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Does biased technological progress facilitate the reduction of transportation carbon emissions? A threshold-based perspective

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Abstract
Rather than relying on traditional factors, low-carbon transportation should be developed by paying more attention to innovation. By constructing an extended stochastic frontier production function, this study explores the threshold effect of technological progress bias on CO_2 emission in the transportation sector in eight different regions of China. It is found as the technological progress bias crosses the threshold, the impact of technological progress bias on transportation CO_2 emission changes from positive to negative in Northeast China, the midstream of the Yellow River, East China, the Southeast Coast, the midstream of the Yangtze River and the Northwest region. In Northeast China, the coefficient changes from 0.121 to −0.168. In the middle reaches of the Yellow River, the coefficient changes from 0.528 to −0.0468. In East China, the coefficient changes from 0.495 to −0.325. In the Southeast Coast, the coefficient changes from 0.112 to −0.757. In the middle reaches of the Yangtze River, the coefficient changes from 0.518 to −0.177. In Southwest China, the coefficient changes from 0.293 to −0.014. In Northwest China, the coefficient changes from 1.021 to −1.436. In North China, when the technological progress bias exceeds the threshold, the biased technological progress still promotes CO_2 emission. The coefficient changes from 0.157 to 0.406. The governments should continue to encourage the transformation of energy technologies from non-renewable energy to renewable energy through differentiated policies.

Keywords Technological progress bias · Transportation CO_2 emission · Threshold effect

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1 Introduction

The "2020 Government Work Report" considers "two new and one focus" as the key task this year. The latest and conventional infrastructures should be integrated and developed in the transportation field. This can enable to realizing an economical, efficient, green and intensive transportation development mode. However, the transportation sector is considered to be the most difficult sector for the reduction of CO_2 emission, because its energy use and CO_2 emissions are growing the swiftest (Pietzcker, 2014). According to IEA in 2020, the CO_2 emissions of China's transportation industry have further increased to 84.35 billion tons, after the USA (IEA, 2020). With the sustained logistics development and the increasing number of cars, CO_2 in China's transportation sector will increase further. "The Outline of Building a Powerful Transportation Country" emphasizes that the low-carbon transportation development should transition from relying on conventional elements to paying more attention to innovation.

To achieve a significant reduction in CO_2 emission from the transport sector by 2030, we encounter significant pressure from energy reform and technological change. Therefore, to achieve the emission reduction target of transportation, comprehensively understanding the mechanism of the energy-saving preference of technological progress on carbon emission reduction is necessary. This is not only conducive to the steady growth of the transportation sector, but also to the promotion of scientific emission reduction in the transportation sector. The contribution of different biased technologies to CO_2 reduction poses a difference. Capital- or labor-biased technological progress may lead to higher energy consumption and CO_2 emission, while energy-biased technological progress may increase or decrease carbon emissions. For example, Jing (2019) found that each unit of labor-or capital-biased technological progress leads to approximately 1% increase in carbon emissions, and each unit of energy-biased technological progress leads to approximately 2% reduction in carbon emissions. Liao (2020) found that technological progress with an energy-saving bias is both likely to increase and reduce carbon emissions. There is a strong nonlinear relation between technological progress bias and carbon emission. Exploring whether there is a threshold effect between technological progress bias and transport carbon emissions is of immense significance, in order to understand the internal mechanism of transport carbon emission reduction and formulate scientific and technological policies.

The main contributions of this study include the following: (1) Based on the biased technology theory and the extended stochastic frontier model, we explore the heterogeneity of the biased technology progress in different regions. (2) By constructing a nonlinear threshold model, this study explores the dynamic threshold effect of biased technological progress on transportation carbon emissions in eight major regions of China. (3) Transportation carbon emission reduction technology policies for nonlinear impact characteristics are proposed.

The remaining paper is structured as follows. Section 2 presents the literature review, whereas Sect. 3 presents the methodology. The results of threshold regression and the discussion are presented in Sects. 4 and 5, respectively. The conclusion and policy suggestions are presented in Sect. 6.

2 Literature review

Technology progress is vital for realizing transportation carbon emission reduction (Cui, 2015). Neutral technological progress or biased technological progress is of immense significance for understanding transportation carbon emission reduction. Neutral technological progress will change the marginal output of energy and other production factors in the same proportion, while biased technological progress will change the relative usage between energy and other factors in different proportions (Aghion, 2016; Chen, 2014). In other words, it will save more energy than the other factors for the same transportation output, influencing traffic CO_2 emissions. With Acemoglu's discussion on biased technological progress in the environmental field (Acemoglu, 2002, 2009), the impact of the nature of technological progress on the environment has gradually shifted from focusing on neutral technological progress to biased technological progress (Dong, 2019; Zha, 2017). However, there is negligible research and analysis on the influence of biased technology on transportation CO_2 emission. Existing literature focuses on the impact of neutral technological progress on transportation CO_2 emission, almost ignoring the effect of biased technological progress (Bai, 2019; Cui, 2015). Furthermore, the role of technological progress in traffic CO_2 emission cannot be comprehensively identified. Based on the technology consistency theory (Antonelli, 2016), the degree of consistency between technology progress bias and local energy factors may have an important impact on carbon emission reduction.

Certain studies explored the relationship between biased technological progress and carbon emissions from a regional perspective. Zhang (2017) found that the degree of technological progress bias and regional energy-saving effect are affected by the regional capital. The greater the degree of capital bias in a region, the slighter the technological energy-saving effect is in the region. Kang (2018) found that the impact of technological progress bias on carbon emissions in different regions is influenced by the local economic level. Furthermore, Jing (2019) found that the impact of energy and low-carbon biased technologies on CO_2 is affected by temporal and spatial differences. Zhou (2020) found that industrial structural change exhibits regional heterogeneity: in eastern China, industrial structural rationalization promotes all types of technological progress; in central China and western China, industrial structural upgrading can accelerate energy-saving and pollution abatement technological progress. Tan (2022) found that the resident consumption improvement and technological progress play the main transmission role through the empirical study of the entire sample and heterogeneous urban samples. There are considerable differences in technology bias in different regions of China. Identifying which factors may affect the relationship between technology bias and traffic CO_2 emission in different regions is significant for realizing technology-driven green transportation in different regions. Based on this, this study further verifies whether it has a threshold effect and has crossed the threshold based on the threshold model in different regions.

Certain researchers investigate the impact of technological bias on energy or CO_2 emission from an industry perspective. Welsch (2005) found that the technology progress with energy bias in the German production sector enables the reduction of carbon emission. Employing the multi-sector equilibrium model, Okushima (2009) found that Japan's technological progress is considerably different across different industries, and its impact on CO_2 emission is also significantly different. Acemoglu (2012) found that, in a two-sector model, the increase of resource price is conducive to the transformation to clean technology and environmental improvement. Employing the three-factor constant elasticity of substitution (CES) model, Zha (2017) found that the efficiency of energy-biased technology progress in the industrial sector decreased annually, and the carbon emission also decreased. There are also extensive studies reported in China, such as Wang's application of data envelopment method. They found that energy-biased technological progress contributes to the improvement of the industrial total factor productivity and energy efficiency (Chen, 2014). Certain studies used transcendental logarithmic cost function analysis to investigate the differences in CO_2 emission across different industries (Binswanger, 1974). Li (2015) found that biased technology progress of different source exhibits different impacts on the energy intensity and CO_2 emission of the industrial sector. Zhang (2017) found that energy-biased technological progress has continuously promoted CO_2 emissions with the decrease in industrial energy efficiency. Chen (2021) found that the impact of technological progress on the energy intensity of the manufacturing industry is different, among which the effect of biased technological progress is more significant based on factor substitution. Liao (2018) developed a two-level CES function based on the perspective of the bias of technical progress. In order to estimate the elasticity of substitution between energy and non-energy factors from 27 sub-divided manufacturing industries based on panel data, Zheng (2022) found that with the development of technology, the industrial structure upgrading under resource dependence could cause an increase in carbon emissions at the beginning, but the increase would be weakened subsequently.

