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The Role of Foreign Technology Transfer in Improving Environmental Efficiency: Empirical Evidence From China's High-Tech Industry

Feng Peng[1], *Xichun Zhang*[1] *and Shuzhen Zhou*[2]*

[1]*School of Economics and Management, China Three Gorges University, Yichang, China,* [2]*School of Management, Nanchang University, Nanchang, China*

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Correspondence:
Shuzhen Zhou
zhoushuzhen@email.ncu.edu.cn

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In recent years, China's high-tech industry has made remarkable technological progress, but it has also brought serious environmental pollution, which has aroused great concern about its environmental efficiency. Although foreign technology transfer is considered as important ways for technological progress of the high-tech industry, the existing research on what role foreign technology transfer plays in improving the environmental efficiency of the high-tech industry is still lacking. Based on China's interprovincial panel data from 2008 to 2017, we evaluated the environmental efficiency of the high-tech industry using the super-efficiency slacks-based measure (SBM) model with undesirable outputs. We then used the Tobit model to analyze the impact of technology introduction (TI) and foreign direct investment (FDI)—two major types of foreign technology transfer—on the environmental efficiency of the high-tech industry. The results of the super-efficiency SBM model show that the average environmental efficiency of China's high-tech industry is only 0.4375. Except for Guangdong, Shanghai, and Beijing, most of the provinces in China have low environmental efficiency. The provinces with high environmental efficiency are in the eastern region, whereas the provinces with low environmental efficiency are concentrated in the central and western regions. Tobit regression results confirm the difference in the role of technology import and foreign direct investment in the improvement of environmental efficiency in China's high-tech industry. Technology introduction has a significant positive impact on environmental efficiency. FDI also promotes environmental efficiency, but it is not statistically significant. These findings were confirmed by a series of robust tests. This study not only deepens our understanding of the environmental efficiency of China's high-tech industry but also expands the theoretical research on the relationship between technology transfer and environmental efficiency.

Keywords: environmental efficiency, foreign technology transfer, high-tech industry, undesirable outputs, super-SBM, tobit model

INTRODUCTION

In the past 2 decades, China's high-tech industry has rapidly narrowed the technological gap with industrial countries and has gained global competitiveness in manned spaceflight, Beidou satellite navigation, supercomputers, high-speed rail equipment, and other fields. Although remarkable technological progress has been made, environmental pollution events brought about by high-tech industries have been frequently reported. For example, the waste gas pollution discharged by the Spark silicon factory resulted in a substantial reduction in production of thousands of acres of fertile farmland (Li and Peng, 2013). In addition, and MEIKO's factory in Wuhan discharges large amounts of wastewater containing heavy metals into the nearby South Prince Lake (Wang, 2012). Therefore, it is increasingly urgent to improve the environmental efficiency of the high-tech industry to coordinate the relationship between industrial development and environmental protection.

Foreign technology transfer refers to the process through which emerging economies acquire required technology from abroad through technology introduction (TI) and foreign direct investment (FDI) (Xu et al., 2020). The use of foreign technology transfer is regarded as one of the important ways of industrial green transformation in emerging countries (Zhou et al., 2021). China is acquiring foreign technology through a variety of means, including TI and FDI, to enhance its industrial environmental technology capability (Hou et al., 2017). Efforts to acquire foreign technologies also include the introduction of supporting policies and measures, for example, guiding domestic enterprises to introduce foreign advanced technologies through the Catalogue of Encouraged Technology Introduction in China (Wu and Zhong, 2020) and providing precise guidance for investment policies with the Guidance Catalogue of Industries for Foreign Investment (Yan and Liu, 2020). At present, with the intensification of international competition in the high-tech field, however, the United States has increased its restrictions on technology transfer to China (Kwan, 2020). As a result, the green transformation of China's high-tech industry has received increased attention.

There is no consistent conclusion on the relationship between foreign technology transfer and industrial environmental efficiency in China (Tu and Liu, 2011; Yue et al., 2017; Yang and Li, 2019; Chen et al., 2020), and empirical research on China's high-tech industry is lacking. This study analyzes the role of foreign technology transfer in improving the environmental efficiency of the high-tech industry. This study not only enriches the theoretical research on the relationship between technology transfer and industrial environmental efficiency, but also provides a decision-making basis for promoting the green transformation of China's high-tech industry.

This study contributed to the existing research from two aspects. First, the existing literature lacks research evaluating the environmental efficiency of China's high-tech industry. We included environmental pollution and energy consumption in the environmental efficiency evaluation index system and evaluated the environmental efficiency of China's provincial high-tech industry using the super-efficiency slacks-based measure (SBM) model while also considering undesirable outputs. Second, although TI and FDI, two types of foreign technology transfer, are considered as important ways for technological progress of China's high-tech industry (Gao, 2019; Lyu et al., 2019), few studies have examined the role of foreign technology transfer on the improvement of environmental efficiency of China's high-tech industry. This study enriched the research achievements in this field. We integrated two foreign technology transfer methods, TI and FDI, into the same analytical framework and used the Tobit model to examine the impact of the two foreign technology transfer methods on the environmental efficiency of China's high-tech industry. At the same time, to improve the accuracy of the estimation results, this study used the method of instrumental variables to deal with the endogeneity problem in the regression estimation and carried out a series of robustness tests on the estimation results.

This study has five parts: the second part is the literature review. The third part introduces the research methods, including the Super-SBM model and panel Tobit regression model. The fourth part provides the results and discussion. The fifth part concludes the study and provides some policy implications.

LITERATURE REVIEW

The environmental efficiency of China's industrial sectors has received widespread attention. The related research can be divided into two categories: one is the evaluation of industrial environmental efficiency; the other is the analysis of the influencing factors of industrial environmental efficiency.

Data envelopment analysis (DEA) is the most used method to evaluate the environmental efficiency of Chinese industrial sectors. Wang et al. (2017) measured the environmental efficiency of 29 manufacturing industries in China by using the SBM model while considering undesirable outputs. Emrouznejad and Yang (2016) introduced the global Malmquist-Luenberger Productivity Index (GMLPI) to construct an evaluation model for environmental efficiency of China's manufacturing industry segments. Xu et al. (2021) used the SBM model and the Malmquist index to measure the environmental efficiency of China's heavily polluting industries from both dynamic and static perspectives. Among various DEA models, the SBM model can effectively deal with the problems of excess inputs and insufficient outputs, and it is one of the most widely used DEA models in the evaluation of industrial environmental efficiency in China.

