*^{2}, *lnpGDP*^{3}) in **Table 7** have no great alteration in direction and significance, and the empirical results are consistent with **Table 2**.

After considering the potential spatial correlations of dependent variables and independent variables, the empirical results in **Table 8** are consistent with **Tables 3**, **6**. In general, the empirical results with this paper are robust and effective relatively.

CONCLUSION

Based on the fact that the energy technical change in China has failed to alleviate the coexistence of high EC and high pollution, this paper holds that economic growth has a rigid demand for energy factors, which is the important reason for the formation of high EC. Facing high EC, if we want to use energy technical change to restrain environmental pollution, it is not enough to only take note of the magnitude of energy technical change; the direction of energy technical change also needs to be paid attention to. From the perspective of reducing pollution emissions from the industrial sector, the DETC is a powerful weapon to control environmental degradation. Through appropriate environmental policies, it is worth noting for stakeholders to change the energy technology from dirty to clean and even develop designated clean energy technologies (such as solar energy, wind energy, and nuclear energy) according to regional features, so as to realize the comprehensive substitution of clean energy for dirty energy, which is a mechanism to realize the rationalization and transformation of the energy structure in China.

Consequently, this paper uses patent application data to analyze the impact of directed technical change in the energy sector on pollution emission. Under the extended STIRPAT model and EKC hypothesis, we employ patenting data onto CNIPA and the economic data between 2000 and 2015 covering 30 main provinces in China. Research shows that 1) the DETC can restrain pollution emission, but the impact of energy efficiency on pollution emission is uncertain. This fact indicates that the prerequisite to restrain the pollution emission through the energy technical change should be to transform its direction, rather than only increase its magnitude. 2) The constraint effect of DETC on pollution emission will be dissimilar according to theifferrence of pollutants. Specifically, solid waste is the most affected, followed by wastewater, while it has a relatively weak purification effect on sulfur dioxide, which shows that there are variances in the path of DETC to achieve emission reduction. 3) The constraint effect of DETC on pollution emission is mainly reflected on the local areas, and its effect on neighboring areas is limited, which indicates that the coordinated management of pollutants and technical cooperation between different areas need to be improved. 4) The correlation between pollution emission and economic growth shows an inverted N type in the EKC hypothesis, which indicates that with the improvement of the DETC, economic growth and environmental quality can be decoupled.

In general, increasing the direction of energy technical change is a vital tool to ease the conflict between economic growth and pollution emission, that is, making the energy technical change show a clear direction. So, the above conclusions provide implications to stakeholders as follows: first, facing the fact that in energy structure, the proportion of fossil energy is high, advocating the clean application of fossil energy is the realistic path to restrain the dirty direction of energy technical change. Second, we should coordinate the development of renewable energy technology in the fields of wind energy, solar energy, marine energy, nuclear energy, and biomass energy, to realize the clean direction of energy technical change. Third, we should actively promote the collaborative management of pollutants and the exchange and cooperation of energy technical change in various areas, to achieve an efficient environment resource-sharing mechanism.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: China Statistical Yearbook, China National Intellectual Property Administration.

AUTHOR CONTRIBUTIONS

FQ: Conceptualization; Methodology; Data curation; Writing-original draft; Writing-Reviewing and Editing. LX: Supervision; Funding acquisition; Writing-Reviewing and Editing. BZ: Methodology; Data curation.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2022.794104/full#supplementary-material

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