Certain studies focus on analyzing the nonlinear relationship between biased technological progress and energy or CO_2 emissions. Peng (2019) found that energy-biased industrial investment exhibits different threshold effects for different threshold variables. Dong (2019) used the double-layer CES function, and found that the technology spillovers of energy-saving bias caused by foreign direct investment (FDI) will have a threshold effect on CO_2. Wu (2018) used the three-factor transcendental logarithmic production function and found that the biased technology caused the total factor energy efficiency to gradually decrease in the upper, middle and lower mainstream of the Yangtze River. Lin (2014) found that energy-biased technology exhibited an inverted U-shaped impact on the industrial energy consumption and CO_2 emission. Qian (2020) argued that if the energy-biased technology was located on the left side of the inverted U-shaped curve, the investment in energy technology could be accelerated. Kivyiro (2014) found that the bias of energy production technology is more apparent than that of energy utilization technology, causing the CO_2 rebound nonlinear effect. Liao (2020) reported the existence of a threshold value of progress in energy-biased technology. Progress in energy-biased technology has a positive effect on energy efficiency below the threshold, and the effect is negative above the threshold. Yang and Liu (2022), Yang and Hao (2022) reported that the GVC embedding position and the energy-biased technology progress show an inverted U-shaped curve relationship. Kha (2020) found that relatively lower endowments with technological knowledge are a barrier to diffusion for new technologies. The study also shows how the evolution of relative stocks of technological knowledge explains different shapes of diffusion curves. Li (2021) found that carbon emission trading schemes (ETSs) can direct innovation activities toward low-carbon technologies. Lyu (2022) found that capital-saving technical change exhibits a negative double-threshold characteristic on urban carbon footprint in China.

Most of the existing studies of the industry or manufacturing pertain to carbon emissions, researching on input factors for analyzing transportation development. There is still no relevant literature that has studied the relationship among technological progress bias, factor substitution and carbon emission in transportation. This study intends to bridge this in the literature. To solve the existing problems, this study has used the stochastic frontier production function model to calculate the transportation technology progress bias. A dynamic threshold model was developed to explore the threshold effect of technology progress bias on transportation CO_2 emission.

3 Research methodology and data sources

From the perspective of methodology, this research is mainly divided into three research steps. Firstly, the stochastic frontier model is constructed, and the elasticity of factor output and the bias of technological progress are calculated. Secondly, the influence mechanism of different types of transportation technology progress bias on carbon emission is analyzed. Finally, the threshold model is constructed based on the above analysis, and the threshold model is tested and regressed (See Fig. 1).

3.1 Measurement method of factor bias

The existing research mainly sets the production function in three forms: C-D production function, CES production function and stochastic frontier production. The C-D production function assumes that labor output elasticity and capital output elasticity are fixed, implying that technological progress is neutral and neglects the skewness of technological progress. Therefore, CES production function is widely used in measuring technological progress deviation (Arrow et al., 1961; Hou, 2021). However, compared with CES production function, stochastic frontier production not only relaxes the strict assumption of neutral technological progress, but also its variable factor output elasticity reflects the substitution effect and interaction between input factors that is more realistic. Simultaneously, stochastic frontier production can also add the time factor to reflect the difference in the technological progress of different investment factors; therefore, it can reveal more internal characteristics of economic system, and its form is flexible, that can effectively avoid the

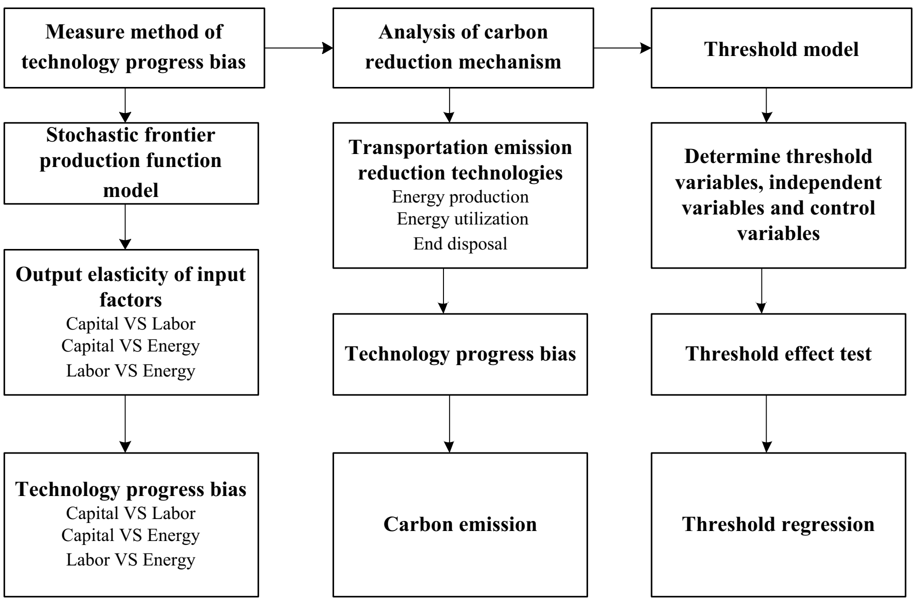

Fig. 1 Flowchart of methodology

deviation caused by the missetting of production function (Yang and Liu, 2022; Yang and Hao, 2022).

Stochastic frontier production function model can be used to study the relationship between the input factors of macroeconomic systems such as country (Lin & Fei, 2015), region (Bristow, 2013) and industry (Smyth, 2011). The stochastic frontier production function model can also be used for the prediction of economic growth and carbon emissions reduction (Yang et al., 2017). This study attempts to apply the model to the input–output analysis of transportation industry. The model setting is expressed as follows:

$$\ln Y = \ln \beta_0 + \sum_i \beta_i \ln X_i + \sum_i \sum_j \beta_{ij} \ln X_i Y_j \tag{1}$$

Y represents the passenger turnover and cargo turnover, and the added value of passenger and freight volume is used as the proxy variable. X_i and X_j represent input factors i and j, and β_i and β_{ij} represent regression coefficients of Eq. (1). The final model can be expressed as Eq. (2):

$$\begin{aligned}\ln Y_t = \varepsilon + \beta_K \ln K_t + \beta_L \ln L_t + \beta_E \ln E_t + \beta_{KL} \ln K_t \ln L_t + \beta_{KE} \ln K_t \ln E_t + \beta_{LE} \ln L_t \ln E_t \\ + \beta_{KK}(\ln K_t)^2 + \beta_{LL}(\ln L_t)^2 + \beta_{EE}(\ln E_t)^2\end{aligned} \tag{2}$$

where Y_t is the passenger and cargo turnover in year t, while *Kt*, *Lt* and *Et* are the transportation capital stock, number of transportation employees and transportation energy consumption. *βi* and *βij* represent regression coefficients, and ε represents the constant terms.