Many studies have made comparative analysis on the environmental efficiency of Chinese industry based on industrial sector data. Shao et al. (2019) confirmed that the environmental efficiency of China's industry shows significant sector differences. Li and Zhang (2021) found that there was a large gap in the environmental efficiency of different subsectors of China's equipment manufacturing industry. Other studies have evaluated the environmental efficiency of Chinese industrial sectors based on interprovincial data. For example, Chen and Jia (2017) found that there were significant differences in industrial environmental efficiency among regions in China. An et al. (2019) confirmed that the gap of industrial environmental efficiency between developed and developing regions in China is widening year by year. These studies also examine the environmental efficiency of highly polluting industrial sectors. Zhou et al. (2013) found significant differences in the environmental efficiency of China's power industry among provinces, and the environmental efficiency of eastern provinces remained at a relatively high level. Similarly, Song and Wang (2018) confirmed that the environmental efficiency of power generation industry in eastern China is the highest, whereas that in central and western China is low. These studies include abundant research on the environmental efficiency of traditional high-pollution industries, but research on the environmental efficiency of the high-tech industry remains lacking.

No consistent conclusions have been drawn about the relationship between foreign technology transfer and industrial environmental efficiency in China. Some studies are positive. Tu and Liu (2011) confirmed that TI is an effective way for Chinese industry to improve environmental efficiency through interprovincial panel data. Chen et al. (2020) also confirmed that FDI has had a positive impact on industrial environmental efficiency based on China's provincial panel data. Other studies are negative. Yue et al. (2017) found a negative correlation between TI and environmental efficiency through regression analysis of China's industrial sectors. Yang and Li (2019) found that FDI reduced industrial environmental efficiency through their analysis of China's provincial panel data. Although there are many empirical studies on China's industry, the existing studies lack empirical evidence on China's high-tech industry.

Industrial environmental efficiency is also influenced by economic development, human resources, and investment in research and development (R&D). Song and Wang (2018) used the Tobit regression model to confirm that both economic development level and human resources have a significant positive impact on environmental efficiency of thermal power industry. Sun et al. (2020) used the system generalized method of moments approach to confirm that R&D investment is an important factor influencing the environmental efficiency of China's power industry. Similarly, Zhou et al. (2013) used the Tobit regression model to confirm that R&D investment is significantly positively correlated with environmental efficiency of China's power industry. In addition, some studies have noted that environmental regulation is also an important factor affecting environmental efficiency. Zhang and Song (2021) used the bootstrap truncated regression method to examine the efficiency of environmental regulation on China metal industry environment and found a significant inverted u-shaped relationship between the two.

Studies have shown that there are significant industry and regional differences in the environmental efficiency of China's industrial sectors, but what is the environmental efficiency of high-tech industry that play a leading role in China's industrial green transformation? Existing literature lacks research. In addition, there is no consistent conclusion about the relationship between foreign technology transfer and environmental efficiency, and there is even less empirical evidence from China's high-tech industry. At present, China's high-tech industry not only is facing the pressure of domestic environmental protection, but also is facing the increasingly strict technical control of industrial countries. What role foreign technology transfer plays in improving environmental efficiency of China's high-tech industry is also an important issue to be studied. The purpose of this study is to answer these questions.

METHODOLOGY

Research Framework

Although foreign technology transfer holds great significance for emerging economies to improve their environmental technology level (Jakobsen and Clausen, 2016), the relationship between foreign technology transfer and environmental efficiency remains controversial. Some scholars believe that foreign technology transfer has had a positive impact on environmental efficiency. Emerging economies can narrow the technological gap with industrial countries through TI and can improve and innovate based on TI (Awate et al., 2015; Andersson and Stone, 2017; Yu et al., 2019). The introduction of high technology has a greater technology spillover effect on emerging economies than the introduction of low technology (Belitz and Molders, 2016). FDI produces technology spillovers to host countries through competition, demonstration, flow, and correlation effects (Suyanto and Salim, 2013; Sari et al., 2016). Such technology spillover provides important support for green innovation in host countries (Feng et al., 2018).

Other scholars hold a different view, however. The imported technology may contain some nonenvironmental protection technologies or highly polluting mechanical equipment, which will have a negative impact on the environment (Danish Wang et al., 2018). In contrast, the potential environmental costs of FDI may offset its economic benefits (Cole et al., 2011; Shehzad et al., 2021). This study aims to analyze the impact of foreign technology transfer on the environmental efficiency of China's high-tech industry. We selected two kinds of foreign technology transfer (i.e., TI and FDI) as independent variables.

Existing literature has shown that the influencing factors of China's industrial environmental efficiency also include economic development level (Song and Wang, 2018), R&D investment (Aldieri et al., 2018), human resources (Chen et al., 2020), and environmental regulation (Zhou et al., 2013). In addition, China actively promotes domestic technology transfer to improve its industrial efficiency (Chen et al., 2016), and domestic technology transfer also may be an influential factor of environmental efficiency. Therefore, taking economic development level, domestic technology transfer, R&D investment, human resources, and environmental regulation as control variables, the regression model is constructed as follows:

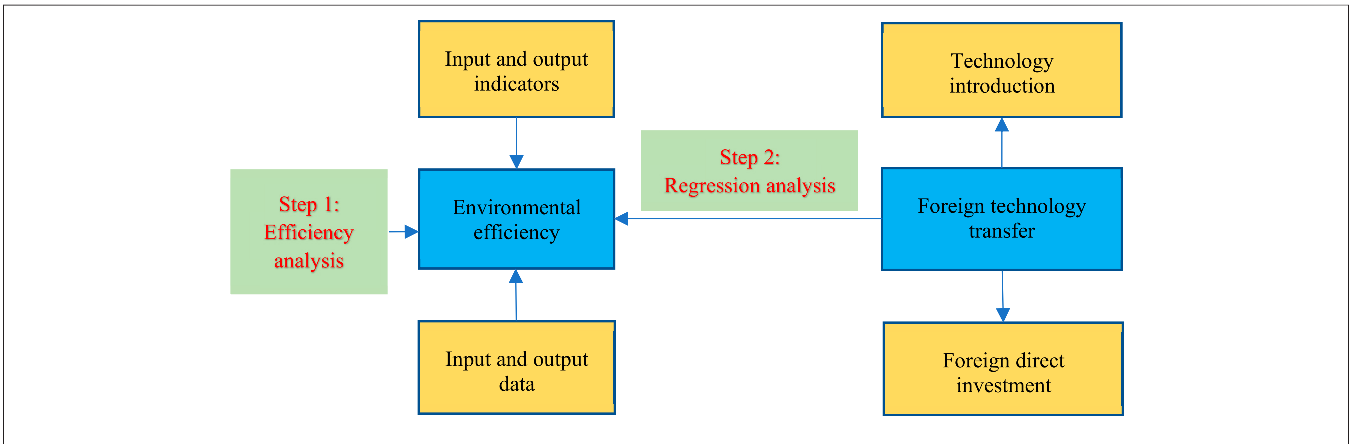

FIGURE 1 | Research framework.

$$EC_{it} = \beta_0 + \beta_1 TI_{it} + \beta_2 FDI_{it} + \beta_3 ED_{it} + \beta_4 DT_{it} + \beta_5 RD_{it} + \beta_6 HC_{it} + \beta_7 ER_{it} + \varepsilon_{it} \tag{1}$$

where EC_{it} represents environmental efficiency; TI_{it} and FDI_{it} refer to foreign technology introduction and foreign direct investment respectively; RD_{it}, HC_{it} and ER_{it} represent RD investment, human resources, and environmental regulation respectively.

This study consists of two steps (see **Figure 1**). In the first step, we set up the super-efficiency SBM model to measure the environmental efficiency of the high-tech industry. Secondly, we build the Tobit regression model to examine the role of foreign technology transfer in improving the environmental efficiency of the high-tech industry.

Models

Super-SBM Model With Undesirable Outputs

The stochastic Frontier analysis (SFA) method and data envelopment analysis (DEA) method are usually used to measure industrial efficiency (Chen and Jia, 2017). The former sets the output as a function of the non-negative random error representing technical inefficiency and the systematic random error representing statistical noise, but it usually cannot measure the efficiency of production activities with multiple outputs. The latter uses the linear programming method to construct the nonparametric Frontier of the observed data to evaluate the relative efficiency of a set of homogeneous decision-making units (Li et al., 2013; Song et al., 2018). The advantage of DEA is that there is no need to set the functional form of the production Frontier before evaluation. In addition, the method also provides measures to improve the performance of decision-making units (Song et al., 2012). When measuring the environmental efficiency of the high-tech industry, it is necessary to consider not only the desirable outputs produced in the production process but also the undesirable outputs that follow. The DEA method usually is used to evaluate the efficiency of the production system with multiple outputs. The traditional DEA method (CCR and BCC models), however, is based on the scaling down (scaling up) of the input (output) vector without considering the existence of slacks (Yang et al., 2021). Tone (2001, 2002) proposed a Super-SBM model that not only directly deals with excess input and insufficient output but also further distinguishes multiple effective decision-making units. Therefore, in this study, we adopted the Super-SBM model considering undesirable outputs to measure the environmental efficiency of China's high-tech industry.

It is assumed that there are n decision-making units, and each decision-making unit has input, desirable output and undesirable output, which are, respectively, expressed by vectors: $x \in R^m$, $y^d \in R^{p_1}$, and $y^u \in R^{p_2}$. Define the following matrix:

$$\begin{aligned} X &= [x_1, x_2, \cdots, x_n] \in R^{m\times n} > 0 \\ Y^d &= \left[y_1^d, y_2^d, \cdots, y_n^d\right] \in R^{p_1\times n} > 0 \\ Y^u &= \left[y_1^u, y_2^u, \cdots, y_n^u\right] \in R^{p_2\times n} > 0 \end{aligned}$$

The production possibility set (P) is defined as follows:

$$P = \left\{\left(x, y^d, y^u\right) | x > X\lambda, y^d \le Y^d\lambda, y^u \ge Y^u\lambda, \lambda \ge 0\right\}$$

where λ is the non-negative intensity vector.

According to Tone (2001, 2002) and Zhang et al. (2019), under the assumption of constant returns to scale, the Super-SBM model with undesirable outputs can be expressed as follows:

$$\rho = min \frac{1 + \frac{1}{m}\sum_{i=1}^{m} s_i^- \big/ x_{ik}}{1 - \frac{1}{p_1+p_2}\left(\sum_{r=1}^{p_1} s_r^+ \big/ y_{rk}^d + \sum_{t=1}^{p_2} s_t^{u-} \big/ y_{rk}^u\right)} \tag{2}$$

$$\begin{aligned} \text{s.t.} \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - s_i^- &\le x_{ik} \\ \sum_{j=1, j\neq k}^{n} y_{rj}^d\lambda_j + s_r^+ &\ge y_{rk}^d \\ \sum_{j=1, j\neq k}^{n} y_{tj}^u\lambda_j - s_t^{u-} &\le y_{tk}^u \\ 1 - \frac{1}{p_1+p_2}\left(\sum_{r=1}^{p_1} s_r^+ \Big/ y_{rk}^d + \sum_{t=1}^{p_2} s_t^{u-} \Big/ y_{rk}^u\right) &> 0 \end{aligned}$$

TABLE 1 | Input and output indicators definitions.

Dimension	Indicator	Definition
Input indicators	Capital input	Capital stock of fixed assets investment
	Labor input	Number of employed personnel
	Energy input	Total energy consumption converted into standard coal
Output indicator	Desirable outputs	Revenue from principal business
	Undesirable outputs	Industrial sulfur dioxide emission

$$s_i^-, s_r^+, s_t^{u-}, \lambda_j \geq 0$$

The above model can be solved by MaxDEA software. MaxDEA is a commonly used software for DEA analysis, and its application method can be found in Cheng (2014).

