



Development strategy, technological progress, and regional environmental performance: empirical evidence from China

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Abstract

Based on regional economic development theories, industrial development strategies implemented by governments can distort factor market allocations, change the viability of firms, and thus bring about structural changes in industries. How such policy changes will affect regional environmental performance has been relatively little discussed in the existing literature. This paper attempts to explain whether the implementation of an industrial catch-up development strategy can be a major influence on the level of regional environmental performance from the perspective of comparative advantage, and how this influence can be achieved by changing technological progress. As for the measurement of environmental performance, this paper innovatively adopts two improved measurements based on by-production technology theory to measure the regional environmental performance of Chinese provincial regions from 1997 to 2016. Moreover, the other main novelty is that it adopts Tobit regression models to explicitly explore the effective effects and impact mechanisms of government development strategies on regional environmental efficiency in China. The key findings are as follows (i) the implementation of an industrial catch-up development strategy that defies the comparative advantage of a region can lead to poor environmental performance. (ii) the comparative advantage defying strategy adopted by the eastern regions with higher level of economic development and the regions with priority protection of resources and environment has less inhibiting effect on environmental performance than the central and western regions. (iii) development strategy does impact environmental efficiency through technological progress; more precisely, through technology import and technological transformation rather than independent R&D.

Keywords Development strategy · By-production technology · Technological progress · Environmental efficiency · Structural change

1 Introduction

During the past 40 years of reform and openness, China's economy has maintained steady, rapid, and sound growth, creating a "growth miracle". However, along with the 'miracle', there are some unnoticed environmental problems that pose great challenges to long-term sustainable development. In recent years, China implemented a series of reform measures, including the establishment of the Ministry of Natural Resources and the Ministry of Ecology and Environment in 2018,¹ demonstrating China's increasing attention paid to environmental issues. In the stage of high-quality development, green development is a hallmark and defining feature of high-quality development, making the study of environmental performance a major topic for the government and academic communities.

Existing studies mainly focus on explaining environmental performance within the framework of foreign trade, policy regulation, market distortions, structural adjustment, and competition between local governments (Klassen and McLaughlin 1996; Esty and Porter 2005; Liu et al. 2021; Song et al. 2015; Li and Ramanathan 2018; Lin and Chen 2018; Ouyang and Sun 2015;). However, in sustainable development, resources and the environment are not only endogenous variables of economic development but also hard constraints to the scale and speed of economic development (Nordhaus 1974; Chai et al. 2021; Halkos and Managi 2023; Trukhachev and Dzhikiya 2023). The underlying issues that economists constantly face in environmental economics are how to explain the relationship between economic development and pollution and how to achieve high growth while also maintaining low emissions. In the classical studies of environmental economics, the Environmental Kuznets Curve (EKC) seems to be solid proof for the relationship trajectories between economic development and environmental performance, which was also cited in the World Bank Development Report 1992. However, many researchers remain skeptical of this hypothesis, and it remains a controversial topic. The mixed conclusions of existing studies on EKC are due to different categories of pollutants, periods of time, and model construction (Dinda 2004; Stern 2004; Harbaugh et al. 2002; Song et al. 2013).

Recently, there has been a wealth of research discussing the relationship between China's development and China's environmental problems. Many studies emphasize the complex relationship between China's environmental problems and industrial structure (Chen and Liu 2018). Although heavy industries and energy-intensive manufacturing sectors are major contributors to environmental problems, technological innovation, industrial restructuring, and effective environmental regulation can help promote environmental sustainability while promoting economic growth (Alshuwaihat and Abubakar 2008; Bai et al. 2019; Ouyang et al. 2020). However, while this literature validates the relationship between industrial development and environmental issues, it rarely discusses the role of government. The industrial structure, especially in the Chinese reality, is often the result of the type of development

¹ The purpose is to integrate responsibilities of environmental protection, centralize supervision and administrative law enforcement for various pollutants discharge, and strengthen pollution management.

strategy that the government implements, and therefore may be a significant cause of regional differences in environmental performance.

In light of China's development reality, a major factor contributing to the unsustainability of the high input–output development mode across various regions is the adoption of heavy industry-focused development strategies by local governments during the early stages of development. These strategies prioritized output while neglecting input constraints, resulting in the heavy industry, a capital-intensive industry that defied China's comparative advantage at the time, being artificially developed (Rawski 1995). This made it impossible for the market mechanism to prioritize its development, as the market would return to competitive equilibrium in response to exogenous shocks to production structure. Therefore, institutional cost reductions were introduced to lower the prices of capital, foreign exchange, energy, raw materials, agriproducts, and labor, and to lower the threshold to capital for the heavy industry. This resulted in an environment of highly centralized macroeconomic policies that extensively distorted the prices of products and factors, accommodating the heavy industry-focused development strategy. While these distortions have been somewhat reduced with the transformation and development of the Chinese economy, the comparative advantage defying (CAD) strategy is still being implemented to varying degrees in various regions (Lin 2003, 2012). This is mainly due to the fact that most pollutants in China come from extensive industries with relatively backward technology. According to China's annual environmental statistics bulletins, despite declines in recent years, emissions of the main air pollutants remain prominent, and the main sources of sulfur dioxide and nitrogen oxides are the power, steelmaking, papermaking, printing, and dyeing industries. These traditional industries are characterized by large-scale, backward technologies.

Theoretically, if a region adopts comparative advantage following development strategy (CAF) (Lin 2003), firms in the region would have better abilities to achieve technological progress, which in turn would be conducive to improving environmental performance. Conversely, if a regional government adopts a CAD strategy, the firms in that region would have weaker abilities to perform technological research and development (R&D). Therefore, even if the government introduces environmental governance policies, firms with weaker viability would make these policies ineffective, resulting in poor environmental performance.

Based on the above analysis, this paper aims to explore the intrinsic influence mechanism of governmental development strategies on environmental performance. This paper differs from other literature in several ways. First, it recognizes the government's development strategy as a significant influencing factor when discussing the environmental problems caused by an unreasonable industrial structure. Second, the paper incorporates the concept of regional comparative advantage to measure the rationality of development strategies. Third, using by-production technology, this paper adopts new technical methods to measure regional environmental efficiency and technical efficiency. Finally, the empirical test aims to explore the direct impact of industrial catch-up development strategies on the environment and analyze the intrinsic mechanisms from the perspective of technological progress.

This paper is structured as follows. Section 2 provides a review of the existing literature on the methodology of environmental performance measurement and

empirical studies on the linkage between environmental performance and economic development issues. In Sect. 3, we calculate regional technical efficiency and environmental efficiency using two efficiency measurements. Section 4 presents the results of a series of empirical analyses conducted to investigate the relationship between development strategy and environmental performance. Section 5 discusses the significance of the empirical results and proposes policy recommendations. Finally, Sect. 6 concludes the paper.

2 Literature review

According to previous literature on production theory, a production unit is considered efficient if it is along the technical frontier of optimal output at a given input level (Koopmans 1951). Therefore, Farrell (1957) proposed two classical efficiency measures that are, respectively, “input-oriented” and “output-oriented” (together known as Debreu-Farrell efficiency measures) and based on radial contraction of all inputs and radial expansion of all outputs. With constant returns to scale, the results of these two measures will be reciprocal to each other. Lovell (1993) defines the efficiency of a production unit in terms of a comparison between observed and optimal values of its output and input according to the measures above. However, Debreu-Farrell efficiency does not yield valid results when pollutant emissions are considered “undesirable output”.

Current measures that integrate environmental issues into the assessment of production efficiency are associated only with quantitative information on pollution, while nonparametric estimation-based evaluation methods do not require specifying the form of the production function and can effectively solve the problem of considering pollution as “undesirable output”. Therefore, defining the relationship between “desirable output” and “undesirable output” is the premise of using nonparametric estimation to measure production efficiency. In recent decades, there has been a great deal of literature on pollutant emissions-related production equations and technical efficiency measures (Coggins and Swinton 1996, 1993, 2005; Färe et al. 1989). However, these investigations, basically based on the hypothesis of a positive correlation between “desirable output” and “undesirable output”, describe the positive relationship between them in an approximately linear way to generalize the nature of pollution-generating technologies. In “undesirable output”, the existing literature asserts that the disposability of emission is not arbitrary and has a proportional correlation with “desirable output” (often called “weak disposability”). In many empirical investigations, the nonparametric or parametric paradigm of “weak disposability” has been widely applied to measure production efficiency, environmental efficiency, and the shadow price of pollutants.