Therefore, the output elasticity of capital, labor and energy can be expressed as Eqs. (3), (4) and (5) respectively:

$$\delta_{Kit} = \frac{dY/Y}{dK/K} = \frac{d\ \ln\ Y}{d\ \ln\ K} = \beta_K + \beta_{KL} \ln L_{it} + \beta_{KE} \ln E_{it} + \beta_{KK} \ln K_{it} \tag{3}$$

$$\delta_{Lit} = \frac{dY/Y}{dK/L} = \frac{d\ \ln\ Y}{d\ \ln L} = \beta_L + \beta_{KL} \ln K_{it} + \beta_{LE} \ln E_{it} + 2\beta_{LL} \ln L_{it} \tag{4}$$

$$\delta_{Eit} = \frac{dY/Y}{dE/E} = \frac{d\ \ln\ Y}{d\ \ln E} = \beta_E + \beta_{KE} \ln K_{it} + \beta_{LE} \ln L_{it} + 2\beta_{EE} \ln E_{it} \tag{5}$$

Substitution elasticity among capital, labor and energy is as follows:

$$\sigma_{KEit} = \left\{ 1 + \left[-\beta_{KE} + 2\frac{\delta_{Kit}}{\delta_{Eit}} * \beta_{EE} \right] * (\delta_{Kit} + \delta_{Eit})^{-1} \right\}^{-1} \tag{6}$$

$$\sigma_{LEit} = \left\{ 1 + \left[-\beta_{LE} + 2\frac{\delta_{Lit}}{\delta_{Eit}} * \beta_{EE} \right] * (\delta_{Lit} + \delta_{Eit})^{-1} \right\}^{-1} \tag{7}$$

This study considers the measurement of technological progress bias. Bias-$_{\mathrm{ij}}$ represents the technological progress difference between factor i and j, β_{it} represents the coefficients, and σ_i represents the output elasticity, When Bias-ij is positive, the technological progress effect of factor i is more than that of j; when Bias-ij is negative, the technological progress effect of factor *i* is less than that of *j*; when Bias-ij is 0, this means that the technological progress effect of factor *i* is equal to that of *j*.

$$Bias_{ijt} = \frac{\beta_i}{\delta_{it}} - \frac{\beta_j}{\delta_{jt}} \tag{8}$$

According to Eqs. (3–8), the following hypotheses can be developed: energy consumption, carbon emissions and technological progress bias are all nonlinear. Suppose δi is the elasticity of capital or labor output, and δj is the elasticity of energy output. When $\delta i < \delta j$, that is, when the elasticity of energy output is significantly higher than that of the capital and labor output, the greater the elasticity of substitution, the greater the transportation output per unit energy input, the higher is the preference given to energy consumption, and the energy-saving biased technological progress increases energy consumption and carbon emissions. When $\delta i > \delta j$, that is, when the elasticity of energy output is significantly lower than that of the capital and labor output, the greater the elasticity of substitution, the greater the transportation output per unit labor or capital input, and the higher is the preference given to labor or capital input, promoting the energy-saving biased technological progress to reduce energy consumption and carbon emissions. Therefore, it features nonlinear characteristics, and Bias-ij changes with the change of the relationship between δi and δj. The nonlinear relationship between energy consumption, carbon emissions and δi and δj finally manifest as the nonlinear relationship between energy consumption, CO_2 emissions and technological progress bias (Bias-$_{ij}$).

3.2 Carbon reduction mechanisms for biased technologies

According to the different types of technologies, transportation emission reduction technologies can be divided into: emission reduction technologies at the production end, emission reduction technologies at the conversion end and emission reduction technologies at the disposal end (Kang, 2018; Lin & Ahmad, 2015).

The production end is fossil energy production and electrification of vehicles. The comprehensive application of management technology and production technology and the other means of promoting clean energy, such as achieving low carbonization of raw materials through grade upgrading of gasoline, and reducing the use of fossil energy through new energy vehicles. The conversion end technology that reduces the scale of energy use indirectly by means of optimizing resource allocation and improving energy efficiency includes improving engine performance, combustion heat release level and waste heat utilization. Disposal end technology absorbs CO_2 through treatment and utilization, such as forest carbon sink, CO_2 capture, storage and resource utilization (Ouyang, 2018; Sun, 2016).

From the perspective of technological progress goals, the three technologies are complementary to each other, minimizing CO_2 emissions regardless of budget constraints. The price effect determines the bias between complementary technologies. Technological progress favors scarce factors. As complementary technologies of energy production, energy utilization and end disposal, the emission reduction process is ultimately biased toward scarce technologies (such as carbon capture and utilization or production of fossil technology) under the influence of the price effect (Lin, 2020; Wang, 2017). The impact mechanism is shown in Fig. 2.

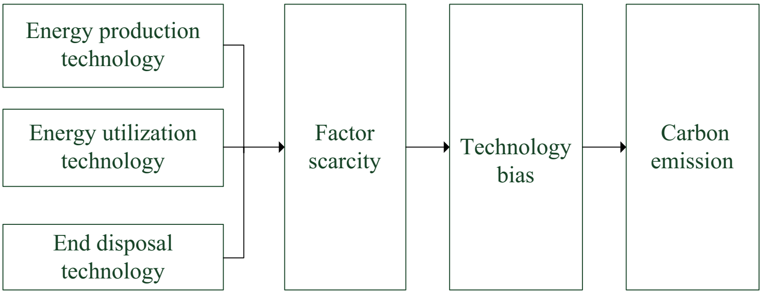

Fig. 2 Influence mechanism of technological progress bias on carbon emission reduction

3.3 Threshold regression model

Based on the analysis of the influencing mechanism, the technological progress bias features a nonlinear effect on CO_2. Due to the rebound effect, the impact of technological progress on energy is generally underestimated. In this part, the dynamic threshold model is used to estimate the nonlinear impact of biased technological progress on traffic CO_2 emissions. The single-threshold model is expressed as follows (Hansen, 1999).

$$C_{it} = \alpha_i + \gamma C_{it-1} + \beta_i X_{1it} + \alpha_2 X_{2it} * I(q_{it} \le \gamma) + \beta_3 X_{2it} * I(q_{it} \ge \gamma) + \mu_i + \varepsilon_{it} \quad (9)$$

where C_{it} is the interpreted variable, transportation CO_2 emission; $C_{it\text{-}1}$represents a lag period of carbon emissions, indicating the dynamics and continuity of transport carbon emissions. X_{1it} is a control variable and is not affected by threshold variables; X_{2it} is an explanatory variable influenced by threshold variables; q_{it} is a threshold variable; γ is a threshold value (there may be multiple thresholds); $I(\cdot)$ is an index function, which is 1 when the bracket condition is met and 0 when it is not met. According to Hansen, three steps can be considered for estimation. The first step is to use q to regress point by point. The second step is to verify the existence of thresholds. The last step is to use the maximum likelihood function to determine the fiducial interval of the threshold.

The aim of this study is to prove the existence of threshold effect in transportation industry and the heterogeneity of threshold effect among different regions based on the discussion of the nonlinear impact of technological progress bias on CO_2. With Bas_{it} representing the progress of energy-biased technology, the panel regression model is as follows:

$$C_{it} = \alpha_i + \gamma * C_{it-1} + \beta_i X_{1it} + \beta_{i1} * Bas_{it} * I(Bas_{it} \le \gamma) + \beta_{i2} Bas_{it} * I(Bas_{it} \ge \gamma) + \mu_i + \varepsilon_{it} \quad (10)$$

3.4 Description of data sources and variables

According to the existing literature (Andress, 2012; Bristow, 2013), the impact factors can be drawn from three aspects: transportation structure, energy structure and technical factors.