Tobit Regression Model

The efficiency values measured by the DEA method are censored. Although the super-efficiency SBM model relaxes the limitation that the efficiency values are less than 1, the efficiency values obtained by this model are still censored (Chen et al., 2017). In this case, if the ordinary least square method (OLS) is used to carry out regression analysis on the influencing factors of environmental efficiency, the consistent estimation will not be obtained (Shuai and Fan, 2020). Tobit regression is a limited dependent variable model, which can effectively deal with this kind of problems by using maximum likelihood estimation (MLE) (Li et al., 2021). The Tobit regression model can be expressed as follows:

$$y_{it}^* = \beta^T x_{it} + \varepsilon_{it} \tag{3}$$

$$y_{it} = \begin{cases} y_{it}^*, y_{it}^* > 0 \\ 0, y_{it}^* \leq 0 \end{cases}$$

where y_{it}^* is a latent variable and represents the environmental efficiency of the i th province in the t year; x_{it} is the explanatory variable; β^T is the regression parameter vector; and ε_{it} is the random error and $\varepsilon_{it} \sim N(0, \sigma^2)$. In this study, we used the Tobit regression model to analyze the impact of foreign technology transfer on the environmental efficiency of China's high-tech industry.

Stata 15.0 was employed to perform panel data model to estimate the impact of technology transfer on the environmental efficiency of the high-tech industry.

Input and Output Indicators

Referring to the evaluation indicator system of industrial environmental efficiency constructed by Chen and Jia (2017), and considering the availability of data, in this study, we selected the main business income as the desirable output of the high-tech industry and selected the industrial sulfur dioxide (SO_2) emissions as the undesirable output of the high-tech industry. Taking capital, labor, and energy as the input factors of the high-tech industry, capital investment is expressed by the capital stock of fixed assets investment; labor input is expressed by the number of employees; and energy input is measured by standard coal consumption (Liu et al., 2015). According to the method provided by Peng and Zhou (2017), the industrial SO_2 emission and energy input are estimated. The data for calculating industrial SO_2 emissions come from the China Environment Database in the EPS data platform, the data for calculating energy input come from the China Energy Database in the EPS data platform, and the data for calculating other input-output indicators come from the China High-Tech Industry Database in the EPS data platform. The definitions of input and output indicators of the high-tech industry are shown in **Table 1**.

Variables

Dependent Variable

Environmental efficiency, which was calculated by the Super-SBM model considering undesirable outputs.

Independent Variables

Independent variables include TI and FDI. We used the perpetual inventory method (PIM) to calculate the capital stock formed by the introduction of foreign technology (Du et al., 2019). We used the proportion of employees of foreign-funded enterprises in the industry as the proxy variable for FDI (Wei and Liu, 2006).

Control Variables

The selection of control variables is based on the following two principles: first, theoretical studies have shown that these variables may be related to industrial environmental efficiency; second, these variables are often used in the analysis of industrial environmental efficiency in China.

1) Economic development level (ED): According to the environmental Kuznets curve, with the improvement of ED level, people's requirements for environmental quality also will increase, thus enhancing people's tendency to improve environmental efficiency (Song et al., 2013; Danish et al., 2019). The relationship between the level of economic development and environmental efficiency is monotonic (Song and Wang, 2018). Gross domestic product (GDP) per capita is usually used to measure the level of economic development (Song and Wang, 2018).
2) Domestic technology transfer (DT): Chinese high-tech enterprises can improve efficiency by obtaining domestic technology transfer through industry-university-research cooperation (Chen et al., 2016). The PIM is used to calculate the capital stock of domestic technology transfer (Shahabadi et al., 2018).
3) R&D investment (RD): R&D investment not only contributes to the introduction of environmentally friendly production technologies and products (Song et al., 2019), but also improves the absorption capacity of external technologies (Spithoven et al., 2010; Aldieri et al., 2018). Compared with enterprises without R&D investment, those enterprises with R&D investment can obtain greater spillover effects (SuyantoSalim et al., 2009). The PIM was used to calculate the capital stock invested by R&D (Coe et al., 2009).
4) Human resources (HR): High-level human resources are conducive to the promotion and application of advanced

TABLE 2 | Variables and definitions.

Variable	Abbr	Definition
Environmental efficiency	EE	Calculated by the Super-SBM model considering undesirable outputs
Technology introduction	TI	The capital stock formed by the introduction of foreign technology
Foreign direct investment	FDI	The proportion of employees of foreign-funded enterprises in the industry
Economic development level	ED	Per capita GDP
Domestic technology transfer	DT	The capital stock formed by domestic technology transfer
R&D investment	RD	The capital stock of R&D investment
Human resource	HR	R&D personnel full-time equivalent
Environmental regulation	ER	Dummy variable, 1 for the province with strict environmental controls, 0 for others

Note: The data used to calculate the relevant variables come from the China High-Tech Industry Database and the China Macroeconomic Database in the EPS data platform.

environmental technologies and the realization of energy conservation and emission reduction goals more efficiently (Wang and Zhao, 2021). In this study, the full-time equivalent of R&D personnel is used as a proxy variable of human resources (Xiao et al., 2018).

5) Environmental regulation (ER): The standard of environmental policy reflects the intensity of environmental regulation to a large extent. Since 2008, China has strengthened environmental policy regulation in the eastern and western regions (Ban et al., 2018). Because of the lack of data on pollutant control cost and pollutant emission reduction, we use environmental policy control standards to measure the intensity of environmental regulation according to Azzam et al. (2015). There are two kinds of environmental policy control standards: "0″ means there is no special environmental control policy, and "1″ means there is a special environmental control policy.

When the PIM is used to estimate the capital stock, the selection of the base period has an important impact on the accuracy of the capital stock estimation results. In general, the earlier the selection of the base period year, the smaller the impact of the estimation error of the base period capital stock on the capital stock in subsequent years (Shan, 2008). To reduce estimation errors, this study selects the year 2000 as the base period when using the PIM to estimate various capital stocks, which is the earliest year in which relevant data can be obtained. **Table 2** provides a list of the variables and their definitions.

In this study, we used the panel data of 30 provinces in China from 2008 to 2017 (the data of other provinces are missing) for empirical analysis. There are two reasons for choosing this period. On the one hand, people pay more attention to the environmental pollution of high-tech industries during this period, and on the other hand, the data during this period is more complete. The data used to calculate the relevant variables come from the China High-Tech Industry Database and the China Macroeconomic Database in the EPS data platform.