However, explaining the relationship in such a simplistic way may lead to a series of problems that do not correspond to reality. A recent study by Murty et al. (2012) shows that the production technology approach based on “weak disposability” can lead to an irregular description of the relationship between inputs, desirable output,

and undesirable output in the production function. To avoid such a situation, Murty et al. (2012) proposed a theoretical approach to explain pollution-generating technologies, which can better reflect the characteristics of the residual mechanism of nature in production and is called the by-production (BP) approach. It clearly distinguishes between two types of inputs in the production equation, i.e., pollution-causing input (e.g. energy inputs such as fossil fuels) and nonpollution-causing input (e.g. capital and labor), and it divides the production process into two subsets of technologies: a. an intended production technology, which satisfies standard free-disposability properties with respect to inputs and outputs; and b. a residual generation technology, which describes the relationship between undesirable output and costly disposability with respect to pollution. Murty et al. (2012) focuses mainly on the production function modeling under pollution constraints, but the index measurements are simulations. Subsequently, Rayl et al. (2018), and Aparicio et al. (2019) applied the BP approach and real-world data to conduct preliminary measurements and empirical tests of environmental performance and green productivity in some regions, but the applicability of the results and the economic and structural factors reflected in the efficiency differences between different production units will be further studied.

In addition to technical approaches for constructing environmental efficiency, recent empirical studies highlight the important linkages between environmental efficiency, energy efficiency, economic activities, and sustainable development. These linkages are multidimensional and complex, involving interactions among industrial, trade, social, and environmental factors (Gladwin et al. 1995; Koengkan and Fuinhas 2022; Leitão et al. 2022; Karimi Alavijeh et al. 2022). For instance, Wang et al. (2017) examine the impact of energy efficiency and economic structure on carbon emissions in China's regions, and suggest that improvements in energy efficiency can help to reduce carbon emissions. Similarly, Li et al. (2018) evaluate the environmental efficiency of China's regional industry using a data envelopment analysis (DEA) approach and show that factors such as industrial structure, technology level, and energy intensity play significant roles in influencing efficiency. Kazemzadeh et al. (2022) adopt a two-step approach that combines the DEA model and panel quantile regression to demonstrate the impact of energy efficiency and export quality on ecological footprint. At the micro level of firm research, Wang et al. (2020) apply a two-stage network DEA model to calculate the energy and environmental efficiency of iron and steel companies and identify the key factors affecting the industry's energy and environmental efficiency, such as the proportion of new technologies and the utilization of clean energy sources. These studies provide valuable insights into the relationship between environmental efficiency, energy efficiency, and sustainable development, and their findings can help guide policy formulation and practice.

In terms of the impact of development strategy, most empirical studies focus on the impact of an economy's choice of its development strategy on different aspects of its economic development. Lin (2003) uses Technology Choice Index (TCI) as an indicator of the strategy followed by a given country, and the TCI is constructed

as the value added to the labor ratio in manufacturing over the total value added to the labor force ratio in the country. To measure the impact of development strategy on economic growth, Lin (2003) developed a cross-sectional model for 51 countries in the period 1970 to 1992. The results show that the impact of the regional development strategy is statistically significant during the period and that the CAD strategy may lead to lower per capita real GDP growth rates in some countries. For provincial-level regions in China, Lin and Liu (2008) show that the choice of development strategy also has a significant impact on their GDP growth rates. Economies adopting a CAD strategy have lower per capita GDP growth rates than those adopting a comparative advantage CAF development strategy. Bruno et al. (2015) further explore the impact of the development strategy on financial structural distortions and economic growth, with special reference to transition economies. Ju et al. (2015) propose a theory of endowment-driven structural change by developing a tractable growth model with infinite industries. In the empirical analysis of industry dynamics, Ju et al. (2015) explore the value added to labor ratio in emerging industries over the total value added to the labor force ratio in the manufacturing industry. The results show that an industry is larger in scale if its capital intensity is consistent with the endowment structure.

After reviewing the literature, it is evident that there are several research gaps that need to be addressed. Firstly, although there have been numerous studies on environmental performance measurement, most of them focus on introducing measurement methods and analyzing regional differences in measurement results. Few studies have analyzed the causes of regional differences, such as policy influence, economic development level, geographical factors, and historical reasons, in measuring regional environmental efficiency in China. Secondly, while the by-production approach is an effective way to separate production efficiency from environmental efficiency, there are no articles that have utilized this method to conduct empirical studies on regional or enterprise-level samples. Lastly, few studies have explored the environmental impact of industrial policies and development strategies formulated by governments. This could be attributed to the difficulty of measuring the effectiveness of development strategies. However, this paper addresses this gap by determining the type of development strategy based on its consistency with comparative advantage and assessing its impact on the environmental issues brought about by industrial development.

This study provides valuable insights into the relationship between development strategies and technical efficiency under environmental constraints and evaluates the impact of different development strategies on environmental efficiency. By highlighting the crucial role of development strategies in improving environmental performance, the findings of this study can guide policy formulation and practice more effectively.

3 Methodology, variables, and data

3.1 Estimation of environmental efficiency under the by-production approach

We will assume that there are N inputs, M desirable outputs, and K emission types (undesirable outputs). Input vector is denoted by $x = (x_1, \dots, x_N) \in \mathbb{R}_+^N$, desirable output vector is denoted by $y = (y_1, \dots, y_M) \in \mathbb{R}_+^M$, and undesirable outputs vector is $z = (z_1, \dots, z_K) \in \mathbb{R}_+^K$. In the BP approach, N inputs will be classified into nonemission-causing and emission-causing inputs. The first N_1 inputs are non-emission causing, while the last N_2 inputs are emission-causing. Hence, $N_1 + N_2 = N$. The vectors of them can be denoted by $x^1 = (x_1, \dots, x_{N_1}) \in \mathbb{R}_+^{N_1}$ and $x^2 = (x_{N_1+1}, \dots, x_N) \in \mathbb{R}_+^{N_2}$ respectively. When producers use pollution-causing inputs, the production of desirable outputs would set a residual mechanism of nature in motion, leading to the generation of undesirable outputs (Murty et al. 2012).² Therefore, the emission-generating technologies can be separated into two sets of technologies: T_1 is the conventional production technologies, which reflects the transformation of all inputs into desirable outputs; and T_2 denotes nature’s residual generating technology of nature, which shows how emission-causing goods used in T_1 generate emissions in nature. Hence, the parametric formulation of a BP emission generating technology is given as

$$\begin{aligned}
 T_{BP} &= T_1 \cap T_2, \\
 T_1 &= \left\{ \langle x^1, x^2, y, z \rangle \in \mathbb{R}_+^{N+M+K} \mid f(x^1, x^2, y) \leq 0 \right\}, \\
 T_2 &= \left\{ \langle x^1, x^2, y, z \rangle \in \mathbb{R}_+^{N+M+K} \mid g(x^2, z) \geq 0 \right\}.
 \end{aligned}
 \tag{1}$$

Functions f and g are the parametric representations of sets T_1 and T_2 respectively. We assume that both functions are continuously differential and nonempty. Hence, we will assume the following signs for the derivatives of function f :

$$\begin{aligned}
 f_{x_n}(x^1, x^2, y) &\leq 0, \forall n = 1, \dots, N_1, \\
 f_{x_n}(x^1, x^2, y) &\leq 0, \forall n = N_1 + 1, \dots, N, \\
 f_{y_m}(x^1, x^2, y) &\geq 0, \forall m = 1, \dots, M.
 \end{aligned}
 \tag{2}$$

The signs of these derivatives imply that all inputs satisfy standard free disposability and all desirable outputs are also freely disposable. In particular, along the frontier of technology T_1 , there is a positive relationship between any input and any desirable output. In addition, the technology set T_1 is independent of the level of emissions, which means that emissions do not affect desirable production.

² The nature’s residual generation is a production technology judged by the final output, and its influencing factors include both the content of elements in pollution causing inputs and the use of pollution abatement techniques in the production process.

Set T_2 in (1) reflects the physical and chemical mechanism of pollution generation in nature. In nature, the more emissions-causing goods are used, the more emissions are generated. should capture this. We assume the following signs for the derivatives of function g .

$$\begin{aligned} g_{x^n} (x^2, z) &\leq 0, \forall n = N_1 + 1, \dots, N, \\ g_{z^k} (x^2, z) &\geq 0, \forall z_k = 1, \dots, K. \end{aligned} \tag{3}$$

Under these sign conventions, the production vectors $\langle x^1, x^2, y, z \rangle \in \mathbb{R}_+^{N+M+K}$ that satisfy $g(x^2, z) = 0$ form the lower frontier of technology T_2 . For every vector of emission-causing inputs, this frontier gives the minimal levels of emissions generated in nature. This property has been called costly disposability of emissions, and it captures our intuition that emissions are not freely disposable as outputs. The use of emission-causing inputs definitely produces some minimal emissions. Using the implicit function theorem, it can be shown that these sign conventions imply that the trade-off between any emission-causing input and any emission type along the lower frontier of technology T_2 is $-\frac{g_{z_k}}{g_{x_n}}$, which is non-negative. Thus, this captures the positive relation between emission-causing goods such as fossil fuels and emissions such as CO_2 and SO_2 .