①Transport structure: The modes of transportation include road, rail, air and water. Road and air passenger freight dominate transport infrastructure in most countries (Gibbons et al., 2019). The ratio of passenger turnover in air transport and road transport

is selected as the measurement indicators of transport structure. The data of these two indicators are sourced from the China Traffic Statistics Yearbook and processed directly.
② Energy structure: The main transportation fuels are electricity, gasoline, kerosene and diesel oil. The carbon emission coefficient of petroleum is higher than that of the other energy sources. Generally, the higher the proportion of a country's oil in the total transportation energy consumption, the lower the rationality of its energy structure. Therefore, the ratio of oil to total transportation energy consumption is selected for measuring the energy structure. The data are sourced from the China Energy Statistics Yearbook and are processed directly.
③ Technical improvement: The main measurement indicator is the bias of technical progress that aims to reflect the current direction of technical improvement; it reflects the direction of China's efforts in improving transportation technology and the investment in energy conservation and emission reduction. Detailed description of each variable and the data sources are shown in Table 1.

4 Empirical results and analysis

In order to analyze the regional differences in the impact of technological progress bias on transport carbon emissions, the research objects are divided into eight regions. Specifically, it includes eight regions: Northeast China, North China, Middle Yellow River, East China, Southeast Coast, Middle Yangtze River, Southwest China and Northwest China (see Table 2 and Fig. 3).

4.1 Regional energy-biased technological progress

According to the index of energy-biased technological progress in Fig. 4a–h, the following conclusions can be drawn. The degree of energy bias of technological change varies from region to region. This study uses DEAP software to calculate the technical progress bias.

First, 12 regions with large energy consumption in the technological change include Beijing, Hebei, Henan, Jiangsu, Zhejiang and Sichuan (see Fig. 4b, c, d and g). The 17 regions with energy-saving or capital-biased technologies include Tianjin, Shanghai and Guangdong (see Fig. 4b, d and e). We can find that the level of energy bias is not consistent with the economic development level of a region, implying that not all technological changes in economically developed Yangtze River Delta, Pearl River Delta and Beijing–Tianjin–Hebei regions are directed toward energy conservation, and the technological changes in the economically underdeveloped Northeast, Northwest, Southwest and middle mainstream of the Yellow River also exhibit energy conservation bias (see Fig. 4c–e).

Second, during the same period, the direction of technological change was inconsistent, and the development trend was also inconsistent. On the one hand, in areas where technology transformation is more focused on energy, the bias level is almost higher than zero, but there are different trends. One shows a steady trend, and the energy consumption increases gradually (see Fig. 4b and d). The other is a J-shaped curve, and the energy consumption shows a rapid upward trend. On the other hand, for regions where the technology adjustment is essentially energy saving, there are also two trends in energy bias level: steady

Table 1 Description and data source of selected variables

Variable	Description	Source
Output (Y_{it})	Passenger turnover/freight turnover	China Traffic Statistics Yearbook
Energy input (E_{it})	Energy consumption	China Traffic Statistics Yearbook
Capital input(K_{it})	Perpetual inventory method: $Kit = Iit + (1\text{-}\delta i)\ Kit\text{-}1$	China Traffic Statistics Yearbook
Labor input (L_{it})	Number of employees at the end of the year	China Traffic Statistics Yearbook
CO_2 emissions (C_{it})	Transportation carbon emission, $CO_2 = \sum NCVi \times CEFi \times COFi \times 44/12$	China Energy Statistical Yearbook
GDP per capita (GDP_{it})	Economic development level	China Statistical Yearbook
Energy structure (ES_{it})	Proportion of oil in the total energy consumption of transportation	China Traffic Statistics Yearbook
Transport structure (TS_{it})	Percentage of railway transportation	China Traffic Statistics Yearbook
Technological progress bias ($Bias\text{-}_{it}$)	Degree of technological progress bias in transportation field	Formula (6)

Table 2 Sample division of eight study areas

Study area	The provinces included in the region
Northeast China	Heilongjiang, Liaoning, Jilin
North China	Beijing, Hebei, Tianjin, Shandong
Middle Yellow River	Neimenggu, Shanxi, Shananxi, Henan
East China	Jiangsu, Shanghai, Zhejiang
Southeast Coast	Fujian, Guangdong, Hainan
Middle Yangtze River	Hubei, Hunan, Jiangxi, Anhui
Southwest	Guizhou, Yunnan, Guangxi, Sichuan
Northwest	Gansu, Qinghai, Ningxia, Xinjiang

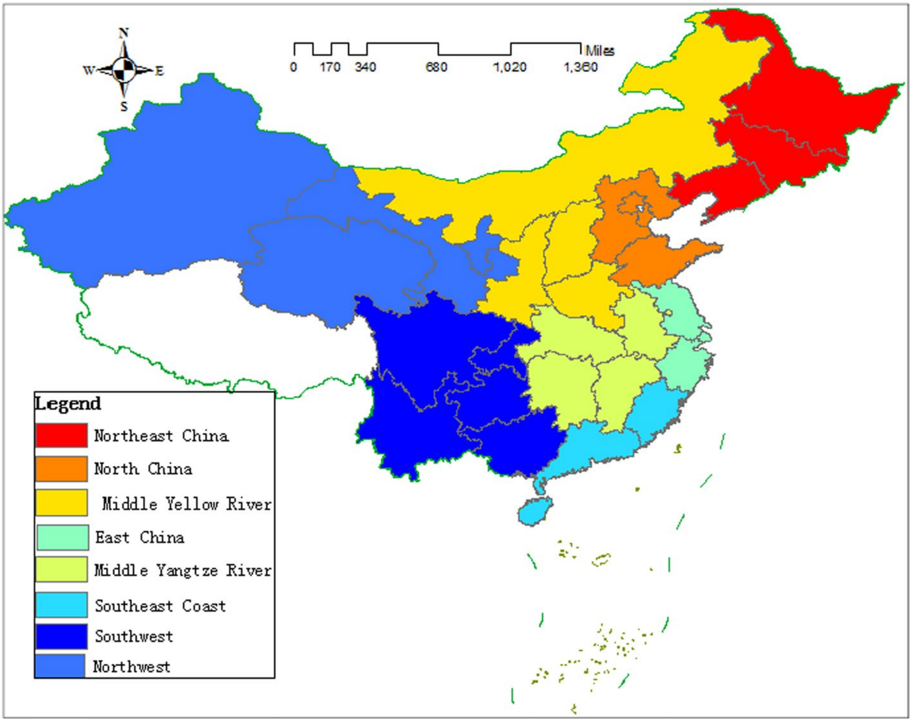

Fig. 3 Provinces encompassed in the different regions of China

decline and continuous rise. In certain specific areas (such as Shanghai), the technological bias is less than zero at the initial stage. However, since 2010, the bias index has become positive, implying the transformation of technological change to energy consumption (See Fig. 4d).

