Dynamic environmental regulation threshold effect of technical progress on green total factor energy efficiency: evidence from China

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Abstract
Sustainability is a strategic choice for the transition to a green economy in China. Improving green total factor energy efficiency (GTFEE) is the key to realizing the dual targets of energy-saving and economic growth. This paper empirically tests the nonlinear effects of environmental regulation on technical innovation affecting GTFEE by using panel data of 271 prefecture-level cities in China from 2004 to 2019. Meanwhile, a system GMM approach is used to verify the channels through which technical innovation affects GTFEE. Finally, the spatial and temporal characteristics of technical innovation affecting GTFEE are analyzed from the perspective of environmental regulation. The empirical results are as follows: (1) Technical innovation can significantly improve GTFEE. However, this improvement effect is a threshold characteristic; when environmental regulation is above the threshold value, technical innovation has a greater improvement effect on GTFEE. (2) Besides directly influencing GTFEE, technical innovation can also indirectly influence GTFEE via channels such as economic growth effect, industrial structure upgrading effect, and foreign investment effect. Meanwhile, indirect influence channels also show environmental regulation heterogeneity. (3) The number of cities crossing the threshold of environmental regulation in China increases year by year, which helps technical innovation play a role in improving GTFEE. However, there are still a small number of cities that do not cross the threshold during the sample period, which should attract the attention of local governments.

Keywords Technical innovation - Environmental regulation - Green total factor energy efficiency - Dynamic panel threshold model

Introduction
China’s economy has been developing in the past decades, but the traditional extensive development has also brought huge losses (Wang et al. 2020; Gao et al. 2021). Referring to the BP World Energy Statistics Yearbook (2018), China’s total energy consumption in 2017 was 4.49 billion tons of standard coal, with a 3.1% growth in energy consumption. Meanwhile, the 2018 Global Environmental Performance Index data demonstrates that among 180 countries and regions participating in the survey, China’s overall environmental performance score was 50.74, the 120th lowest worldwide. In the face of the growing imbalance between energy supply and demand, the Chinese government has incorporated energy conservation into its long-term strategic planning. In the Eleventh, Twelfth, and Thirteenth Five-Year Plans, targets were set to decrease energy consumption per unit of GDP by 20%, 17%, and 15% (Yang et al. 2020). Under the dual pressure of economic growth and energy conservation and emission reduction, enhancing energy efficiency is a must for China to realize sustainability (Sun et al. 2019). Since environmental issues have been a vital dilemma limiting the transition to a low-carbon economy in China, we focus on green total factor energy efficiency (GTFEE) and incorporate
environmental regulation (ER) and technological innovation (TI) into a unified research framework.

TI and ER have become important enablers to enhance energy efficiency and realize high-quality growth of China’s economy. TI could decrease energy consumption and pollutant emissions per unit of output, which is helpful to a sustainable economy and environmental protection (Hashmi and Alam 2019). ER has proved favorable in enhancing energy efficiency and eliminating the externalities of pollution (Bi et al. 2014). The Chinese government has introduced innovative deployment models at the institutional level, focusing on reforming the present environmental governance system, fulfilling local government environmental responsibilities, and protecting the population’s health and sustainable social development. In response to environmental issues at various developing periods, China has proposed a flexible ER system tailored to local conditions in China (Tong et al. 2020). Meanwhile, China’s investment in environmental governance rose from RMB 449 billion in 2008 to RMB 953.9 billion in 2017. These investments were aimed at improving the ecological environment and energy efficiency but rarely succeeded. As a result, the Chinese government is vibrantly looking for measures to enhance energy efficiency. Studies have shown that technical innovations covering pollution control, ecological processes, and recycling are significant in promoting sustainable economic development (Braun and Wield 1994). Pursuing TI is an effective means of breaking through current resource and environmental problems and promoting green economic growth under the new normal. In essence, ER is closely linked to TI, which is a crucial determinant for energy efficiency.

So, is the relationship between TI and energy efficiency linear or nonlinear? What are the mechanisms and pathways through which TI contributes to energy efficiency? A study of these questions is helpful to learn the current effect of TI on energy efficiency and its underlying mechanisms so that TI can play a vital role in green development. At present, China’s environmental governance model is shifting from end-of-pipe governance to comprehensive governance with preventive governance at the source (Wu et al. 2019a). Therefore, is the present government ER efficient? How does ER contribute to the impact of TI on energy efficiency? This study addresses these questions, which are immediately related to the policy effectiveness, assessment, and development of ER in China. Therefore, it is of great practical importance.