Under the BP approach, the technical efficiency of production under environmental constraints can be measured by constructing a nonparametric formulation, and a DEA construction of the nonparametric version of the BP technology is as follows: the matrix of observations on non-pollution causing inputs be denoted by $X_{D \times N_1}^1$ and the pollution causing inputs be denoted by $X_{D \times N_2}^2$. Let the matrices of observations on desirable and undesirable outputs be denoted as before by $Y_{D \times M}$ and $Z_{D \times K}$, respectively. Then the standard DEA nonparametric representation of BP can be specified as

$$\begin{aligned} T_1 &= \left\{ \langle x, y, z \rangle \in \mathbb{R}_+^{N+M+K} \mid \lambda [X^1, X^2] \leq \langle x^1, x^2 \rangle \wedge \lambda Y \geq y, \lambda \in \mathbb{R}_+^D \right\} \\ T_2 &= \left\{ \langle x^1, x^2, y, z \rangle \in \mathbb{R}_+^{N+M+K} \mid \mu X^2 \geq x^2 \wedge x^2 \wedge \mu Z \leq z, \mu \in \mathbb{R}_+^D \right\} \\ T_{BP} &= T_1 \cap T_2 = \left\{ \langle x^1, x^2, y, z \rangle \in \mathbb{R}_+^{N+M+K} \mid \lambda [X^1, X^2] \leq \langle x^1, x^2 \rangle \wedge \lambda Y \geq y \wedge \mu Z \leq z, \langle \lambda, \mu \in \mathbb{R}_+^{2D} \rangle \right\} \end{aligned} \tag{4}$$

Here, λ and μ represent the intensity vectors, which are the weights assigned to each decision making unit (DMU) to construct the technically efficient frontiers of T_1 and T_2 under DEA. Following by the concept of nonparametric technical efficiency measurement under the BP approach, in this paper, we will focus on output-based measures of efficiency and consider two types of efficiency index: the hyperbolic (HYP) efficiency index and the modified Färe-Grosskopf-Lovell (FGL) efficiency. Since the BP approach distinguishes between desirable production technology T_1 and nature’s emission-generating technology T_2 , a technical efficiency index defined under the BP approach can be implicitly or explicitly decomposed into two components: the index of desirable production efficiency (production) and an index of

undesirable production efficiency (environmental). In the case of the HYP measure of efficiency in a BP technology, this decomposition is explicit, while in the case of the FGL measure, the decomposition is implicit.

The HYP measure of efficiency decomposes efficiency explicitly into desirable production efficiency, which is defined relative to set T_1 , and environmental efficiency, which is defined relative to T_2 . The former is denoted by $D_{HYP(1)}$ and the latter is denoted by $D_{HYP(2)}$. Intuitively, holding all inputs fixed, $\frac{1}{D_{HYP(1)}}$ measures the maximal factor by which the given desirable output vector can be scaled down and yet be technologically feasible, while $\frac{1}{D_{HYP(2)}}$ captures the maximal factor by which the bad output vector can be scaled down and yet be technologically feasible. The overall index of efficiency, denoted by D_{HYP} is obtained by taking the maximum of $D_{HYP(1)}$ and $D_{HYP(2)}$. This implies that $\frac{1}{D_{HYP}}$ is the maximal extent to which the good output vector and the bad output vector can be simultaneously scaled up and scaled down, respectively, and yet be technologically feasible. In the BP approach, given a vector of inputs, the output possibility sets corresponding to T_1 and T_2 are independent. When $D_{HYP(1)} = 1$, the observed point is on the weakly efficient frontier of T_1 and when $D_{HYP(2)} = 1$, the observed point is on the weakly efficient lower frontier of T_2 . An observation is inefficient when D_{HYP} is strictly less than 1.

In the following, we present the DEA program for measuring hyperbolic efficiency: for each DMU d in each different year t , the HYP efficiency is measured as

$$\begin{aligned}
 &D_{HYP}(x_d^t, y_d^t, z_d^t) = \min(\beta_1, \beta_2), \\
 &D_{HYP(1)} = \min_{\lambda, \beta_1} \beta_1 \\
 &s.t. \sum_{t=1}^T \sum_{d=1}^D \lambda_d^t x_{d,m}^t \geq \frac{y_{d,m}^t}{\beta_1}, \quad \forall m = 1, \dots, M \\
 &\quad \sum_{t=1}^T \sum_{d=1}^D \lambda_d^t x_{d,n}^t \leq x_{d,n}^t, \quad \forall n = 1, \dots, N \\
 &\quad \lambda_d^t \geq 0, \quad \forall d = 1, \dots, D. \tag{5} \\
 &D_{HYP(2)} = \min_{\lambda, \beta_2} \beta_2 \\
 &s.t. \sum_{t=1}^T \sum_{d=1}^D \lambda_d^t x_{d,k}^t \geq \frac{y_{d,k}^t}{\beta_2}, \quad \forall K = 1, \dots, K \\
 &\quad \sum_{t=1}^T \sum_{d=1}^D \lambda_d^t x_{d,m}^t \leq x_{d,m}^t, \quad \forall n = 1, \dots, N \\
 &\quad \mu_d^t \geq 0, \quad \forall d = 1, \dots, D.
 \end{aligned}$$

FGL calculates the single efficiency value of each desirable and undesirable output and then adopts a weighted average to calculate the production efficiency and environmental efficiency of each production unit. $D_{FGL(1)}$ measures the production efficiency of the DMU in desirable production, while $D_{FGL(2)}$ measures its environmental efficiency. The key feature of this index is that the final weighted composite efficiency value is efficient when and only when the DMU is efficient in vectors of

both desirable and undesirable output, and its optimization algorithm is expressed as follows.

$$\begin{aligned}
 D_{FGL}(x_d^t, y_d^t, z_d^t) &= \min_{\lambda, \theta, \mu, \gamma} \frac{1}{2} \left[\frac{\sum_{m+1}^M \theta_m}{M} + \frac{\sum_{k+1}^K \gamma_k}{K} \right], \\
 D_{FGL(1)} &= \min_{\lambda, \theta} \frac{\sum_{m+1}^M \theta_m}{M} \\
 \text{s.t. } \sum_{t=1}^T \sum_{d=1}^D \lambda_d^t x_{d,m}^t &\geq \frac{y_{d,m}^t}{\theta_m}, \quad \forall m = 1, \dots, M \\
 \sum_{t=1}^T \sum_{d=1}^D \lambda_d^t x_{d,n}^t &\leq x_{d,n}^t, \quad \forall n = 1, \dots, N \\
 \lambda_d^t &\geq 0, \quad \forall d = 1, \dots, D. \\
 D_{FGL(2)} &= \min_{\lambda, \theta} \frac{\sum_{k+1}^K \gamma_k}{K} \\
 \text{s.t. } \sum_{t=1}^T \sum_{d=1}^D \mu_d^t z_{d,m}^t &\leq z_{d,k}^t \gamma_k, \quad \forall k = 1, \dots, K \\
 \sum_{t=1}^T \sum_{d=1}^D \mu_d^t x_{d,m}^t &\leq x_{d,m}^t, \quad \forall n = N_1 + 1, \dots, N \\
 \mu_d^t &\geq 0, \quad \forall d = 1, \dots, D.
 \end{aligned} \tag{6}$$

3.2 Tobit regression model

Based on similar studies (Lin and Xu 2021; Liu et al. 2023; Asar and Ögütçüoğlu 2021; Laura et al. 2023; Dalei and Joshi 2023; Harvey and Liao 2023), this paper uses the Tobit model as the basic model to test the relationship between development strategy and regional environmental efficiency. This is because the values of the environmental performance index are all doubly truncated data between 0 and 1. When using the DEA method to estimate efficiency, there will be one or more DMUs at the efficiency boundary of DEA (efficiency of 1). In this case, where multiple samples are at some limiting value in a given range, conventional regression methods cannot explain the difference in nature between the limiting and non-limiting observations. The implementation steps of empirical analysis are shown in Fig. 1.