Third, it should be emphasized that Beijing, Jiangsu, Zhejiang and other economically developed and high-income provinces have not comprehensively demonstrated the energy-saving characteristics of technological change (see Fig. 4b and d). However, there are some underdeveloped low-income provinces such as Jiangxi, Guangxi, Yunnan

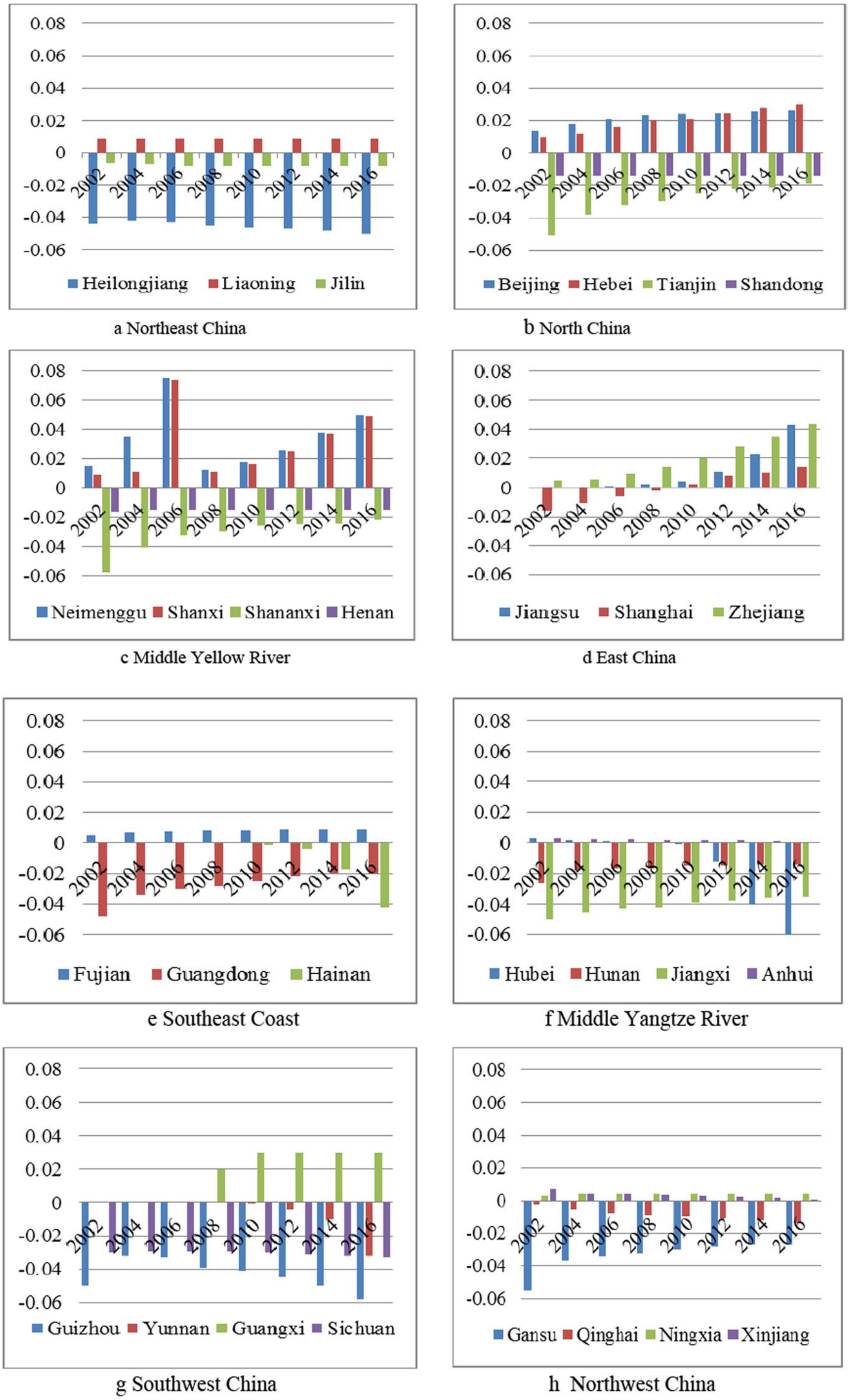

Fig. 4 Technical progress bias of each region

and Qinghai, whose technological changes exhibit energy-saving characteristics (see Fig. 4f–h).

Therefore, our results show that there is a significant influence of inequality in the economic development level on the regional energy preference.

4.2 Dynamic threshold estimation

Most studies on carbon emissions are based on the provincial level or generally divide China into three regions: East, Central and West. However, the research report of the National Development and Reform Commission indicated that roughly dividing China into East, West and East is no longer consistent with the current situation of China's regional transportation development. Based on the development status of China's metropolitan area, this study divides China into eight regions with strong traffic links and spatial dependence on economic development: Northeast China, North China, East Coast, Southeast Coast, Middle Yellow River, Middle Yangtze River, Southwest China and Northwest China.

The newly developed dynamic threshold panel model was adopted in this study. The model combines the characteristics of Gaussian mixture model (GMM) method and the existing time series technology on threshold model, and it can effectively solve the potential endogenous problem (Ouyang, 2018). Tool variable estimator, particularly the GMM method,-can appropriately solve any internal variability problem (Wang, 2018).

Firstly, threshold test is conducted to test the threshold value and the number of threshold values of technology bias and traffic carbon emissions in different regions, and subsequently, the specific expression form of the model is determined. Considering technology bias as the threshold variable, model (11) is tested under single threshold and double threshold. Figures 5, 6, 7, 8, 9, 10, 11, 12 suggest that the technology bias in different regions exhibits different threshold effects on traffic CO_2 emission. Although the results of the threshold test appear to be complex, LR tests can lead to only one or two threshold variables. Figures 5, 6, 7, 8, 9, 10, 11, 12 show the threshold values of the Northeast, East Coast, Southeast Coast, middle mainstream of Yellow River, middle mainstream