There are at least three contributions to the existing literature. Firstly, environmental regulation, technological innovation, and GTFEE are included in the same framework, and the joint impact of environmental regulation and technological innovation on GTFEE is empirically analyzed, which is a beneficial supplement to the literature on the factors affecting energy efficiency. Secondly, it is proposed for the first time that there may be a nonlinear relationship between technological progress and GTFEE. Environmental regulation is included in the nonlinear panel threshold model of technological innovation on GTFEE. The dynamic panel threshold model is used to test it, expanding the discussion on the nonlinear relationship between technological innovation and energy efficiency. Thirdly, it elaborates on the influence of technological innovation on energy efficiency and its internal mechanism. This paper examines the direct impact of technological innovation and analyzes the indirect impact mechanism of technological innovation on GTFEE from multiple perspectives.

The following study is structured as follows: the “Literature review” section is a review of the relevant literature; the “Research hypothesis” section provides the hypothesis of the influence of TI on GTFEE in different channels; the “Methods and data” section introduces the research design; the “Analysis of empirical results” section is the result of the empirical analysis, and the “Conclusions and policy implications” concludes.

Literature review

Extant literature has examined issues such as the energy efficiency measurement and its influencing factors, the relationship between ER and energy efficiency, the relationship between TI and energy efficiency, and the relationship between ER and TI. There are abundant indicators for measuring energy efficiency, and the significant indicators that are expansively used are single-factor and total factor energy efficiency. The single-factor energy efficiency indicators primarily reflect the relationship between energy consumption and effective economic output. The most widely employed single-factor index is energy consumption intensity, usually defined as energy consumption per unit of GDP. Some studies in the literature that introduce energy consumption per unit of GDP as a proxy for energy efficiency have found that TI, R&D expenditure, ownership reform, and industrial structure would significantly impact energy efficiency (Kofi 2019; Wei et al. 2007; Crompton and Wu 2005). Total factor energy efficiency is regarded as a more efficient measure of energy efficiency than single-factor energy efficiency. Hu and Wang (2006) pioneered data envelopment analysis (DEA) to measure the total factor energy efficiency. However, the total factor energy efficiency index they adopted only included the expected output of energy use. Watanabe and Tanaka (2007) pointed out that the pollution emissions associated with energy use cannot be ignored to analyze energy efficiency. The unexpected output measured by pollution emissions is also a social cost, dramatically counteracting the favorable impact of expected output. Li and Lin (2017) combine the SBM model and meta-frontier technology to evaluate GTFEE. Hong and Shi (2014) proposed an improved Super-SBM model based on an SBM
model with non-consensual outputs and weak disposability assumptions. Yan et al. (2019a, 2019b) also consider the effect of unexpected output factors and used the Super-SBM model separately to calculate GTFEE.

Recently, conclusions of studies on the relationship between ER and energy efficiency have been inconsistent. Some scholars have argued that environmental regulations increase firms’ production costs, reduce their competitiveness, and negatively affect energy efficiency. For example, Ramiah et al. (2013) investigated the impact on stock returns and discovered that nearly all of the oil and electricity industries showed pronounced adverse abnormal returns when the Australian government announced “carbon reduction” environmental regulations. Hancevic (2016) analyzed the impact of the 1990 amendments to the Clean Air Act on productivity and energy efficiency in Mexico, and they thought that the negative effect of ER on energy efficiency came from the changed productivity. However, some scholars argue that appropriate ER can incentivize TI and partly or entirely counteract cost effects, reduce production costs, and increase productivity (Porter and Linde 1995). For example, Bi et al. (2014) conducted a study on ER and its influences on energy efficiency, demonstrating that energy efficiency in the thermal power sector has improved thanks to ER. Curtis and Lee (2019) examined micro-data at the factory stage in the annual survey of manufacturers. They found that ER could directly stimulate investment related to improving energy efficiency, improving energy efficiency, and reducing emissions.

Among the studies on the relationship between TI and energy efficiency, Garbaccio et al. (1999) decomposed the factors influencing energy efficiency with the input-output approach, in terms of both technology and structural change, and demonstrated that TI was a significant factor in enhancing energy efficiency. Popp (2002) found that energy prices influence the extent to which TI improves energy efficiency. Fisher et al. (2006) using annual data on the industrial sector in China, found that TI and industrial restructuring were the primary reasons for descending energy intensity. Finally, Wang et al. (2019) argued that TI had heterogeneity in carbon emissions across sectors. While TI can increase energy efficiency in the industrial sector, it can also contribute to carbon emissions. However, few studies are examining the nonlinear relationship between TI and energy efficiency.