$$\begin{aligned}
 EFF_{it}^* &= \alpha_0 + \alpha_1 TCI_{it} + X_{it} \beta + \gamma_i + \delta_t + \varepsilon_{it} \\
 EFF_{it} &= EFF_{it}^*, \text{ if } EFF_{it}^* \in (0, 1]; \\
 EFF_{it} &= 0, \text{ if } EFF_{it}^* \in (-\infty, 0]; \\
 EFF_{it} &= 1, \text{ if } EFF_{it}^* \in (1, +\infty].
 \end{aligned} \tag{7}$$

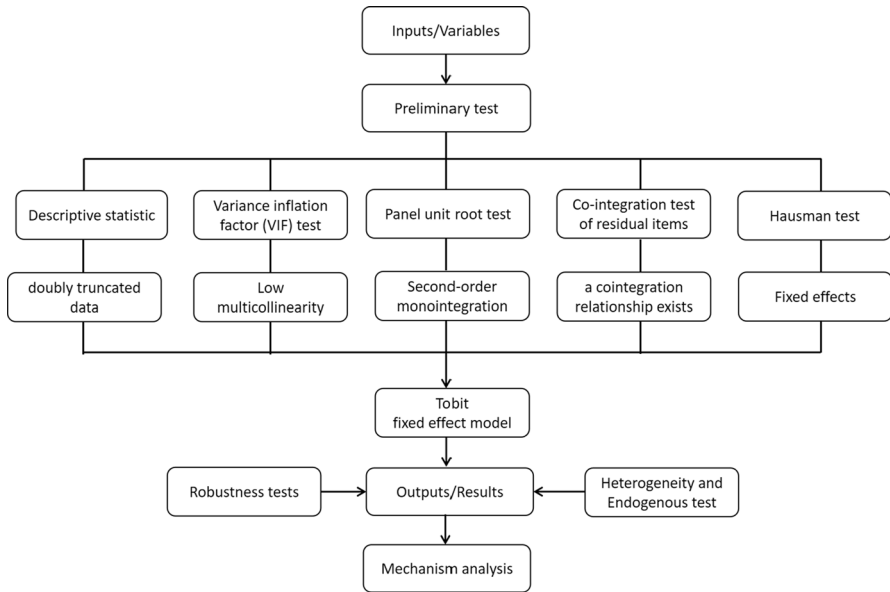


Fig. 1 The implementation steps of empirical analysis

EFF_{it} denotes the actual environmental performance variable measured during the time period t in region i ; EFF_{it}^* denotes the hidden variable, which satisfies the classical assumptions of the econometric model; TCI_{it} denotes the extent to which the development strategy during the time period t in region i defies comparative advantage, and we expect its estimated coefficient to be negative; X_{it} denotes other control variables; γ_i denotes the region fixed effect of the region, which is used to control persistent individual differences between regions; δ_t denotes time fixed effects to control the impact of time-varying factors; ε_{it} denotes random error.

3.3 Variables and data

Dependent variable: Environmental efficiency is used as a dependent variable in the Tobit regression model. This paper measures environmental efficiency and its components in 30 provincial-level regions in China. The inputs include capital, labor, fuel coal (total consumption of raw coal and coke), and fuel oil (total consumption of kerosene, diesel, and gasoline); the outputs include GDP, industrial sulfur dioxide, industrial soot, and industrial solid waste. The descriptive statistics are shown in Table 1.

Core independent variables: The core independent variables in this paper are crucial for testing its hypothesis. According to Lin (2003), the factor endowment

Table 1 Descriptions and data sources for each variable

Variable	Definition	Obs	Mean	Std. dev	Min	Max
K	Capital stock (billion CNY)	600	801.11	970.73	21.29	6780.73
LABOR	Employees (10,000 persons)	600	2451.62	1640.25	254.84	6726.00
LOIL	Fuel consumption (kerosene + diesel + gasoline) (10,000 tons)	600	687.19	578.91	1.04	3470.70
COAL	Coal consumption (coal + coke) (10,000 tons)	600	10,610.02	9389.98	139.18	44,657.56
GDP	Per 100 million CNY	600	2640.44	2933.13	56.27	19,209.90
SO	Industrial SO ₂ (ton)	600	580,782.80	379,002.90	10,257.00	1,800,000
DUST	Industrial soot emissions (ton)	600	307,447.20	239,226.80	6520.00	1,500,000
SOLID	Industrial solid waste (10,000 tons)	600	6235.82	6750.95	69.00	45,576.00
TCI	Development strategy	600	2.126	0.839	0.750	7.470
ZZYF	Independent R&D	600	0.009	0.005	0.000	0.030
JSYJ	Technology import	600	0.002	0.002	0.000	0.013
JSGZ	Technological transformation	600	0.011	0.007	0.000	0.043
RGDP	Per capita GDP	600	2.581	2.240	0.223	11.813
RGDP2	Per capita GDP ²	600	11.669	20.256	0.050	139.541
FDI	FDI	600	0.027	0.026	0.000	0.165
OPEN	Openness	600	0.320	0.610	0.032	12.050
PDEN	Population density	600	3.913	4.657	0.069	29.445
FDEC	Fiscal decentralization	600	0.530	0.183	0.148	0.951
SOE	Share of SOEs	600	0.450	0.209	0.094	0.899
PFEE	Environmental governance	600	0.001	0.001	0.000	0.008

structure of an economy (including a country or region) determines its optimal industrial structure, and a development strategy that goes against comparative advantage is a distortion of the optimal industrial structure. Therefore, the degree of distortion in the industrial structure can be used as a reasonable measurement index for the development strategy.

$$TCI_{it} = \frac{AVM_{it}/LM_{it}}{GDP_{it}/L_{it}}$$

AVM_{it} denotes industrial added value of economy i in year t ; GDP_{it} denotes the GDP of economy i in year t ; LM_{it} denotes the number of employees in the industrial sector of economy i in year t ; and L_{it} denotes the total employees in economy i in year t . The TCI indicates that the deviation of the economic development strategy i away from its comparative advantage: the larger the TCI value, the further it deviates.

Mechanism variables: To test the hypothesis of the mechanism proposed in this paper, we examine how the development strategy influences environmental performance through technological progress. Technological progress is divided into three

aspects: technology import, technological transformation, and independent R&D. The corresponding indices for the three aspects are the ratio of technology import expenditure to GDP, the ratio of technological transformation expenditure to GDP, and the ratio of R&D expenditure to GDP.

Control variables: (i) GDP per capita and its quadratic term. Considering the Environmental Kuznets Curve, we introduce the logarithm of GDP per capita and its quadratic term into the model to reflect the relationship between economic development stage and environmental pollution. The study expects an inverted U-shaped curve. In contrast, regarding environmental efficiency, we expect a U-shaped curve. Therefore, we anticipate the estimated coefficient of the linear term of per capita GDP to be negative and the estimated coefficient of the quadratic term to be positive. (ii) Foreign direct investment (FDI). It is indicated by the FDI to GDP ratio and is mainly used to test the hypothesis of a “pollution haven.” (iii) The degree of openness, denoted by the ratio of total imports and exports to GDP, which we expect to be positive. (iv) Population density, denoted by the ratio of year-end total population to the total area of the region, which we expect to be positive. (v) Fiscal decentralization, denoted by the ratio of provincial fiscal expenditure per capita to central government fiscal expenditure per capita. We expect its estimated coefficient to be positive. (vi) Share of state-owned enterprises (SOEs), denoted by the ratio of the total output value of SOEs and state-owned holding companies to the total industrial output value, which we expect to be negative. (vii) Environmental governance, denoted by the ratio of emission charges to industrial added value, which we expect to be positive.

The samples in this paper consist of the longitudinal data of 30 provincial-level regions in China from 1997 to 2016. Raw data for each variable are obtained from sources such as “China Statistical Yearbook,” “China Statistical Yearbook on Environment,” “China Environment Yearbook,” “China Industry Economy Statistical Yearbook,” “China Energy Statistical Yearbook,” and statistical yearbooks of province-level regions. All price-based indices were adjusted to constant prices in 1997. Table 1 includes descriptions of each variable, revealing that some variables have outliers. Therefore, outlier treatment is adopted in the following empirical tests.

3.4 Production and environmental efficiency measurements

Figure 2 presents the mean values of production efficiency, environmental efficiency and overall efficiency measured using the HYP method. During the sample period, the production efficiency shows a decreasing trend, while the environmental efficiency has a decreasing trend during 1997–2003, while it shows an increasing trend year by year from 2003–2016, and the overall efficiency is the lowest among these three indices, but its direction coincides with the environmental efficiency. Figure 3 presents the mean values of production efficiency, environmental efficiency and overall efficiency in the country measured by the FGL method. The environmental efficiency is the lowest among the three indices during 1997–2015, and the trend of the overall efficiency coincides with the environmental efficiency.