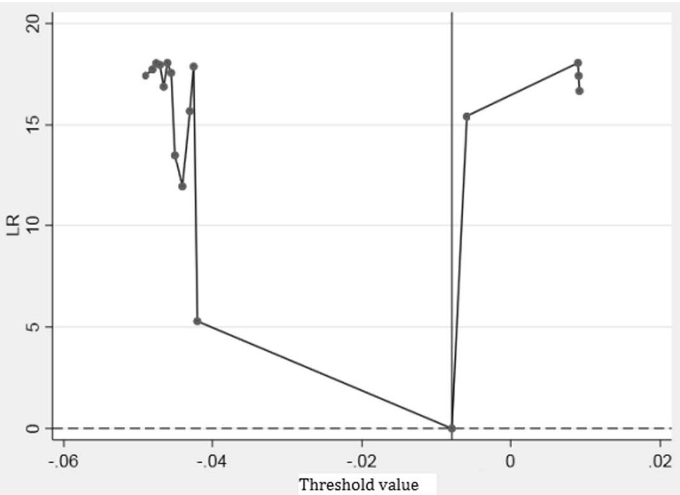

Fig. 5 Threshold effect of Northeast China

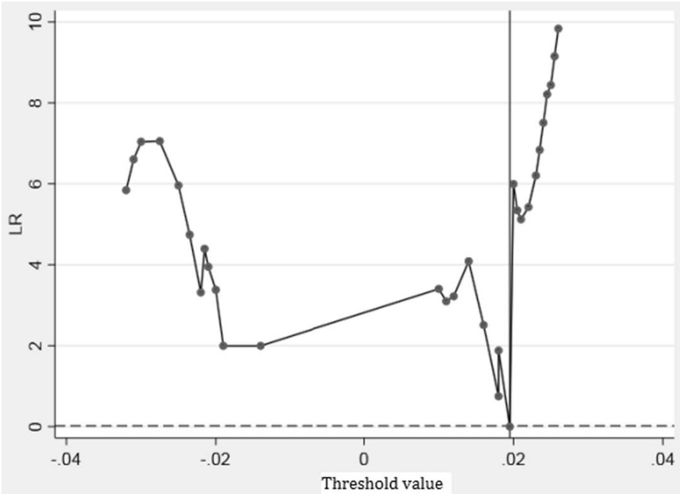

Fig. 6 Threshold effect of North China

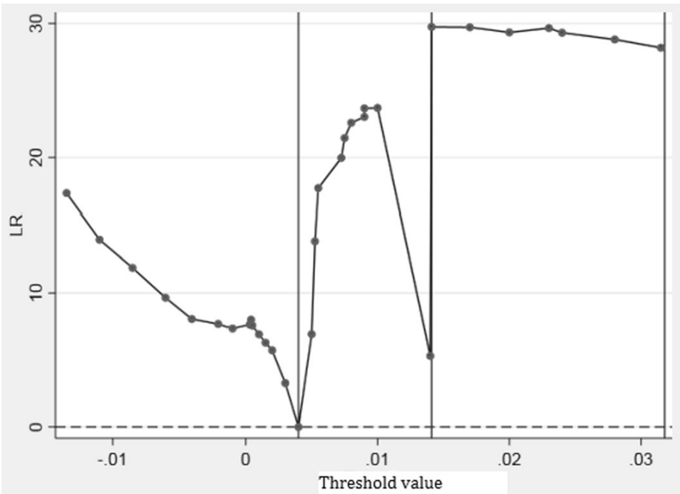

Fig. 7 Threshold effect of East Coast

of Yangtze River, Northwest and Southwest regions, among which the eastern coastal region presents a double-threshold effect, while the other regions exhibit single-threshold effect. To summarize, the influence of technology bias and carbon emissions in different regions presents complex nonlinear threshold effects other than simple linear characteristics. Therefore, this study conducts an empirical analysis of the single or double-threshold effect. Thereafter, the threshold value of technology bias in different regions is estimated and tested (Table 2).

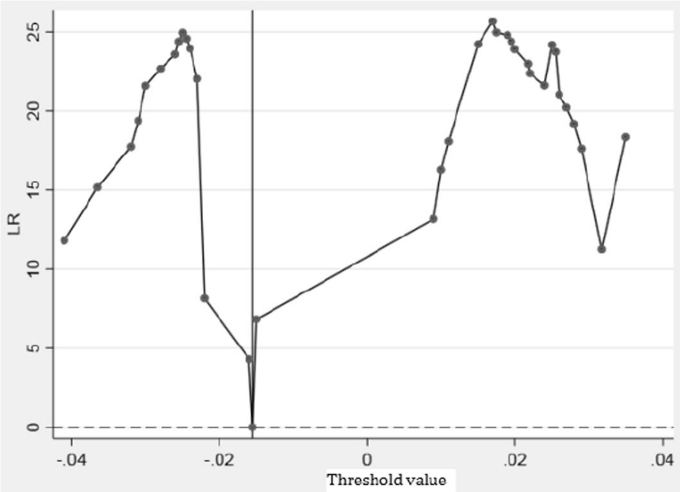

Fig. 8 Threshold effect of Southeast Coast

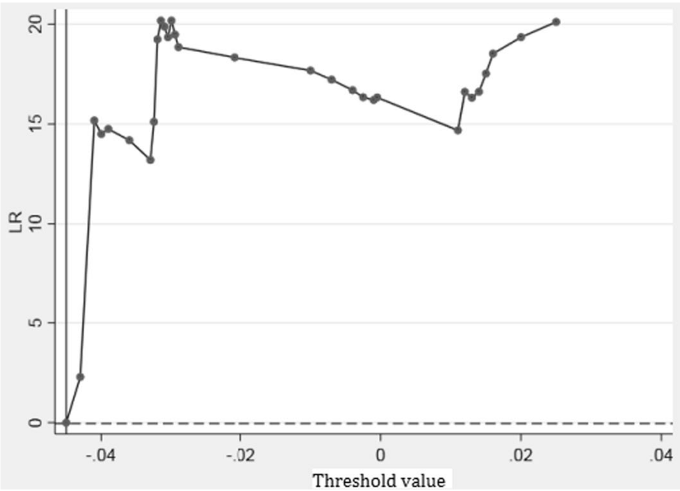

Fig. 9 Threshold effect of Middle Yellow River

4.3 Threshold effect of technological progress bias on traffic CO_2 emission

This study mainly investigates the impact of technological progress bias on carbon emissions in eight regions of China. The regression results are shown in Table 3, and the research conclusions are as follows:

There is a single threshold between energy-saving technological progress and carbon emission in Northeast China and the middle mainstream of the Yellow River. Overall, the technological progress is biased toward labor saving, and the use of energy or

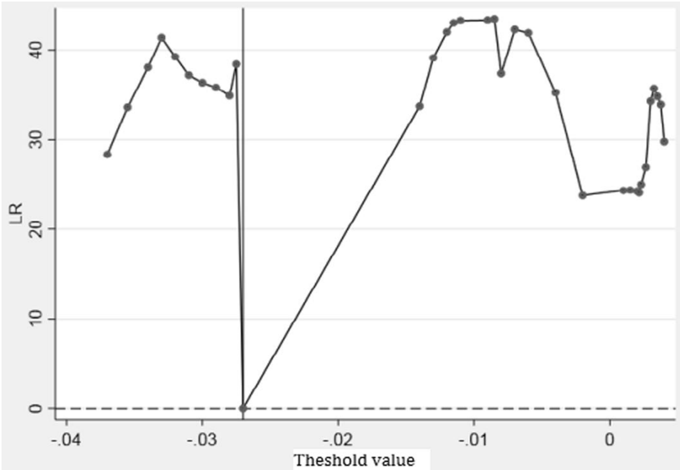

Fig. 10 Threshold effect of Middle Yangtze River

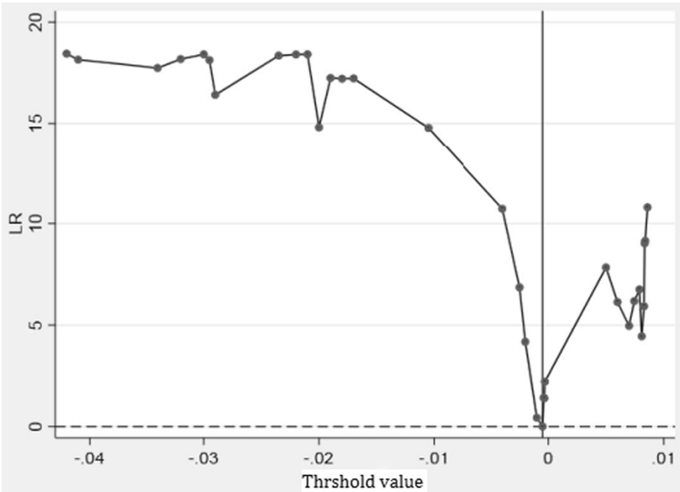

Fig. 11 Threshold effect of Southwest China

capital coexists. When the technological progress bias is lower than the threshold values of −0.009 and −0.0155, the continuous energy-enhanced technological progress leads to the continuous increase in CO_2 emissions in the transportation industry. When the technological progress crosses the threshold, the energy-saving biased technological progress causes a reduction in CO_2 emission in the transportation industry; however, it is not statistically significant because only a small number of regions cross the threshold. Therefore, the overall impact is not significant.