There has been a heated debate about the impact of ER on TI, and there are currently three main views. ER encourages firms to modify their emission management strategies, forcing them to look for optimal technological adaptation and further improve TI’s efficiency and level (Testa et al. 2011; Porter and Linde 1995). Second, to avoid penalties from strict ER, firms will restrict their production scale and raise their investment in pollutant management, which leads them to decrease their R&D investment and discourages technological importation and cooperation (Lanoie et al. 2008; Li et al. 2019). Third, the effect of ER on TI is nonlinear (Pan et al. 2019). When ER is weak, firms prefer lower-cost pollution penalties to technological change. However, as ER is strengthened, firms must enhance technological transformation to avoid pollution penalties and improve productivity and energy efficiency to cover technological transition costs. It can be inferred from this that the different ER levels are likely to influence the role of TI on energy efficiency. Thus, it is important to use ER as a threshold to explore TI’s effect on energy efficiency.

In summary, although scholars have widely studied energy efficiency, the existing literature is mostly about isolated studies on how ER or TI affects energy efficiency. There is almost no literature examining the various effects of TI on energy efficiency under different ER levels. Secondly, there is little literature on the nonlinear relationship between TI and energy efficiency. The traditional static panel threshold model ignores the lagged effects of the explanatory variables, leading to estimating errors. Finally, there is relatively little research on the affecting pathways of TI on energy efficiency. The mechanisms of its direct or indirect effect have not been completely elucidated and verified. In view of this, this study takes GTFEE as a measure of energy efficiency, places it, TI, and ER in the same research framework. And constructing dataset from 271 prefecture-level cities in China from 2004 to 2019, a dynamic panel threshold model is adopted to examine how ER acts on a nonlinear effect between TI and GTFEE. We also attempt to verify the mechanism of the impact of TI on GTFEE through an interaction effect test to disclose the mechanisms of the effects both theoretically and empirically. These studies provide an essential basis for formulating targeted economic and energy policies in China’s green and sustainable development stage.

Research hypothesis

The influence of TI on GTFEE in different channels is different under different ER intensities, and it is not ideal for improving energy efficiency only by increasing local TI or ER intensity. Therefore, the government should fully consider the dual role of local ER and TI when formulating environmental policies and considering the management path, and implement a comprehensive policy combining the two. The mechanisms of the threshold effect are described in Figure 1. It is clear that TI directly affects GTFEE via the green technology progress effect. Moreover, TI will also indirectly affect GTFEE via the economic growth effect, industrial upgrading effect, and foreign direct investment effect. Nevertheless, once the intensity of ER varies, these channels of influence would also change, ultimately leading to different impacts on GTFEE. Namely, the impact of TI on energy efficiency is different under different ERs. In this study, based on the analysis of the nonlinear
effects of TI on GTFEE with a dynamic panel threshold model, the direct and indirect paths of TI on GTFEE under various ER intensities are tested by introducing TI and its interaction term with channel variables. Regarding this, we formulate the following research hypotheses:

Hypothesis 1: TI is the primary measure for China to achieve economic growth while improving environmental quality, and it tends to improve energy use efficiency and clean production. TI can directly modify the traditional technologies in the production process and apply new energy-saving technologies to enhance energy efficiency (Li et al. 2019). Namely, the green technology innovation effect channel is positive.

Hypothesis 2: TI will contribute to economic development, but the rough development model will certainly lead to energy inefficiency in the early period. As economic growth invests in scientific research increases, different regional development strategies gradually shift from economic growth-centered to green and clean development, thus indirectly improving energy efficiency in the production process. Namely, the economic growth mechanism is present and uncertain.

Hypothesis 3: TI can accelerate the flow of resources to the tertiary industry (Tian et al. 2019); thus, the proportion of tertiary industrial output is growing. Furthermore, as the overall industrial structure changes from the energy-intensive and resource-intensive secondary industry to the low-energy-intensive and knowledge-intensive tertiary industry, the overall economy develops environmentally friendly. Therefore, improving energy efficiency becomes a top priority. Namely, the industrial upgrading effect channels is positive.

Hypothesis 4: TI is helpful in attracting FDI. On the one hand, FDI may produce a “pollution halo” effect, where the advanced management experience and environmental technology brought by the investment will improve the environmental quality for developing countries. On the other hand, FDI may also produce a “pollution paradise” effect, which will export a large number of polluting industries, while developing countries will lower their ER standards to attract foreign investment, thus deteriorating the environment. That is, the channel of foreign direct investment effect exists and is uncertain.