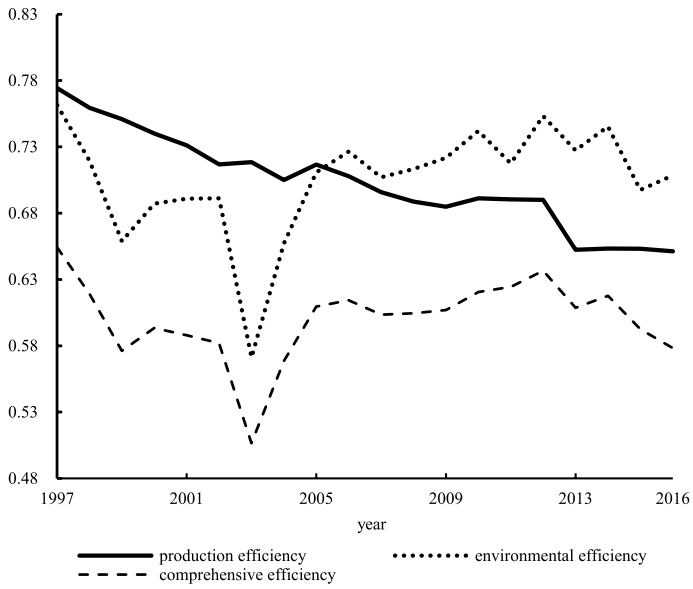


Fig. 2 HYP measurement

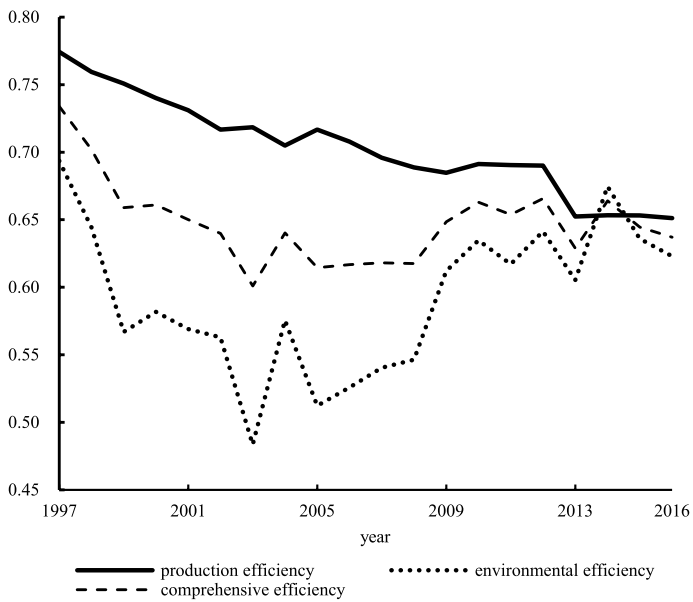


Fig. 3 FGL measurement

Based on the measured performance of each type of efficiency, the eastern region of China exhibits a clear advantage over the central and western regions, with the central region in the middle, and the western region being the worst performer in terms of both production technology and environmental performance (see, Figs. 4, 5, 6, 7, 8 and 9). An interesting observation is that the environmental efficiency of the eastern region and the central region were almost at the same level by the HYP method until 2003, as shown in Fig. 6. Even in some early years, the central region was slightly higher than the eastern region. Similarly, the results measured by the FGL method show that the difference in environmental efficiency between the eastern and central regions is not too significant in the early years of the sample. However, the difference between the eastern region and the central region gradually widens in the subsequent sample years. This indicates that before 2003, the production technology level in the eastern region was significantly higher than that in the central and western regions, but there was no significant advantage in environmental management technology. As the gap between the regional economic development levels continues to widen, the level of environmental management technology in the eastern region continues to improve and surpasses that of other regions.

4 Empirical analysis

4.1 Preliminary tests

In order to employ the Tobit fixed effect model in this paper, a sequence of preliminary tests are conducted on the variables (see, Fig. 1). Firstly, a variance inflation factor (VIF) test is conducted, result reveals that $\max\{vif_1, vif_2, \dots, vif_k\} = 3.49$, indicating that the statistical value of all variables is significantly lower than the minimum value (10) required by the rule of thumb. This suggests that the problem

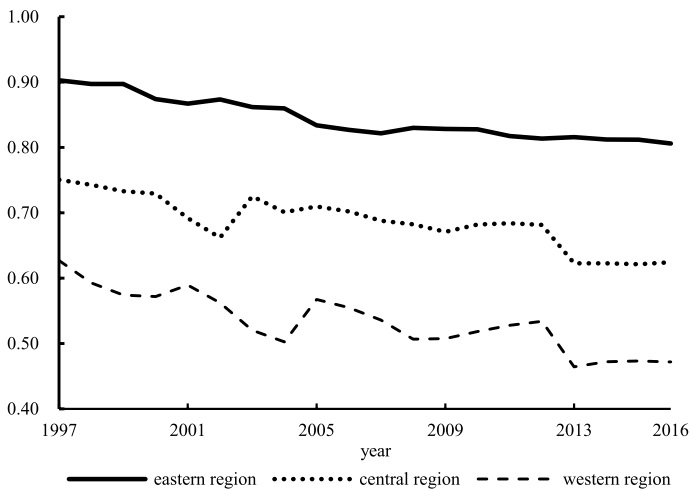


Fig. 4 Production efficiency by HYP

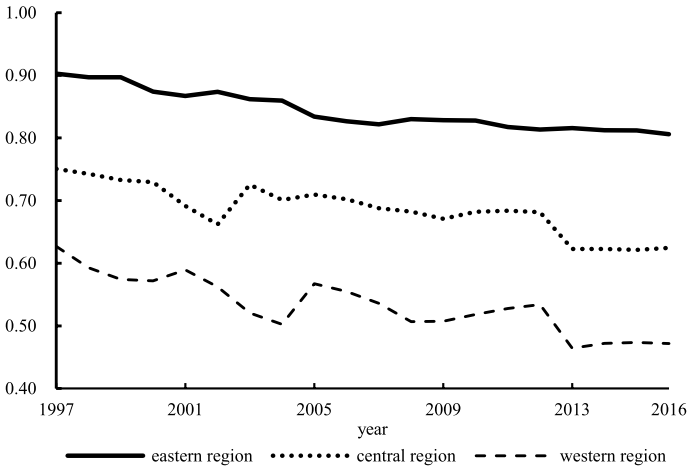


Fig. 5 Production efficiency by FGL

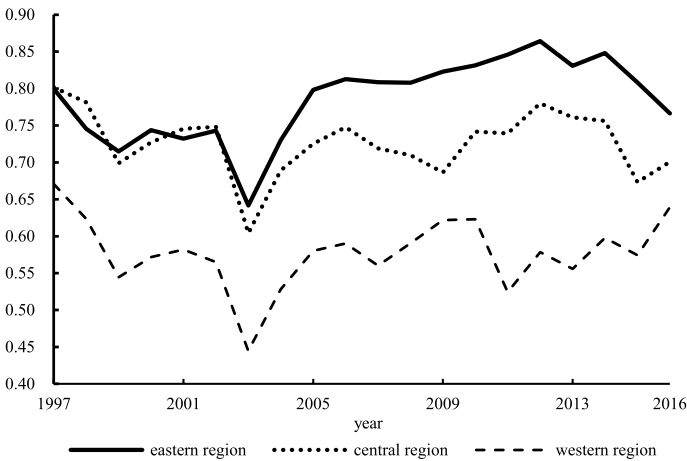


Fig. 6 Environmental efficiency by HYP

of multicollinearity does not have a significant influence on the model. Meanwhile, panel unit root tests (CIPS) are conducted, which shows that the dependent variables are stable, and some control variables have first-order integrations.³ Based on this, a co-integration test is carried out using residual terms, and the results indicate that the statistic $Z(t)$ passed the 1% significance test, signifying that the test outcomes significantly reject the null hypothesis and that there is a long-term stable equilibrium relationship between the variables. Lastly, a Hausman test is conducted, which

³ Variables such as *fdi*, *open*, *pden*, *fdec*, *soe*, and *pfee* have first-order integrations, and variables *rgdp* and *rgdp2* have second-order integrations.