There is also a single threshold between energy-saving biased technological progress and carbon emissions in North China. Overall, technological progress is biased toward energy enhancement in its entirety. Tianjin shows capital bias, but this characteristic

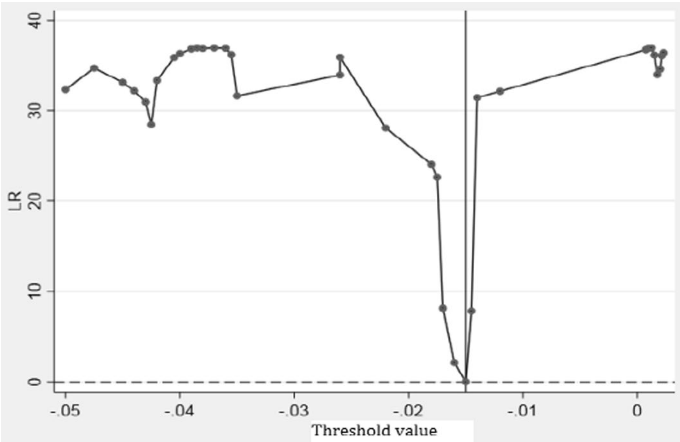

Fig. 12 Threshold effect of Northwest China

is weakening. When technological progress bias crosses the threshold value of 0.0195, the influence of energy-enhanced technological progress on CO_2 emission is further enhanced. This indicates that technological progress in North China does not render the transportation industry more energy saving, but promotes the continuous expansion of transportation industry, resulting in more traffic CO_2 emission.

There is a double-threshold effect between energy-saving biased technological progress and carbon emissions in the eastern coastal areas, and the threshold values of technological progress bias in the eastern coastal areas are 0.004 and 0.141. When the technological progress bias is lower than the first threshold value, the influence of technological progress bias on traffic CO_2 emission in eastern coastal areas is positive, and it passes the significance test at 1%. When the technological progress bias in the eastern coastal areas is between 0.004 and 0.141, the influence coefficient of technological progress bias on CO_2 emission in the eastern coastal areas decreases significantly (0.046), that indicates that the energy-saving effect of technological progress begins to appear only when the technological progress bias exceeds 0.141. The technological progress bias has a negative impact on CO_2 emission in the eastern coastal areas. The eastern region transformed and upgraded the industry earlier and applied many technologies to the transportation field, and the energy-saving effect of technological progress in the transportation field was highly significant. It showed an inverted U-shaped curve, that is, with the continuous enhancement of the technological progress bias in the eastern region, the energy rebound effect appeared initially, and the energy-saving and emission reduction effect appeared subsequently.

There is a single-threshold effect between energy-saving biased technological progress and traffic carbon emissions in the Southeast coastal area and the middle mainstream of the Yangtze River. The threshold values of technological progress bias in the two areas are −0.0005 and −0.015, respectively. When the technological bias is lower than the threshold value, the technological progress bias exhibits a positive impact on CO_2 emissions in the Southeast coastal area and the middle mainstream of the Yangtze River, and promotes CO_2 emissions significantly at 5 and 1% respectively. When the technological progress bias crosses the threshold value, the influence coefficient of technological progress bias on CO_2 emission is negative. However, the elasticity in the Southeast Coast increases and the middle mainstream of the Yangtze River decreases, indicating that the energy-saving

Table 3 Threshold regression result for different regions

Variable	Northeast China	North China	Middle Yellow River	East Coast	Southeast Coast	Middle Yangtze River	Southwest China	Northwest China
Threshold value	−0.0009	0.0195	−0.0155	0.004 ~ 0.141	−0.0005	−0.015	−0.043	−0.027
GDP pet capita (GDP)	−0.277*** (0.000)	–0.282*** (0.000)	−0.290*** (0.003)	−0.288*** (0.005)	−0.241*** (0.000)	−0.265** (0.045)	−0.249*** (0.000)	−0.290** (0.016)
GDP^2	0.021*** (0.000)	0.034*** (0.001)	0.032*** (0.000)	0.037** (0.019)	0.030* (0.068)	0.044*** (0.000)	0.043** (0.025)	0.031*** (0.000)
Energy Structure *(ES)*	−0.999*** (0.000)	2.207*** (0.000)	0.700*** (0.002)	0.710*** (0.000)	0.141*** (0.000)	1.158*** (0.000)	0.609*** (0.000)	−0.811*** (0.000)
Transportation Structure *(TS)*	0.144** (0.046)	0.022 (0.648)	0.316*** (0.000)	−0.119* (0.076)	−0.065 0.566	0.369*** (0.000)	0.293*** (0.000)	0.492*** (0.000)
Bias(*Bias* < λ1)	0.121*** (0.000)	0.157** (0.005)	0.528*** (0.000)	0.495*** (0.000)	0.112** (0.012)	0.518*** (0.004)	−0.014** (0.013)	1.021 (0.172)
Bias (λ1 < *Bias* < λ2)				0.046 (0.368)				
Bias(*Bias* > λ2)				−0.352*** (0.000)				
Bias(*Bias* > λ1)	−0.168 (0.64)	0.406*** (0.000)	−0.046 (0.676)		−0.757*(0.088)	−0.177** (0.030)	−0.355***(0.000)	−1.436***(0.000)
Cons	0.694***(0.000)	7.129***(0.000)	7.727***(0.000)	7.256***(0.000)	6.304***(0.000)	7.535***(0.000)	7.019***(0.000)	6.607***(0.000)
R^2	0.883	0.771	0.695	0.923	0.771	0.837	0.709	0.787
Wald test	2121.04***	2148.09***	2011.58**	4152.01***	1631.03***	3014.28***	3764.21***	1801.09***

***, **,* denote 1, 5, 10% significance level.

technological progress has a more significant effect on energy conservation and emission reduction in the Southeast Coast than in the middle reaches of the Yangtze River.

There is a single-threshold effect between energy-saving biased technological progress and traffic carbon emissions in Southwest China. The threshold value of technological progress bias in Southwest China is −0.043, and biased technological progress always features a negative impact on traffic CO_2 emissions in Southwest China. When the technological bias crosses the threshold, the elasticity of the influence of technological progress bias on CO_2 emission in Southwest China increases significantly, from 0.014 to 0.35, and the significance level also increases significantly. It shows that the energy-saving technology progress has always played a role in saving energy and reducing emissions in Southwest China. With the high-quality development in Southwest China, clean technology further promotes the healthy development of transportation in Southwest China.

There is a single-threshold effect between energy-saving biased technological progress and traffic carbon emissions in Northwest China. The threshold value of technological progress bias in Northwest China is -0.027. When the technological bias crosses the threshold value, the influence of biased technological progress on traffic CO_2 emissions in Northwest China changes from positive to negative, and the significance level also changes from insignificant to significant. It shows that when the threshold value is not crossed, the level of energy-saving technology progress bias is low in Northwest China, and the effect of energy saving and emission reduction is not obvious. With the development of western China, energy-saving technologies are being accumulated and transportation becomes more energy-saving.

5 Discussion

Based on the threshold regression model, this study analyzes the regional differences in the threshold impact of technological progress bias on traffic CO_2 emission. This study has found that the impact of technological progress bias on traffic CO_2 is affected by the degree of technological progress bias, and there is a large regional difference, that is in line with the research conclusions of Zhang (2017), Kang (2018) and Jing (2019). However, different from the aforementioned studies, this study focuses on transportation sector CO_2 emission and the double-threshold effect in different regions.