Methods and data

Methods

To test whether there is a dynamic nonlinear relationship between TI and GTFEE under different ER intensities, we employ the dynamic panel threshold model proposed by Kremer et al. (2013) with GTFEE as the dependent variable and ER the threshold variable. The model introduces the lagged terms of the explanatory variables into the static threshold model proposed by Hansen (2000) for estimation and can avoid estimation errors due to endogeneity (Wu et al. 2019b). We consider the following model:

$$ GFTEE_{it} = \alpha + \beta_0 GFTEE_{i,t-1} + \beta_1 TI_{it} \cdot I(ER_{it} < \gamma) + \beta_2 TI_{it} \cdot I(ER_{it} \geq \gamma) + \sum_{k=1}^{4} \delta_k Z_{it} + u_t + v_i + \varepsilon_{it} $$

(1)

In model (1), $GFTEE_{it}$ denotes the green total factor energy efficiency of the city $i$ in year $t$, $TI_{it}$ denotes the level of...
technical innovation of city \( i \) in year \( t \), ER\(_{it} \) denotes the level of environmental regulation of city \( i \) in year \( t \), \( Z_{it} \) signifies other control variables affecting GTFEE, and \( \beta_1 \) and \( \beta_2 \) denote the impact coefficients of technological innovation on GTFEE under the different intensities of ERs, respectively. \( I \) represents the indicative function, \( \gamma \) means the threshold of ER, \( \alpha \) and \( \nu \) represent the individual and time effects respectively, and \( \varepsilon_\gamma \) represents the random disturbance term.

Furthermore, to assess the direct and indirect effects, we introduce the interaction terms of TI and economic growth level (PGDP), industrial structure level (STR), and foreign direct investment level (FDI), and establish the following model, where other variables are the same as the above.

\[
GFTEE_{it} = \gamma + \beta_0 GFTEE_{it-1} + \beta_1 TI_{it} \cdot PGDP + \beta_2 TI_{it} \cdot STR + \beta_3 TI_{it} \cdot FDI + u_i + v_t + \varepsilon_{it}
\]  

(2)

**Variable description**

**Total factor energy efficiency** Following the method of Yan et al. (2017) and Wu et al. (2021), this paper uses the undesirable-SBM model to calculate the dependent variables total factor energy efficiency (GTFEE) of 271 cities in China from 2004 to 2019. To be specific, we assume that there are \( N \) decision-making units (DMU), each of which has \( M \) inputs, \( S_1 \) expected outputs, and \( S_2 \) unexpected outputs, respectively, which can be expressed in the form of matrix \( X = (x_{ij}) \in \mathbb{R}^{m \times n} \), \( Y^g = (y^g_{ij}) \in \mathbb{R}^{d_1 \times n} \), and \( Y^b = (y^b_{ij}) \in \mathbb{R}^{d_2 \times n} \); the corresponding relaxation vectors of input, expected output, and unexpected output are \( s^- \in \mathbb{R}^m \), \( s^g \in \mathbb{R}^{d_1} \), and \( s^b \in \mathbb{R}^{d_2} \). \( \lambda \) is the weight vector. The calculation formula is as follows (3):

\[
\min \frac{1 - (1/m) \sum_{j=1}^{m} x^j_i / x^j_{lo}}{1 + \frac{1}{s_1 + s_2} \left( \sum_{j=1}^{m} x^j_i / s^j_{lo} + \sum_{j=1}^{m} y^g_{ij} / s^g_{lo} + \sum_{j=1}^{m} y^b_{ij} / s^b_{lo} \right)}
\]  

(3)

**Technological innovation** Intuitively, common indicators for technological innovation (TI) consist of R&D investment, total factor productivity, and the number of patents (Cheng et al. 2017; Alam and Murad 2020; Fei and Lin 2017). Regardless of the industry, TI is closely related to patent applications, and thus the number of patents is intensively employed to measure TI (Du and Li 2019). Regarding this, we use the total number of patents granted to represent the R&D innovation capacity of cities.

**Environmental regulation** The choice of environmental regulation (ER) strategy is primarily influenced by local governments’ willingness to govern the environment, and the intensity of ER varies from region to region. Based on such typical characteristics, it is relatively more objective to reflect the intensity of ER from the results of pollution control. This study extends the measurement of ER at the provincial level by Wu et al. (2020) to the city level. In view of data availability and completeness, a composite index of ER was
constructed based on the two individual indexes of industrial fume and dust removal rate and the centralized treatment rate of sewage treatment plants. The precise method is as follows.