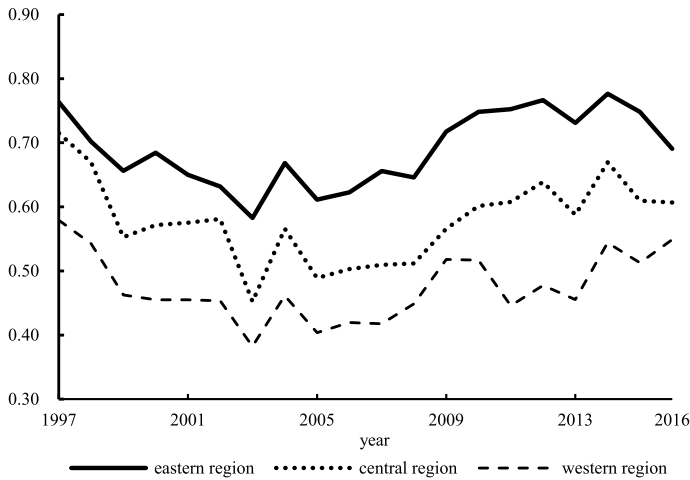


Fig. 7 Environmental efficiency by FGL



Fig. 8 Comprehensive efficiency by HYP

demonstrates that the fixed effect model is reasonable. In summary, the Tobit fixed effect model will be employed in this paper to perform empirical analysis.

4.2 Baseline regression

Table 2 presents the estimation results of the baseline regression. Columns (1) and (2) only include the development strategy as a variable, and the results show that the estimated coefficient of the development strategy is significantly negative, indicating that the more the development strategy defies comparative advantage, the less it is conducive to improving environmental performance.

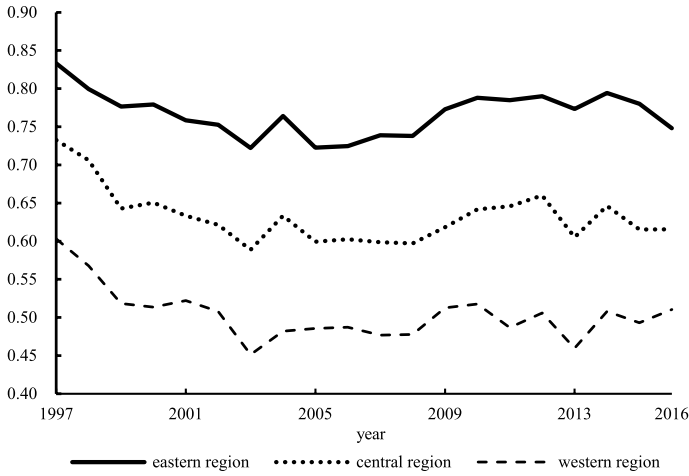


Fig. 9 Comprehensive efficiency by FGL

Table 2 Estimation of the baseline regression

	(1) FGL	(2) HYP	(3) FGL	(4) HYP	(5) FGL	(6) HYP
TCI	-0.295*** (-20.518)	-0.315*** (-17.736)	-0.275*** (-17.152)	-0.270*** (-13.586)	-0.074*** (-3.777)	-0.036 (-1.461)
RGDP			-0.031*** (-4.619)	-0.017** (-2.039)	-0.025*** (-3.559)	-0.009 (-0.989)
RGDP2			0.005*** (6.326)	0.004*** (4.280)	0.003*** (4.054)	0.002* (1.734)
FDI					0.828*** (3.640)	0.544* (1.901)
OPEN					0.010 (1.122)	0.017 (1.520)
PDEN					0.007*** (4.749)	0.011*** (6.109)
FDEC					0.298*** (6.545)	0.332*** (5.794)
SOE					-0.043 (-1.416)	-0.066* (-1.738)
PFEE					-9.761 (-1.540)	-1.783 (-0.224)
Constant	0.851*** (75.943)	0.817*** (59.016)	0.863*** (47.588)	0.785*** (34.822)	0.548*** (13.384)	0.420*** (8.151)
N	600	600	600	600	600	600

*, **, and *** denote the acceptance of significance tests at 10%, 5%, and 1% levels, respectively, with t-values in parentheses, the same as below

Columns (3) and (4) add per capita GDP and its quadratic term, and the results show that the estimated coefficient of the development strategy is still significantly negative, which is consistent with our expectations. Additionally, the estimated coefficient of per capita GDP is significantly negative in the linear term and positive in the quadratic term, implying a U-shaped curve and supporting the EKC hypothesis. Furthermore, by adding other control variables in columns (5) and (6), the estimated coefficient of the development strategy remains significantly negative, supporting the hypothesis. Thus, adding control variables one by one identifies the relationship between development strategy and environmental performance, which suggests that the omission of variables does not fundamentally affect the empirical findings of this study.

Among the control variables, the estimated coefficient of FDI is significantly positive, indicating that FDI is conducive to improving environmental performance and does not support the hypothesis of a “pollution haven”. The estimated coefficient of openness is positive but insignificant, which suggests that openness may benefit environmental performance to some extent. The estimated coefficient of population density is significantly positive, indicating that population concentration is beneficial for environmental performance. The estimated coefficient of fiscal decentralization is also significantly positive, implying that fiscal decentralization is conducive to environmental performance. However, the estimated coefficient of the share of SOEs is significantly negative, indicating that a large share of SOEs in the ownership structure can hinder environmental performance. The estimated coefficient of environmental governance is negative, which is contrary to our expectations. This may be due to the endogeneity of emission charges, which requires further analysis.

4.3 Endogeneity treatment

Endogeneity is often present in empirical analysis, particularly when using macro-data. We have also observed that some variables have become unstable due to endogeneity in the baseline regression. Hence, this section focuses on checking endogeneity and describes our econometric strategy. Firstly, we adopt the common practice in existing literature by selecting the lag of the variable as its instrumental variable (IV), which can mitigate the impact of endogeneity on estimation results to some extent. Secondly, we select “the minimum distance from the threat” and “the number of old industrial bases” as exogenous IVs for TCI, which can better explain the causality between development strategy and environmental performance.

The rationale for this strategy is that the Chinese government adopted a heavy industry-focused development strategy in the early days since the founding of the People’s Republic of China, with the aim of catching up with developed countries like the United Kingdom and the United States, achieving rapid industrialization, and strengthening national defense. The ‘third front movement’ initiated in 1964 had a significant impact, and its heavy industry structure has directly influenced China’s economic development even after reform and opening-up began in 1978. During this period, heavy industries were generally located far from the Soviet Union, the

Table 3 Estimation results of endogeneity tests

	(1)	(2)	(3)	(4)	(5)	(6)
	FGL	HYP	FGL	HYP	FGL	HYP
TCI	−0.076*** (−3.773)	−0.036 (−1.418)	−0.091*** (−4.155)	−0.049* (−1.792)	−1.022*** (−3.363)	−0.980*** (−3.386)
RGDP	−0.015** (−2.020)	−0.001 (−0.017)	−0.018** (−2.319)	−0.004 (−0.436)	−0.073*** (−3.377)	−0.057*** (−2.610)
RGDP2	0.002*** (2.614)	0.001 (0.698)	0.002*** (2.953)	0.001 (1.156)	0.006*** (3.311)	0.005** (2.543)
FDI	0.774*** (3.400)	0.475* (1.652)	0.829*** (3.279)	0.440 (1.380)	0.466 (0.719)	0.742 (1.129)
OPEN	0.003 (0.392)	0.006 (0.518)	−0.005 (−0.206)	0.002 (0.069)	0.004 (0.199)	0.003 (0.149)
PDEN	0.008*** (5.360)	0.013*** (6.519)	0.008*** (4.687)	0.012*** (5.810)	0.004 (0.765)	0.001 (0.173)
FDEC	0.292*** (6.220)	0.346*** (5.829)	0.292*** (5.628)	0.341*** (5.213)	0.587** (1.965)	0.550* (1.914)
SOE	−0.032 (−1.021)	−0.050 (−1.277)	−0.015 (−0.460)	−0.047 (−1.114)	−0.141 (−1.588)	−0.117 (−1.303)
PFEE	−10.227 (−1.609)	−6.553 (−0.815)	−9.040 (−1.402)	−1.474 (−0.181)	15.093 (0.941)	22.960 (1.389)
Constant	0.528*** (12.426)	0.398*** (7.416)	0.540*** (11.719)	0.413*** (7.124)	1.722*** (4.491)	1.588*** (4.334)
N	570	570	540	540	600	600

United States, and China's Taiwan, such as Shaanxi, Gansu, and Sichuan, forming the layout of China's heavy industry at that time. Therefore, "the minimum distance from the threat" can be used as the IV for TCI. "The minimum distance from threat" is defined as the minimum distance between the northern border, the eastern coast, or the southern coast and the capital city of each region. The minimum distance from the threat can be measured using the China map and Google Maps. Furthermore, during the 'third front movement', China's heavy industries were gradually relocated to inland regions, shaping the pattern of industrial bases. There are 120 old industrial cities in 27 provinces (autonomous regions and municipalities directly under the central government), including 95 prefecture-level cities and 25 municipalities directly under the central government/cities under separate state planning/provincial capitals. Therefore, "the number of old industrial bases" is taken as the IV for TCI.