RESULTS AND DISCUSSION

Environmental Efficiency of China's High-Tech Industry

We used the Super-SBM model considering undesired outputs to measure the environmental efficiency of China's provincial high-tech industry from 2008 to 2017. The results are shown in **Table 3**.

It can be seen from **Table 3** that among these provinces, only Guangdong, Shanghai, and Beijing are efficient, with annual average environmental efficiency of these three provinces being 1.4108, 1.1719, and 1.1638, respectively. Except for these three provinces, the environmental efficiency of the other provinces is inefficient. Among them, the three provinces with the lowest environmental efficiency are Xinjiang, Gansu, and Heilongjiang, and their environmental efficiency is 0.0906, 0.1525, and 0.2131, respectively. Because of the low environmental efficiency in most provinces, the average environmental efficiency of China's high-tech industries is only 0.4375.

According to the 2010 China Statistical Yearbook, the country has three regions: eastern, central, and western. Provinces with high environmental efficiency are in eastern China, whereas provinces with low environmental efficiency are concentrated in central and western China. As shown in **Figure 2**, the average environmental efficiency of the high-tech industry in eastern, central, and western regions is 0.7171, 0.2679, and 0.2813, respectively. The environmental efficiency of the eastern region is much higher than that of the central and western regions, and the environmental efficiency of the central region is lower than that of the western region.

From 2008 to 2017, the environmental efficiency in eastern China followed an increasing trend. In the central and western regions, environmental efficiency increased from 2008 to 2016, but declined in 2017 (see **Figure 3**). This may have been because of China's revised energy Conservation Law and Environmental Impact Assessment Law in 2016, which set higher standards for energy conservation and emission reduction. Because of the relatively high level of environmental technology in eastern China, it can better adapt to the requirements of national pollution discharge. The relatively low level of environmental technology in the central and western regions, however, makes it difficult to adapt to the new environmental standards in the short term, which leads to a decline in environmental efficiency in the central and western regions. In general, the environmental efficiency of the high-tech industry in China is low, and the environmental efficiency of the high-tech industry in eastern China is much higher than that in central and western China. The regional differences in environmental efficiency have followed an increasing trend.

Tobit Regression Results

In this study, the Tobit model is used to analyze the role of TI and FDI in improving environmental efficiency of high-tech industry. Control variables are gradually added into model 1, model 2, and model 3: economic factors (level of economic development),

TABLE 3 | Environmental efficiency of China's high-tech industry from 2008 to 2017.

Province	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	1.2736	1.2145	1.1067	1.0410	1.0689	1.1568	1.1983	1.1355	1.1818	1.2603
Tianjin	0.6353	0.6523	0.6496	0.7481	0.8420	1.1357	1.0802	1.1659	1.1302	0.6694
Hebei	0.1644	0.1915	0.2076	0.2252	0.2478	0.2463	0.2457	0.2791	0.2646	0.1927
Liaoning	0.2884	0.3036	0.3237	0.3689	0.3762	0.3607	0.3411	0.3247	0.3260	1.1491
Shanghai	1.4063	1.3411	1.3457	1.2004	1.1669	1.0339	1.0622	1.0552	1.0574	1.0505
Jiangsu	0.5173	0.5372	0.5309	0.5844	0.5990	0.5806	0.5405	0.5730	0.5613	0.4377
Zhejiang	0.3798	0.3775	0.4185	0.4793	0.4593	0.4330	0.4115	0.4266	0.4117	0.3807
Fujian	0.7530	0.7884	0.7826	0.8365	0.8784	1.0167	0.8112	0.7683	0.7652	0.7576
Shandong	0.4015	0.4358	0.4272	0.4959	0.5013	0.5058	0.4923	0.5370	0.5018	0.3484
Guangdong	1.1713	1.1734	1.1672	1.1862	1.3043	1.3943	1.5102	1.5983	1.7778	1.8251
Hainan	0.2600	0.3124	0.3725	0.4037	0.5063	0.3317	0.3578	0.4306	0.4246	0.4305
Shanxi	0.1153	0.1340	0.1373	0.1602	0.2502	0.2662	0.2736	0.3219	0.3195	0.2628
Jilin	0.1967	0.2260	0.2650	0.3034	0.3088	0.3460	0.3552	0.3835	0.3777	0.2570
Heilongjiang	0.1642	0.2127	0.2023	0.2174	0.2124	0.2278	0.2273	0.2694	0.2204	0.1773
Anhui	0.1576	0.1775	0.1828	0.2431	0.2660	0.2790	0.3021	0.3457	0.3341	0.2708
Jiangxi	0.1721	0.2118	0.2043	0.2324	0.2509	0.2655	0.2474	0.2841	0.2743	0.2299
Henan	0.1817	0.2123	0.2093	0.2507	0.2918	0.2983	0.2916	0.3237	0.3039	0.2334
Hubei	0.2798	0.3304	0.3227	0.3572	0.3572	0.3486	0.3501	0.3932	0.3899	0.3211
Hunan	0.2161	0.2454	0.2657	0.3375	0.3418	0.3595	0.3413	0.3630	0.3410	0.2544
Inner Mongolia	0.3135	0.3510	0.2682	0.3087	0.2664	0.2745	0.2795	0.2554	0.2450	0.2105
Guangxi	0.1599	0.1798	0.1997	0.2382	0.2891	0.3322	0.3337	0.3772	0.3678	0.2519
Chongqing	0.2511	0.2755	0.3205	0.5313	0.6033	0.6590	0.6862	0.6623	0.6708	0.5209
Sichuan	0.3033	0.3464	0.3778	0.4491	0.4753	0.5311	0.4914	0.4529	0.4804	0.4143
Guizhou	0.1878	0.2407	0.2429	0.2644	0.3094	0.2909	0.3060	0.3578	0.3424	0.2753
Yunnan	0.2335	0.2675	0.2766	0.3296	0.3386	0.3509	0.3207	0.3447	0.3707	0.3521
Shaanxi	0.2283	0.2457	0.2712	0.2919	0.3064	0.2917	0.2933	0.3270	0.3398	0.2822
Gansu	0.1188	0.1252	0.1157	0.1267	0.1450	0.1461	0.1652	0.2052	0.2046	0.1727
Qinghai	0.1295	0.1567	0.1937	0.1852	0.2576	0.2709	0.2342	0.3636	0.3676	0.2266
Ningxia	0.1452	0.1706	0.1591	0.1970	0.1631	0.1592	0.1625	0.3848	0.4133	0.2878
Xinjiang	0.0871	0.0930	0.0903	0.0934	0.0656	0.0623	0.0541	0.1155	0.1147	0.1296
Mean	0.3631	0.3843	0.3879	0.4229	0.4483	0.4652	0.4589	0.4942	0.4960	0.4544

technical factors (domestic technology transfer and R&D investment), and social factors (human resources and environmental regulations). **Table 4** shows the regression results of Tobit model. The LR test results showed that the random effects Tobit model should be used for regression analysis of these three models.