First, the two indicators, industrial fume and dust removal rate and centralized treatment rate of sewage treatment plants, are standardized according to Eq. (4), where \( p_{ij} \) denotes the original value of the indicator of category \( j \) in city \( i \), and \( \min(p_{ij}) \) and \( \max(p_{ij}) \) denote the minimum and maximum values of the indicator of category \( j \) in all cities, respectively.

\[
p_{ij}^* = \frac{p_{ij} - \min(p_{ij})}{\max(p_{ij}) - \min(p_{ij})} \tag{4}
\]

Then, the adjustment coefficients \( A_{ij} \) for the two indicators are calculated separately for different cities, indicating the ratio of the share of pollutant \( j \) emitted by city \( i \) in the country to the percentage of GDP of the city \( i \), and the calculation formula is as in Eq. (5). The calculation of \( A_{ij} \) shows that if a city has higher emissions of a certain pollutant, then the same pollutant treatment rate implies higher ER and therefore gives a greater weight.

\[
A_{ij} = \frac{p_{ij}}{\sum_i p_{ij}} \cdot \frac{gdpi}{\sum_i gdpi} \tag{5}
\]

Finally, from the standardized values and adjustment coefficients of the industrial fume and dust removal rate and the centralized treatment rate of the wastewater treatment plant, the degree of ER for the city \( i \) is obtained, calculated as in Eq. (6).

\[
ER_i = \sum_{j=1}^{n} A_{ij} p_{ij}^* / 2 \tag{6}
\]

**Control variables** To alleviate the error of regression results caused by missing variables in the model, the important variables affecting the GFTEE at the city level are controlled as follows: (1) Per-capita regional GDP (PGDP) is measured by dividing the total GDP of the city by the total population at the end of the year. Energy efficiency will also vary in different economic development stages (Liou & Liou and Wu 2011), and changes in technical level and institutional objectives in the process of economic development will have an impact on energy consumption and technological progress, which will affect the effective use of energy (Suri and Chapman 1998). (2) Industrial structure (STR) is measured by the proportion of GDP of the second industry to GDP. The industrial structure is an important factor in energy efficiency. A lot of research confirms the influence of industrial structure on energy efficiency (Liu and Lin 2018; Yang and Wei 2019); as the transfer of input to output, industrial structure determines energy allocation between different industries (Bai et al. 2018). As a result, there are significant differences in energy efficiency between various industries. Therefore, controlling the development of high energy consumption and high pollution industries, accelerating the elimination of backward production capacity, and optimizing industrial structure can help to improve energy efficiency (Xiong et al. 2019). (3) Foreign direct investment (FDI) is expressed as a foreign direct investment after the exchange rate between the US dollar and RMB. As an important channel of international technology diffusion, FDI also has an important impact on energy efficiency (Robert et al. 2013; Zhao et al. 2019). Meanwhile, foreign enterprises with pollution-intensive type may transfer energy and pollution-intensive industries to developing countries, which is not conducive to energy efficiency improvement (López et al. 2018). The specific meaning and measurement criteria of each variable are shown in Table 1.

The data in this study cover 271 Chinese prefecture-level city-level data from 2004 to 2019, and data on per-capita gross regional product are price-deflated with 2003 as the base year. The energy consumption data are accessible in the China Energy Statistical Yearbook, and other variables are derived from the China Environmental Statistical Yearbook, China Environmental Yearbook, China Energy Statistical Yearbook, China Science and Technology Statistical Yearbook, and the National Bureau of Statistics. Table 2 provides the descriptive statistics.

### Analysis of empirical results

#### Estimation of the dynamic panel threshold model and robustness test

Based on the introduction of a lag period of green total factor energy efficiency, this paper takes environmental regulation as the threshold variable and uses the dynamic panel threshold model proposed by Kremer et al. (2013) to study the impact of technological innovation on GFTEE empirically. The empirical results are shown in Table 3. Model (1) represents the regression results without adding other control variables. At this time, the threshold value of environmental regulation is 0.2805. Figure 3 shows the confidence interval construction of the threshold model and the significance of the threshold effect. In this figure, the blue curve represents the likelihood ratio statistic LR (R). The x-axis value of 0.2805 corresponding to the lowest point of the curve is the threshold parameter estimation. The green line represents the percentage of the asymptotic distribution of the likelihood ratio statistic. The interval between the intersections of the two lines is the 90% confidence interval of the threshold parameter estimation, which indicates the significance of the threshold effect. At the same time, the corresponding panel threshold regression results are obtained. The results of model (1) show that when the intensity of environmental regulation is higher than its
threshold, the impact coefficient of technological innovation on green total factor energy efficiency is 0.032, which is significant at the level of 1%; when the intensity of environmental regulation is lower than the threshold, the impact coefficient of technological innovation on green total factor energy efficiency is 0.049, which is significant at the level of 5%. Thus, it shows that the dynamic threshold effect of technological innovation on GTFEE does exist. In higher environmental regulation, technological innovation plays a greater role in improving total factor energy efficiency.