Table 3 presents the estimated results of endogeneity treatment. In columns (1) and (2), all independent variables are lagged by one period for estimation, but the results have little change compared with those in columns (5) and (6) of Table 3, indicating that this endogeneity treatment approach is insignificant. For this reason, columns (3) and (4) select the period lagged 1 and 2 of the development strategy as

the IV for estimation. The results show a marked increase in the importance of the estimated coefficients of the development strategy and an increase in the importance of other control variables in general, indicating that the estimation structure is basically consistent with the theoretical expectations of the article when some endogeneity is under control. Furthermore, in columns (5) and (6), two IVs that are exogenous, and the estimated coefficients of the development strategy are negative at the level of significance of 1%. This implies that the more the development strategy defies comparative advantage, the more environmental performance is suppressed, which is consistent with our expectations.

4.4 Robustness tests

The empirical tests use comprehensive efficiency as the index of environmental performance, and Table 4 presents the estimation results of robustness by using production efficiency and environmental efficiency as the indices for environmental performance, respectively. Columns (1) and (2) use the production efficiency and environmental efficiency measured by FGL as dependent variables. From

Table 4 Results of the efficiency index estimate

	(1) FGL- Production efficiency	(2) FGL- Environmental efficiency	(3) HYP- Production efficiency	(4) HYP- Envi- ronmental efficiency
TCI	−0.092*** (−3.916)	−0.057* (−1.807)	−0.092*** (−3.916)	−0.075** (−2.124)
RGDP	−0.093*** (−11.229)	0.044*** (3.952)	−0.093*** (−11.229)	0.063*** (5.065)
RGDP2	0.007*** (8.630)	−0.002 (−1.381)	0.007*** (8.630)	−0.004*** (−3.230)
FDI	0.312 (1.148)	1.344*** (3.711)	0.312 (1.148)	0.874** (2.155)
OPEN	−0.007 (−0.667)	0.027* (1.910)	−0.007 (−0.667)	0.027* (1.746)
PDEN	0.009*** (5.180)	0.005** (2.079)	0.009*** (5.180)	0.004 (1.454)
FDEC	0.362*** (6.654)	0.234*** (3.229)	0.362*** (6.654)	0.259*** (3.187)
SOE	−0.302*** (−8.318)	0.216*** (4.460)	−0.302*** (−8.318)	0.233*** (4.291)
PFEE	−20.649*** (−2.728)	1.127 (0.112)	−20.649*** (−2.728)	15.337 (1.357)
Constant	0.847*** (17.307)	0.250*** (3.830)	0.847*** (17.307)	0.335*** (4.592)
N	600	600	600	600

the estimation results, it can be found that the estimated coefficients of development strategy in the two columns are significantly negative, which supports the hypothesis of this paper. Columns (3) and (4) take the production efficiency and environmental efficiency measured by HYP as the dependent variables, and the estimated coefficients of the development strategy are also significantly negative, which indicates that different matrices do not change the hypothesis and hence the hypothesis is robust.

4.5 Heterogeneity analysis

As a vast country with a wide range of geographies, China sees great differences among different regions. Therefore, this section takes different regions as samples for analysis. First, Eastern, Central, and Western regions are used as samples for empirical testing. Second, the Yangtze River Economic Belt (YREB) and Yellow River Basin (YRB) are major regions for national strategic development, which requires the ecological security and the coordinated development of the upper, middle, and lower reaches of the rivers and the high-quality development of the regions along mentioned rivers, so YREB and YRB are two focal points for our analysis.

Table 5 Estimation results by region

	Eastern (1)	Central (2)	Western (3)	YREB (4)	YRB (5)
TCI	−0.009 (−0.208)	−0.127*** (−4.080)	−0.093*** (−3.790)	−0.002 (−0.066)	−0.004 (−0.076)
RGDP	−0.056*** (−4.771)	−0.011 (−0.475)	−0.059*** (−3.813)	−0.017 (−1.503)	−0.018 (−0.981)
RGDP2	0.005*** (5.179)	−0.001 (−0.112)	0.011*** (4.490)	−0.001 (−0.149)	0.004 (1.580)
FDI	0.538** (2.029)	−5.027*** (−6.622)	−1.418* (−1.967)	−0.780* (−1.661)	−2.843*** (−2.843)
OPEN	0.016* (1.864)	0.391** (2.055)	0.068 (0.594)	−0.192** (−4.091)	0.365** (2.275)
PDEN	0.006*** (3.516)	0.005 (0.935)	−0.001 (−0.119)	0.021*** (8.601)	0.039*** (5.543)
FDEC	0.124 (1.499)	0.206** (2.019)	0.178** (2.052)	0.609*** (8.229)	0.147 (1.555)
SOE	0.094* (1.898)	−0.104* (−1.783)	−0.003 (−0.055)	−0.276** (−5.389)	−0.046 (−0.611)
PFEE	−118.680*** (−4.955)	−15.913*** (−2.242)	3.703 (0.408)	−19.523* (−1.781)	21.593** (2.550)
Constant	0.816*** (9.338)	0.666*** (7.912)	0.578*** (9.676)	0.453*** (7.075)	0.373*** (4.830)
N	220	160	220	220	180

Table 5 presents the results of the regional heterogeneity estimation. The estimated coefficient of the development strategy in column (1) is negative but insignificant, indicating that the eastern region has a low degree of CAD and has less inhibitory effect on environmental performance. A plausible reason is that the eastern region is in an advanced stage of development. This means that it has larger factor endowments and relevant structure, can upgrade faster, and boasts a more compatible industrial structure, which makes its development strategy basically consistent with its comparative advantage and less inhibitory on environmental performance. In contrast, the estimated coefficients of the development strategy in columns (2) and (3) are significantly negative, indicating that the central and western regions are at a less advanced stage of economic development, with CAD development strategies of higher degrees, which has a significant inhibitory effect on environmental performance. The estimated coefficients of columns (4) and (5) are negative but insignificant, indicating to some extent that the YREB and YRB development strategies are not significantly compared to the competition and have very little inhibitory effect on environmental performance. This further proves that taking environmental protection and high-quality development of YREB and YRB as major national strategies are conducive to improving environmental performance.

4.6 Mechanism analysis

This section presents additional empirical testing to evaluate the mechanism hypothesis proposed in this paper. The identification strategy involves using technological progress as the dependent variable and development strategy as the key independent variable to analyze the impact of development strategy on technological progress. Subsequently, technological progress is introduced as a variable in the baseline model to explain its effect on environmental efficiency. Finally, a robustness test is conducted by introducing the interaction of development strategy and technological progress in the baseline model.

Table 6 shows the estimation results of the mechanism test. Columns (1), (2) and (3) take independent R&D, technology import, and technological transformation as dependent variables, respectively, and the estimated coefficients of development strategy are basically significantly negative, which indicates that the more CAD the development strategy is, the less conducive it is to the investment in independent R&D, technology import, and technological transformation, thus obstructing technological progress. Columns (4), (5), and (6) introduce independent R&D, technology import, and technological transformation as independent variables, respectively, into the baseline model, and it can be found that the estimated coefficients of independent R&D in column (4) are significantly negative, which implies that the more investment in independent R&D is, the poorer the environmental efficiency is. However, it is theoretically logical in the context of the reality of China. China is still a developing economy, and most of its technologies are based on imitations, and the innovation structure suitable for the factor endowment structure is dominated by imitation-based innovation (Wu et al. 2020). Therefore, investing in independent