For TI, the regression coefficients of model 1, model 2, and model 3 are 0.0466, 0.0469, and 0.0413, respectively, and all of them are significant at the statistical level of 1%. This shows that TI has significantly promoted the environmental efficiency of the high-tech industry. For FDI, the regression coefficients of model 1, model 2, and model 3 are 0.0026, 0.0725, and 0.0335, respectively, but these coefficients are not statistically significant. This means that FDI has no significant positive impact on the environmental efficiency of the high-tech industry.

As for the level of economic development, the regression coefficients of model 1, model 2, and model 3 are all significantly positive, which confirms that economic development has a significant positive impact on the environmental efficiency of the high-tech industry. For domestic technology transfer, the regression coefficients of model 2 and model 3 are significantly negative, indicating that domestic technology transfer has a significant inhibitory effect on the environmental efficiency of the high-tech industry. For R&D investment, the regression coefficients of model 2 and model 3 are 0.0028 and 0.0027, respectively, and these coefficients are significant at the statistical level of 1%. This confirms that R&D investment has a significant promoting effect on the environmental efficiency of the high-tech industry. Model 3 examines the role of human resources and environmental regulation. The results show that both have significant positive effects on the environmental efficiency of the high-tech industry.

The results of model 3 show that the environmental efficiency of the high-tech industry will increase by 0.0413 for every 1 billion yuan increase in TI funds. For every 1 billion yuan increase in R&D investment, the environmental efficiency of the high-tech industry will increase by 0.0027. In addition, the level of economic development, human resources, and environmental regulations all have a significant positive impact on the environmental efficiency of China's high-tech industry, whereas FDI has no significant impact on the environmental efficiency and domestic technology transfer has a restraining effect on the environmental efficiency. Therefore, the improvement of environmental efficiency depends on the joint action of many factors, such as TI, economic development level, and R&D investment, and TI is one of the important ways to improve the environmental efficiency of the high-tech industry.

Robustness Test

The robustness of regression model is largely influenced by endogeneity. When establishing a regression model to analyse

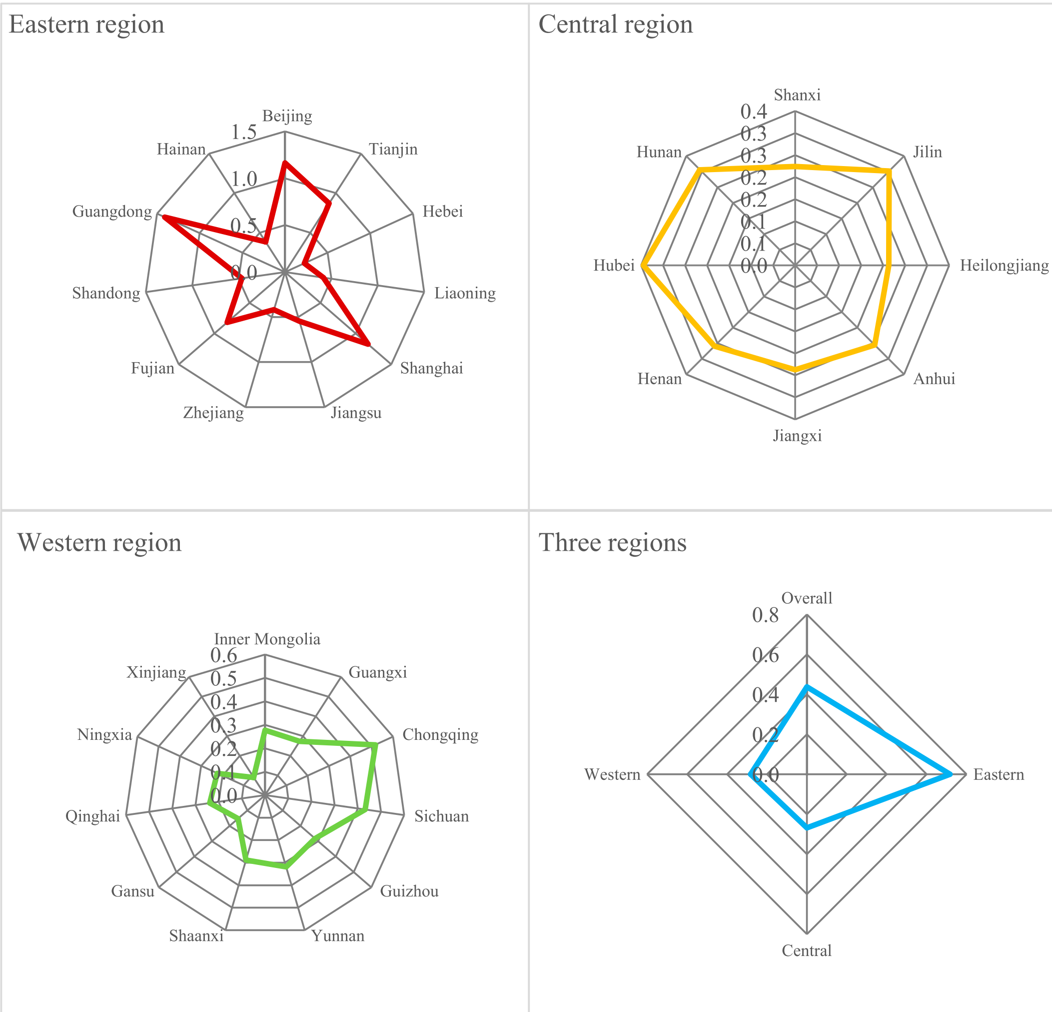

FIGURE 2 | Comparison of the average environmental efficiency in China's three regions.