The economic reasons behind the nonlinear effect may lie in the fact that when a region is at the poverty stage, economic growth is the main development objective, and the level of ER is lower. During this period, TI tends to increase output, and although it witnesses a favorable influence on energy efficiency, it is relatively ineffective. When a region reaches a particular stage of economic growth and begins to focus on green and sustainable development, the level of ER will increase. TI is more inclined to green at this period, which can help economic growth, an improved environment, and energy efficiency. Therefore, TI has a more significant role in improving GTFEE when ER crosses the threshold. China’s current strict ER has improved China’s overall energy efficiency, but environmental control is a long-term course that cannot depend merely on policies and should focus on the linkage between TI and ER. Meanwhile, the lagged terms of GTFEE are all pronounced (1% level) under different control variables, indicating that GTFEE has a certain path dependence, and past energy efficiency affects current energy efficiency.

To further verify the reliability of the regression results, two methods are adopted to test the robustness of the conclusion. First, add control variables step by step. Models (2)–(4) represent the regression results of adding other control variables based on model (1). Model (2) adds industrial structure (STR) as control variable based on model (1), and model (3) adds foreign direct investment (FDI) as control variable based on model (2). Model (4) adds the level of economic development (GDP) as the control variable based on model (3). The regression results of the three models show that the threshold value of environmental regulation is still 0.2805, which indicates that the impact of technological innovation on green total factor energy efficiency is nonlinear. The relationship between them changes with the relative size of environmental regulation. Second, replacing the GTFEE measurement method. We use the alternative EBM method to calculate GTFEE as the explained variable. The regression results are shown in model (5). It can be seen that the dynamic threshold effect of technological innovation on GTFEE still exists after changing the calculation method of total factor energy efficiency. At the same time, we observed that in model (2)–model (5), although the coefficient of the threshold effect $\beta_1$ and $\beta_2$ has changed, it is still significantly positive, and $\beta_2$ is always greater than $\beta_1$. The consistency of the regression results of the five models also proves the robustness of the conclusion.

### Test of impact channels

To estimate Eq. (2), OLS, differential GMM, and systematic GMM estimators are extensively employed, while only the third method is helpful to eliminate endogeneity and avoid weak instrumental variables (Blundell and Bond 1998). Thus, we adopt the systematic GMM design to estimate Eq. (2). Simultaneously, based on the previous analysis, we explore the impact of TI on GTFEE in the full sample, the low ER level sample (the sample with ER level below the threshold), and the high ER level sample (the sample with ER level above the threshold), respectively, and Table 4 reports the results.

Firstly, the coefficient on TI is significantly positive in all three estimations, indicating that TI has a favorable direct impact on GTFEE for the full sample, the low ER level...
sample, and the high ER level sample. Thus, hypothesis 1 is further confirmed. Moreover, we also find that the direct effect is more robust in the high ER level sample than in the low ER level, suggesting that TI at high ER levels is more conducive to energy efficiency. The reasons may be that high ER levels force firms to introduce clean production technology, and the firms will allocate more capital in green R&D (Pan et al. 2019) to enhance the energy efficiency, resulting in the decline of

Table 3  Estimation of the dynamic panel threshold model and robustness test

|                      | Model 1     | Model 2     | Model 3     | Model 4     | Model 5     |
|----------------------|-------------|-------------|-------------|-------------|-------------|
| A1: estimation of the threshold value |             |             |             |             |             |
| r                    | 0.2805      |             |             |             |             |
| B1: influence of TP on lnGTFEE |             |             |             |             |             |
| β1                   | 0.032***    | 0.039***    | 0.043***    | 0.039***    | 0.044***    |
| (3.15)               | (7.23)      | (7.51)      | (2.84)      | (6.23)      |
| β2                   | 0.049***    | 0.044***    | 0.046***    | 0.044***    | 0.051***    |
| (4.70)               | (7.28)      | (7.09)      | (2.74)      | (6.35)      |
| C1: influence of the lnGTFEE on one lag of lnGTFEE |             |             |             |             |             |
| L.GTTFP              | 0.950***    | 0.805***    | 0.815***    | 0.823***    | 0.856***    |
| (17.78)              | (24.74)     | (24.86)     | (25.77)     | (22.32)     |
| D1: influence of control variables on lnGTFEE |             |             |             |             |             |
| STR                  | 0.430**     | 0.518***    | 0.481**     | 0.462**     |
| (2.26)               | (2.67)      | (2.23)      | (2.25)      |
| FDI                  | −0.179**    | −0.203***   | −0.186**    |             |
| (−2.47)              | (−3.01)     | (−2.36)     |             |
| lnPGDP               |              |             |             |             |             |
| _cons                | −0.318***   | −0.471***   | −0.498***   | −0.523***   | −0.563***   |
| (−4.76)              | (−4.74)     | (−4.99)     | (−2.91)     | (−3.56)     |
| N                    | 4065        | 4065        | 4065        | 4065        | 4065        |
| N_individual         | 271         | 271         | 271         | 271         | 271         |
| Individual FE        | YES         | YES         | YES         | YES         | YES         |
| Time FE              | YES         | YES         | YES         | YES         | YES         |
| Wald test            | 1548.9      | 2352.3      | 2061.3      | 2274.6      | 2597.3      |

***, **, and * indicate the significance at 1%, 5%, and 10% levels, respectively; t values are denoted in parentheses

Fig. 3  Test diagram of the nonlinear effect
energy consumption of the entire areas. Thus, TI inspired by stronger ER is more favorable to enhancing GTEE (Barbieri 2015).