The complex relationship between the energy bias of technology and transport carbon emissions is highly correlated with the proportion of investment in renewable and non-renewable energy technologies (Walheer, 2018). In Northeast China, the middle mainstream of the Yellow River, the East Coast, the Southeast Coast, the middle mainstream of the Yangtze River and the Northwest region, the impact of technological progress bias on transportation CO_2 emission changes from positive to negative as the technological progress bias exceeds the threshold. This has been supported by Dong (2019) and Zha (2017), who believe that technology spillovers of energy-saving bias have a threshold effect on carbon emission. When the technology bias is inclined to cross the threshold value, the transportation technological progress is more energy saving, thus reducing the transportation carbon emission. The energy technology bias across the threshold implies that renewable energy technologies exceed non-renewable energy technologies in transportation. Acemoglu (2003) divides biased technological progress into two categories. One is the factor-enhanced technological progress that refers to the marginal productivity of a factor that technological progress can change. The other is the factor-biased technological progress that implies that it has an impact on the marginal substitution rate between factors. Wang (2017) and Lin (2020) considered that there are two effects such as price effect and market size effect that affect the technical change represented by the factors. The price effect directly stimulates innovation of scarce elements (such as renewable energy technology), while the market size effect stimulates innovation of abundant elements (such as non-renewable energy technology). The increase of output elasticity of renewable energy technologies is higher than the proportion of non-renewable energy technologies during the study period (Ouyang, 2018). Indeed, the development of energy-saving technology and advanced equipment also promote an increase in the output elasticity of renewable energy technologies (Lin, 2020; Smyth, 2011). Compared with non-renewable energy technologies, renewable energy technologies feature significant emission reduction effects, while non-renewable energy technologies do not reduce emissions or even increase carbon emissions. The technologies in the South are more likely to be bioenergy conversion and carbon capture. Therefore, the effect of emission reduction is from positive to negative.

In North China, when the technology bias crosses the threshold value, transportation carbon emissions increase, contrary to the expected reduction. This indicates that the transportation technology in the Beijing–Tianjin–Hebei region failed to develop toward the direction of energy conservation or renewable energy, and the transportation technology rendered the energy consumption more substantial. Technological progress in this area is more in favor of labor, capital or energy, resulting in unreasonable technological structure in the field of transportation (Zhang, 2017). On the one hand, the difference of technical structure in the region influences the change of energy structure in the region, it leads to more demand for transportation terminal products. On the other hand, changes in the energy structure such as crude oil and electricity generate higher transportation carbon emissions. The upgrading of vehicles on the demand side not only changes the energy demand, but also causes energy rebound effect of the transportation sector. In fact, progress in energy-biased technologies may have a “double-edged effect” on energy efficiency. Specifically, energy-biased technological progress may reduce the energy consumption per unit of output by increasing the production efficiency, but it may also increase energy consumption per unit because it is energy biased (Liao, 2020). With the “double-edged effect,” when energy-biased technological progress reaches a level higher than the threshold, a negative impact on energy efficiency is experienced, mainly owing to the high energy consumption caused by the technological progress itself, while the rebound effect is due to the increase in the energy consumption caused by the application of technologies (Lin, 2019; Yan, 2019). Overall, carbon emission reduction effect in the transportation sector is closely related to the characteristics of local technology bias. The technology in the north is biased toward fossil energy production and electric vehicle manufacturing; therefore, the carbon emissions are higher.

6 Conclusion and policy suggestions

6.1 Conclusion

In this paper, based on the panel data, considering technology bias as the threshold variable, a nonlinear dynamic threshold effect model of the influence of biased technology on traffic CO_2 emissions in different regions is constructed via the GMM method. The research conclusion shows that the threshold value of technological bias is different in eight different regions, and with the change in the threshold value, the influence of technological progress bias on traffic carbon emissions exhibits considerable spatial differentiation. The conclusions are as follows: In Northeast China, the middle mainstream of the Yellow River, the eastern coast, the Southeast Coast, the middle mainstream of the Yangtze River and the Northwest region, as the technological progress bias crosses the threshold value, the influence of technological progress bias on traffic CO_2 emission changes from positive to negative. These areas show the characteristics of inverted U emission, that is, due to industrial upgrading or environmental regulation constraints in these areas, the energy-enhanced technological progress is gradually replaced by energy-saving technologies, and the transportation industry shows the energy rebound effect initially, followed by the energy-saving and emission reduction effect subsequently. In North China, with the enhancement of energy-biased technological progress and the further expansion of transportation energy demand, it is in the left part of inverted U curve, and the CO_2 emission level increases further. In Northwest China, due to the lag of industrial development, the transportation energy consumption is relatively constant, and the energy rebound effect is not significant. However, when the energy-saving technology advances to a certain level, it can reduce the traffic CO_2 emission. The carbon emission reduction caused by technological progress bias is closely related to the technology structure, industrial development and energy demand in different regions. These findings have a strong reference value for the technological path of low-carbon transportation in the other developing countries.

6.2 Policy suggestions

Based on the above research conclusions, the following are the policy suggestions:

First, regional traffic emission reduction measures should anchor the biased characteristics of regional technological progress. At present, the energy-saving biased technological progress of transportation industry in Northeast China, the middle mainstream of the Yellow River, the Southeast Coast, the middle mainstream of the Yangtze River and Northwest China is on the left side of the inverted U-shaped curve, and the energy consumption and carbon emissions increase further. Therefore, it is necessary to broaden the acquisition renewable technology, and provide cross-regional technology spillover platform construction, speedily accumulate renewable technologies and cross the threshold as soon as possible. For example, the "Measures for the Implementation of the Law of China on Energy Conservation for Highway and Waterway Transportation" published the technical catalog of energy-saving products for operating vehicles and vessels to guide the use of advanced energy-saving products and technologies in order to promote the innovation of energy-saving technologies and the transformation of achievements. The eastern coastal areas and Southwest areas have crossed the threshold value, and their main task is to focus on building a perfect transfer and transformation mechanism of green technology. The white paper "China's Policies and Actions to Address Climate Change" proposes the support of the transfer and transformation of green technology achievements and establishment of a comprehensive national green technology trading market. Compared with technology accumulation, Beijing–Tianjin–Hebei region should pay more attention to the improvement of its energy structure and transportation structure. For example, the "Beijing–Tianjin–Hebei transportation structure adjustment demonstration area construction plan (2018–2020)" organized the implementation of special railway construction, port bulk cargo freight services improvement, the development of hot metal container multimodal transport and multimodal transport information connectivity project.

Second, the formulation of relevant incentive policies for transportation energy substitution factors needs to be accelerated. The substitution of renewable energy for non-renewable energy has a significant impact on the energy-biased technology. Therefore, carbon neutrality in transportation can be improved by developing new energy fuels and equipment, expanding business scale and increasing capital through mergers and acquisitions. For example, the "14th Five-Year Plan for Renewable Energy Development" proposes to promote the replacement of green hydrogen in key areas such as transportation. We intend to promote the demonstration application of fuel cells in port areas, ships, and key industrial parks, coordinate the development of green hydrogen terminal supply facilities and capacity, and increase the proportion of green hydrogen used in transportation. In terms of capital-biased technology, energy efficiency can offset within the service life of low-energy equipment.

Despite this, the study features a few limitations. The analysis is nonlinear for eight regions in China. However, for the individual subsectors of road, rail, and aviation, no further investigation has been undertaken. Analysis of individual transport sectors can reveal more details, such as firm-level determinants of the direction of technological change, the distribution of certain parameters or their evolution over time.

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Author contributions XY was involved in conceptualization, methodology, software, validation, formal analysis, investigation; ZZJ helped in resources, data curation, writing—original draft preparation, writing—review and editing, visualization. All authors have read and agreed to the published version of the manuscript.

Declarations

Conflict of interest The authors declare no conflict of interest.

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