the influencing factors of environmental efficiency, it is inevitable to miss some explanatory variables (Zhou et al., 2020). Moreover, FDI and environmental efficiency may have a two-way causal relationship (Zhou and Wang, 2017), which may cause endogenous problems. For the endogeneity of panel data, lagged variables can be used as instrumental variables to solve the problem (Lu et al., 2018). We took the lagged term of the independent variables as the instrumental variable to conduct Tobit regression, and Wald test results show that the exogenous null hypothesis was accepted (see **Table 5**). For explanatory variables, by comparing model 4, model 5, and model 6 in **Table 5**, it can be found that the regression coefficients of TI are significantly positive at the statistical level of 1%. Although the regression coefficients of FDI are all positive, they are not statistically significant. This is consistent with the results in **Table 4**. For control variables, the significance of variable coefficients in **Table 5** is consistent with that in **Table 4**. Therefore, the estimation results of the Tobit regression are robust.

DISCUSSION

The evaluation results of environmental efficiency of high-tech industry in China show that the environmental efficiency is low in most provinces, except for Guangdong, Shanghai, and Beijing. The provinces with high environmental efficiency are in the eastern region, whereas the provinces with low environmental efficiency are concentrated in the central and western regions. Chen et al. (2019) have reported that the environmental efficiency of China's industry has similar characteristics, that is, the environmental efficiency of most provinces is low, and the environmental efficiency of the eastern region is higher than that of central and western regions. However, there are also differences in environmental efficiency between them. Chen et al. (2019) have reported that the industrial environmental efficiency gradually decreases from the east, central, and western regions, whereas our results confirmed that the environmental efficiency of high-tech industries gradually decreases from the east, western, and central regions. The reason may be that as

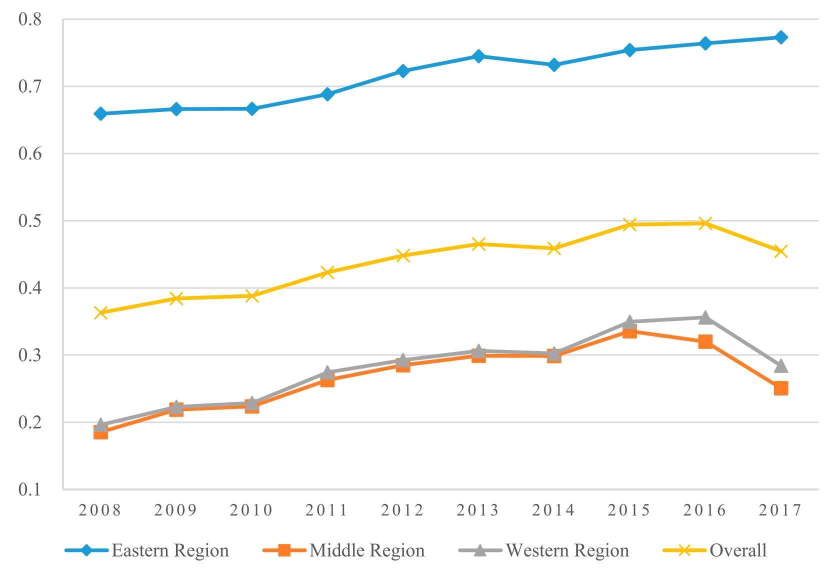

FIGURE 3 | The development trend of environmental efficiency in China's three regions.

TABLE 4 | Results of Tobit regression.

Variables	Model 1	Model 2	Model 3
TI	0.0466***	0.0469***	0.0413***
	(5.70)	(5.58)	(4.88)
FDI	0.0026	0.0725	0.0335
	(0.03)	(0.73)	(0.34)
ED	0.0370***	0.0266***	0.0156**
	(7.93)	(5.20)	(2.43)
DT	—	−0.0448**	−0.0379*
	—	(−2.02)	(−1.73)
RD	—	0.0028***	0.0027***
	—	(4.45)	(4.44)
HR	—	—	0.0313***
	—	—	(2.76)
ER	—	—	0.1181*
	—	—	(1.73)
Constant	0.2022***	0.2101***	0.1327**
	(4.17)	(4.88)	(2.20)
LR test	299.91***	251.11***	250.95***
Log likelihood	223.3871	234.4322	239.0585

*Note: *, **, and *** indicate significance levels of 10, 5, and 1%, respectively. The value in parentheses is z statistics.*

TABLE 5 | Results of the robustness test.

Variables	Model 4	Model 5	Model 6
TI	0.0763***	0.0489***	0.0463***
	(10.41)	(6.31)	(6.00)
FDI	0.0087	0.1618	0.1173
	(0.08)	(1.56)	(1.12)
ED	0.0442***	0.0398***	0.0362***
	(6.80)	(6.83)	(6.17)
DT	—	−0.1118***	−0.1187***
	—	(−4.13)	(−4.41)
RD	—	0.0048***	0.0045***
	—	(8.39)	(7.69)
HR	—	—	0.0186**
	—	—	(2.24)
ER	—	—	0.0619**
	—	—	(2.41)
Constant	0.1257***	0.1247***	0.0810***
	(4.44)	(4.94)	(2.73)
Wald test	0.6316	0.5666	0.7032

*Note: *, **, and *** indicate significance levels of 10, 5, and 1%, respectively. The value in parentheses is z statistics.*

environmental regulations are tightened in eastern China; high-tech enterprises that do not meet local environmental standards are forced to move to other regions. As an ecologically fragile region, the western region faces strict environmental control, and its industrial foundation and technological level are relatively weak. Therefore, many high-tech enterprises eliminated from the eastern region are transferred to the central region, which aggravates local environmental pollution and makes the central region become the region with the lowest environmental efficiency.

This study analyzes the difference of the impact of TI and FDI on environmental efficiency of the high-tech industry. The results show that TI significantly improves the environmental efficiency of China's high-tech industry. This is consistent with the results of Li and Peng (2013). Similarly, Tu and Liu (2011) found that TI would be an effective way for Chinese industry to improve environmental efficiency. This study confirms the positive role of TI in the high-tech industry. The reason may be that policy makers focus on guiding domestic enterprises to introduce foreign advanced environmental protection technologies through the Catalogue of Technologies Encouraged by China. This approach will not only help enterprises achieve the goal of energy saving and pollution reduction in the production process, but also enable these enterprises to accumulate environmental production experience in the learning process. Therefore, TI will help improve environmental efficiency.