Secondly, from the full sample, the economic growth effect, the industrial structure effect, and the foreign direct investment effect are all significant; thus, the indirect influence mechanisms are effective. The coefficient of the cross-sectional term between TI and GDP per capita is significantly negative at the 1% level, which confirms hypothesis 2 and verifies that China’s overall economic growth is still in a rough development mode. For the economic growth effect of TI, the rough development model in an early stage may lead to low green energy efficiency; moreover, it can improve green energy efficiency by increasing R&D investment production efficiency. The negative cross coefficient demonstrates the rough development model is still dominant in the overall economy. It is clear that the coefficient of the cross term between TI and STR is significantly positive at the 5% level, and hypothesis 3 is confirmed. TI accelerates the flow of resources to the tertiary sector for the industrial structure effect of TI, thereby raising tertiary output share, the overall economy moves towards an environmentally friendly development, and improving energy use efficiency becomes a top priority. The coefficient of the cross-sectional term between TI and GFDI is significantly positive at the 5% level, confirming hypothesis 4, namely, TI can influence GTFEE through the foreign investment effect. At the early stage of foreign investment introduction, the technology absorption capacity is insufficient. With the low ERs, there may be a “pollution paradise effect,” failing to improve the GTFEE significantly. With the introduction of foreign capital, its knowledge spillover effect and demonstration effect are enhanced, manifested as the “pollution halo effect.” The level of local TI is continuously enhanced, and the GTFEE is also greatly enhanced improved. The significant positive coefficient of the cross term in the empirical results indicates the dominance of the pollution halo effect.

Finally, different impact mechanisms are shown for the sub-sample at low and high levels of ER. The indirect impact mechanism of TI on GTFEE is not pronounced when ER is in the low ER level range, but it starts to be effective when the ER level exceeds the threshold. When ER is in the high ER level range, TI will improve GTFEE via economic growth effect, industrial structure upgrading effect, and foreign direct investment effect, confirming hypotheses 2, 3, and 4. This heterogeneity is because when the ER level is low, it cannot encourage the optimal industrial upgrading from a green development direction, making it hard to use resources intensively (Brunel and Johnson 2019; Zhou et al. 2017). When the ER increases, TI shows a clear preference for green technology and can improve GTFEE through industrial upgrading and foreign direct investment effects. Therefore, the channels through which TI affects GTFEE vary under different levels of ER.

Table 4 Channel analysis of TP affecting GTFEE

| Variables | Model 6 All sample | Model 7 Low_ER | Model 8 High_ER |
|-----------|-------------------|----------------|----------------|
| TI        | 0.064***          | 0.58*          | 0.135***       |
|           | (3.94)            | (1.75)         | (3.84)         |
| TI×PGDP   | −0.015***         | 0.038          | −0.011***      |
|           | (−4.30)           | (0.95)         | (−2.85)        |
| TI×STR    | 0.033***          | −0.086         | 0.060***       |
|           | (2.26)            | (−0.01)        | (5.64)         |
| TI×FDI    | 0.042***          | −0.022         | 0.027***       |
|           | (5.51)            | (−0.98)        | (3.63)         |
| _cons     | 0.139             | 0.276          | 0.212          |
|           | (1.32)            | (0.18)         | (0.01)         |
| N         | 4059              | 345            | 3526           |
| N_individual | 271              | 94             | 266            |
| Individual FE | YES             | YES            | YES            |
| Time FE   | YES               | YES            | YES            |
| Wald test | 5887.23           | 454.07         | 4066.04        |
| Prob>χ²   | 0.000             | 0.000          | 0.000          |

***, **, and * indicate the significance at 1%, 5%, and 10% levels, respectively; t values are denoted in parentheses

Fig. 4 The number of cities with ER greater/less than the threshold
Analysis of spatiotemporal heterogeneity

In fact, due to the threshold effect of technological innovation on GTFEE, the impact of technological innovation on GTFEE is also spatio-temporal heterogeneous. For example, in a given year, the ER level varies across cities, with some cities exceeding the threshold and others falling below it, resulting in spatial heterogeneity as the effect of TI on GTFEE is greater among areas that cross the threshold than among areas that do not. Similarly, ER level varies between years in the same city, with some years exceeding the threshold and others not, thus creating temporal heterogeneity. Thus, spatial and temporal heterogeneity of TI works in improving GTFEE across regions and years.