Table 6 Estimation results of the mechanism analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Independent R&D	Technology import	Technological transformation	FGL	FGL	FGL	FGL	FGL	FGL
TCI	-0.319*** (-3.458)	-0.291 (-1.466)	-0.242* (-1.811)	-0.031 (-1.577)	-0.043** (-2.191)	-0.033* (-1.690)	-0.001 (-0.062)	-0.053*** (-2.594)	-0.033 (-1.569)
TECH				-0.029*** (-3.537)	0.010*** (2.961)	0.001 (0.042)			
TCI_TECH							-0.029*** (-3.537)	0.010*** (2.961)	0.001 (0.042)
RGDP	0.149*** (4.587)	-0.540*** (-7.707)	-0.191*** (-4.057)	-0.021*** (-3.659)	-0.019*** (-3.141)	-0.026*** (-4.484)	-0.021*** (-3.659)	-0.019*** (-3.141)	-0.026*** (-4.484)
RGDP2	-0.011*** (-3.259)	0.028*** (3.890)	-0.001 (-0.171)	0.003*** (5.491)	0.003*** (5.395)	0.003*** (6.110)	0.003*** (5.491)	0.003*** (5.395)	0.003*** (6.110)
FDI	-2.633** (-2.470)	-7.717*** (-3.343)	-12.097*** (-7.844)	0.538** (2.416)	0.753*** (3.267)	0.590** (2.556)	0.538** (2.416)	0.753*** (3.267)	0.590** (2.556)
OPEN	-0.009 (-0.228)	0.033 (0.371)	-0.004 (-0.075)	0.012* (1.821)	0.012* (1.815)	0.012* (1.861)	0.012* (1.821)	0.012* (1.815)	0.012* (1.861)
PDEN	0.038*** (5.456)	0.078*** (5.212)	0.061*** (6.009)	0.001 (0.244)	-0.000 (-0.124)	0.000 (0.095)	0.001 (0.244)	-0.000 (-0.124)	0.000 (0.095)
FDEC	0.327 (1.533)	3.847*** (8.365)	0.696** (2.254)	0.266*** (5.137)	0.247*** (4.739)	0.282*** (5.484)	0.266*** (5.137)	0.247*** (4.739)	0.282*** (5.484)
SOE	-0.184 (-1.293)	0.609** (1.981)	-0.407** (-1.976)	-0.018 (-0.557)	-0.017 (-0.519)	-0.023 (-0.690)	-0.018 (-0.557)	-0.017 (-0.519)	-0.023 (-0.690)

Table 6 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Independent R&D	Technology import	Technological transformation	FGL	FGL	FGL	FGL	FGL	FGL
PFEE	137.471*** (4.628)	89.238 (1.396)	268.872*** (6.258)	-6.358 (-1.078)	-12.136** (-2.108)	-11.325* (-1.952)	-6.358 (-1.078)	-12.136** (-2.108)	-11.325* (-1.952)
Constant	3.989*** (20.776)	0.773* (1.868)	4.653*** (16.756)	0.667*** (12.313)	0.539*** (12.650)	0.550*** (10.393)	0.667*** (12.313)	0.539*** (12.650)	0.550*** (10.393)
N	600	599	600	600	600	600	600	600	600
r2	0.345	0.419	0.302						

innovation may not be effective in directly improving environmental efficiency (Zheng et al. 2022). This is supported by the positive estimated coefficient of technology import in column (5), which shows that technology import is beneficial to environmental efficiency and supports to some extent by the positive estimated coefficient of technological transformation in column (6). Furthermore, columns (7) to (9) incorporate the interactions of development strategy and the three channels of technological progress into the model. The results show that the estimated coefficients of the interactions between the development strategy and independent R&D in column (7) are negative. This indicates that investments in independent R&D may play an important role in the influence mechanism of technology progress on environmental efficiency, but do not necessarily lead to better environmental performance. This finding is consistent with some recent studies (Zheng et al. 2022). The estimated coefficients of the interactions between the development strategy and technology progress in column (8) are significantly positive, which indicates that with a constant development strategy, the investment in the import of technology is beneficial to the environmental performance, which is consistent with the results in column (5). Meanwhile, the results of the interactions between development strategy and technological transformation in column (9) are also consistent with those in column (6). The analysis shows that the development strategy has an impact on environmental performance through technological progress. More precisely, technology import and technological transformation are the main channels, while independent R&D is not.

5 Discussion and policy implications

This study establishes an experimental basis for subsequent studies on environmental performance measurement. Various measurement models exist for examining regional environmental performance, but the results of different models often differ significantly (Färe et al. 2005; Aparicio et al. 2019). Establishing a more scientific and rational measurement method under the selected target objects is a common challenge in conducting environmental performance studies. In this paper, we use the modified HYP and FGL methods to simulate the production efficiency, environmental performance, and overall technical efficiency of China's provincial regions in the context of China's development reality. The results indicate that production technology and environmental efficiency in the eastern region are significantly better than those in the central and western regions over the last two decades (Lv et al. 2017). This work is innovative in the efficiency measurement model and promotes the practical application of the by-production technology theory proposed by Murty et al. (2012). It also establishes a relatively reasonable assessment system and measurement method for future research on environmental performance.

This study contributes to the practical application of technological pathways affecting environmental performance as a policy analysis instrument. Currently,

few studies explore the impact of development strategies on environmental performance through different channels of technological progress. The few studies that do exist mostly remain at the stage of qualitatively portraying the overall performance of the measurement results and are far from guiding different regions in formulating development strategies, selecting technological paths, and optimizing environmental performance. Indeed, different regions in China differ substantially in terms of innovation factor accumulation, economic structural changes, and industrial dynamics transformation (Alder et al. 2016). These differences naturally affect regional development strategies and technology path differences, which, in turn, lead to regional differences in environmental performance.

The results of this study can contribute to an accurate understanding of the current development reality of environmental performance and to identifying policy focus for improving environmental performance. This paper finds that development strategies can influence environmental efficiency through technological progress, and regions that adopt development strategies that are against their comparative advantage have lower environmental efficiency. The mechanism tests suggest that development strategies influence environmental efficiency through the main channels of technology import and technological transformation, while independent R&D is currently not the primary channel. These findings provide valid arguments to support both problem recognition and problem-solving by relevant policy-making and management authorities. Based on the above discussion, this article proposes the following policy recommendations:

The optimal environmental governance strategy is to follow the endogenous results of comparative advantage in development. The success of environmental governance in a region does not solely rely on administrative and campaign-style environmental law enforcement, but on the self-sufficiency of enterprises in industries with comparative advantages. Only when enterprises have self-sufficiency can government environmental governance policies be effectively implemented and become hard constraints. Under such constraints, enterprises can stimulate green technological innovation, optimize production capacity structure, which can achieve optimal environmental governance. Moreover, the government needs to take more actions in environmental governance. For example, it should appropriately enhance the monitoring authority, improve the monitoring, warning, and evaluation systems, or actively introduce clean energy and green technologies from developed countries.

Secondly, as a complex pollution control process, environmental governance also needs to further improve the environmental governance system and optimize the environmental governance mechanism. In the context of China, the establishment of specialized ecological protection areas and environmental governance demonstration zones is a crucial “bottom-up” environmental governance mechanism. The government should appropriately increase the decentralization of environmental management affairs, especially in local government expenditures and responsibilities for environmental protection construction, fully leveraging the information and cost advantages of local governments in pollution control.

Finally, it is necessary to continuously optimize the structure of government fiscal expenditures. When formulating fiscal and subsidy policies, the country needs to consider the externality of environmental governance and the distortion of fiscal expenditures in environmental governance. The main role of subsidies should be in the rational selection of industries, encouraging supported enterprises to continuously innovate technologies, and stimulating the “innovation compensation” effect. This will promote the improvement of environmental efficiency in the entire region and enhance regional competitiveness.

6 Conclusion and limitations

This paper applies HYP and FGL efficiency measurements under by-production approach to decompose performance explicitly into production efficiency and environmental efficiency of 30 provincial level regions in China. To further investigate the reasons for the discrepancies in environmental performance across different regions in China, this study employs the industrial development strategy based on comparative advantages to evaluate its impact on environmental efficiency. The findings indicate that government development strategies have a direct impact on the environmental performance of each region. To address potential endogeneity issues, two instrumental variables associated with government industrial development strategies are utilized as proxies to strengthen the validity of the research conclusions. During the regional examination, the impact of development strategies on the environment shows significant variation across different regions. Additionally, the effect of development strategies on regional environmental performance is achieved through its influence on regional technological advancement.

The empirical analysis yielded the following findings: (i) Environmental performance is negatively affected the further a development strategy deviates from its comparative advantage. This conclusion remains robust even after conducting various endogeneity treatments and tests. (ii) Heterogeneity analysis revealed that the CAD development strategy in the Eastern region, YREB, and YRB had less inhibitory effects on environmental performance than in the Central and Western regions. (iii) The test of the theoretical mechanism showed that the development strategy impacts environmental efficiency through technological progress, specifically through technology import and technological transformation, rather than independent R&D. (iv) The results of the control variables indicate that per capita GDP and its quadratic term, FDI, openness, population density, fiscal decentralization, the share of SOEs, and environmental governance also have varying degrees of impact on environmental performance.

This study has two limitations that future research can expand on. Firstly, this study examined the relationship between development strategies, technological progress, and environmental performance at the macro-regional level. However, there is a need for in-depth analysis at the meso and micro levels, such as industries or enterprises, which can be explored in future studies. Secondly, this study did not consider the impact of spatial correlation effects on the model during the research process. The development strategy or technological progress of one region may affect the

development of adjacent or related regions. Future research will fully consider spatial correlation effects, and the challenge may lie in the selection of spatial units and the interpretation of spatial correlation effects.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants performed by any of the authors.

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