This study finds that FDI has no significant impact on the environmental efficiency of China's high-tech industry. This result is consistent with the results of Zhou et al. (2021). Following are reasons for this lack of impact: 1) foreign capital enterprises engaged in processing and manufacturing occupy a higher proportion in China's high-technology industry, 2) strict environmental standards are lacking in some provinces, and 3) foreign capital enterprises are in these provinces with high environmental cost, which is offset by economic returns (Zhou et al., 2021), and therefore there is no significant positive spillover effects on environmental efficiency.

This study confirms that the level of economic development has a positive impact on environmental efficiency, which is consistent with the results of Song and Wang (2018), because the improvement of the level of economic development enhances people's tendency to protect the environment. This study also confirms the positive role of R&D investment and human resources in improving environmental efficiency, which is consistent with the results of Chen et al. (2020). Increased investment in R&D is conducive to the adoption and dissemination of advanced environmental technologies, thus improving the environmental efficiency of the high-tech industry. In addition, more abundant human resources help to enhance the absorption capacity of foreign technology. The results of this study show that environmental regulation is significantly positively correlated with environmental efficiency, which is consistent with the conclusion of Qiu and Wang (2018). Environmental regulations urge enterprises to reduce environmental pollution (Ghazouani et al., 2021), thus having a positive impact on environmental efficiency.

Contrary to theoretical expectations, however, we find that domestic technology transfer has an inhibiting effect on environmental efficiency. This is similar to the results of Li and Peng (2013). The reason may be that China still lacks a perfect transformation mechanism of scientific and technological achievements, and the environmental technologies acquired from domestic universities and research institutes cannot be effectively transformed into economic and environmental benefits.

CONCLUSIONS AND POLICY IMPLICATIONS

To examine the role of foreign technology transfer in improving the environmental efficiency of China's high-tech industry, this study measures the environmental efficiency of the high-tech industry by using the super-efficiency SBM model considering undesirable outputs. Then, the Tobit regression method is used to test the influence of TI and FDI on the environmental efficiency of the high-tech industry, and the main conclusions are as follows. The average environmental efficiency of China's high-tech industry is only 0.4375. Except for Guangdong, Shanghai, and Beijing, most provinces have low environmental efficiency. The provinces with high environmental efficiency are in the eastern region, whereas the provinces with low environmental efficiency are concentrated in the central and western regions. TI has a significant role in promoting the environmental efficiency of the high-tech industry. FDI has a positive impact on the environmental efficiency of the high-tech industry, but it is not statistically significant.

The existing literature focuses on the environmental efficiency of traditional high-pollution industries (Wang et al., 2017; Xu et al., 2021), but few studies have examined the environmental efficiency of China's high-tech industry. In this study, environmental pollution and energy consumption are included in the environmental efficiency evaluation index system, and the environmental efficiency of China's provincial high-tech industry is evaluated using the super-efficiency SBM model considering undesirable outputs. This approach not only improves the evaluation index system of the environmental efficiency of the high-tech industry, but also reveals the difference between the environmental efficiency of the high-tech industry and industrial environmental efficiency. Secondly, existing studies on the role of foreign technology transfer in improving industrial environmental efficiency in China remain controversial. This study analyzes the role of TI and FDI in improving environmental efficiency under a unified framework. This analysis not only provides empirical evidence from China's high-tech industry, but also expands the theoretical research on the relationship between technology transfer and environmental efficiency. In addition, the existing literature has pointed out that endogenous problems may occur when analyzing factors affecting environmental efficiency (Zhou et al., 2020). This study used the instrumental variable method to solve this problem, thus improving the accuracy of estimation results.

These conclusions have important policy implications. First, we will strengthen policy support for TI. In combination with the development plan of high-tech industry, and on the basis of further improving the Catalogue of Encouraged Technology Introduction in China, an information system service platform for TI will be established to provide decision-making support for high-tech enterprises to introduce appropriate environmental protection technology. At the same time, in the face of the technology export control of some countries, China should strengthen technical cooperation with other countries in the field of science and technology, constantly expand new channels of TI, and avoid overdependence on a single source of technology. Second, we will actively introduce high-quality green FDI. The environmental control level of each region should be improved according to local conditions, and the environmental supervision of foreign investment should be strengthened to avoid excessive environmental costs. At the same time, foreign investment access and negative list rules will be further improved through the Catalogue for the Guidance of Foreign Investment Industries to create a good market environment to attract high-quality green FDI.

This study also has some shortcomings. First, typical environmental pollutants in the high-tech industry include sulfur dioxide, carbon dioxide, industrial wastewater, solid waste, radioactive substances, and other undesirable outputs.

Because of the availability of data, this study can only select sulfur dioxide as an undesirable output when evaluating the environmental efficiency of the high-tech industry. Subsequent studies need to estimate other environmental pollutants to improve the evaluation index system of environmental efficiency. Second, using non-stationary panel data for regression analysis may cause the problem of spurious regression. However, this paper can only collect panel data of 30 provinces in China from 2008 to 2017. In this case, the power of unit root test and cointegration analysis tends to be weak. For this kind of short panel data, the problems caused by spurious regression are often not serious. In addition, the environmental efficiency calculated by the SBM model is truncated. Therefore, this paper uses panel Tobit model to analyze the relationship between technology transfer and environmental efficiency. In the future research, we need to collect more years of data, using Fully Modified OLS (FMOLS) or Dynamic OLS (DOLS) model to analyze the long-term relationship between technology transfer and environmental efficiency. In addition, the high-tech industry includes pharmaceutical manufacturing, communication equipment manufacturing, and other subsectors. In different industry segments, not only is the environmental pollution status not the same, but the availability and utility of foreign technology are also different. Therefore, the relationship between foreign technology transfer and environmental efficiency will be examined in combination with the characteristics of these subsectors.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

Conceptualization, writing—review and editing, supervision, project administration, FP; Writing—review and editing, XZ; Methodology, software, validation, formal analysis, data curation, writing—original draft preparation, SZ All authors have read and agreed to the published version of the manuscript.

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