From a temporal perspective, Figure 4 reports cities with ER levels above the threshold in each of the 271 sample cities over the sample period. It can be seen that in each year from 2004 to 2019, more than half of the cities had ER levels above the threshold, with 3,954 samples above the threshold over the last 16 years, accounting for 91.19% of the total sample size. At the same time, the intensity of ER has been increasing, from 0.949 in 2004 to 2.47 in 2019, indicating that more and more cities are exceeding the ER threshold over time and that China’s ER has generally increased, which is conducive to TI playing a role in improving GTFEE.

From a spatial perspective, Figure 5 reports how many years in which the level of ER exceeded the threshold for each prefecture-level city. In the 16 years from 2004 to 2019, most cities exceeded the threshold in at least half of the years, and we focus on those cities that exceeded the ER threshold in only a small number of years. Therefore, prefectoral threshold in data is more relevant than local data suggesting appropriate environmental management policies to local governments. As shown in Figure 5, Qingdao and Changsha City exceeded the ER threshold in only 1 year, Sanya in only 2 years, and Guangzhou and Qingyang City in only 3 years. On the other hand, Weihai, Suihua, Wenzhou, Bazhong, and Putian City exceeded the environmental regulation threshold value in fewer years. Therefore, the level of ER in these cities needs to be further improved; otherwise, the role of TI in improving GTFEE will be limited. At present, China’s environmental protection legal system includes the local governments’ environmental protection laws and regulations. It forms an environmental supervision system combining unified supervision and management with labor supervision and management division. The differences in the supervision of local governments lead to different environmental regulations in different regions.

Conclusions and policy implications

This paper empirically tests the nonlinear effects of environmental regulation on technical innovation affecting GTFEE by using panel data of 271 prefecture-level cities in China from 2004 to 2019. Additionally, we adopt the System GMM to verify the channel of technological innovation affecting GTFEE. We draw the following conclusions. Firstly, a
nonlinear dynamic threshold effect of TI on GTFEE indeed exists. On the one hand, GTFEE has a certain path dependency, where past energy efficiency affects current energy efficiency. On the other hand, TI can significantly enhance GTFEE. This enhancement effect differs under different ER levels, with the enhancement effect under high levels of ER being more significant than that under low levels of ER. Secondly, examining the channels of influence shows that when the ER level is below its threshold, TI’s indirect channel of influence on GTFEE is not smooth. Still, when ER level crosses its threshold, TI can influence GTFEE through indirect channels, including economic growth effect, industrial structure effect, and foreign direct investment effect. Thirdly, from the perspective of ER, the impact of TI on GTFEE is spatially and temporally heterogeneous. As time changes, more and more cities in China exceed the threshold of ER, which facilitates the role of TI in improving GTFEE. From a spatial perspective, there are still some cities in China with low ER levels, limiting the role of TI in improving GTFEE.

The following policy recommendations are made in response to these findings. Firstly, the local government should develop TI to enhance energy efficiency industriously. They should also encourage cooperation between industry, universities, and research institutes and support research and development by enterprises and research institutes in clean production and ecological protection. Deepen the rigid system that hinders scientific and TI improves supporting mechanisms and optimizes the environment for scientific and TI. Secondly, the intensity of ERs should be increased to stimulate enterprises to carry out green TI to realize the linkage between TI and ERs. In areas with higher ERs, focus on promoting TI. In comparison, in areas with lower ERs, such as cities like Changsha, Qingdao, Sanya, Guangzhou, Qingyang, Weihai, Suihua, Wenzhou, Bazhong, Putian City and other cities, ERs should be further strengthened to focus on promoting green-biased TI. Thirdly, gradually realize the green-sustainable, high-quality development mode to replace the traditional extensive development mode. Further, expand the scope of R&D and promote green technology change, promote high energy consumption industries’ transformation, accelerate industrial upgrading, and realize rational energy use. The introduction of foreign-funded enterprises should combine with the local ER level, focus on high-tech industry, improve the absorption capacity of advanced technology, and prevent the pollution paradise effect.

Author contribution Da Gao and Yi Li conceived and designed the research question. Ge Li constructed the models and analyzed the optimal solutions. Ge Li wrote the paper. Da Gao reviewed and edited the manuscript. All authors read and approved the manuscript.

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Data availability The datasets generated and/or analyzed during the current study are property of the National Bureau of Statistics; they are available from the corresponding author who will inform the National Bureau of Statistics that the data will be released on reasonable request.

Declarations

Ethics approval and consent to participate Not applicable

Consent to participate Not applicable

Consent to publish Not applicable

Conflict of interest The authors declare no competing interests.

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