

## Retraction

# Retracted: Environmental Efficiency of Node Cities in Chinese Section of Silk Road Economic Zone and Its Influencing Factors

### Discrete Dynamics in Nature and Society

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### References

- [1] L. Zhang and X. Peng, "Environmental Efficiency of Node Cities in Chinese Section of Silk Road Economic Zone and Its Influencing Factors," *Discrete Dynamics in Nature and Society*, vol. 2021, Article ID 6405394, 9 pages, 2021.

## Research Article

# Environmental Efficiency of Node Cities in Chinese Section of Silk Road Economic Zone and Its Influencing Factors

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This paper adopts an environmental data envelopment analysis (DEA) model containing pollution emissions to measure the environmental efficiency of node cities in the Chinese section of Silk Road Economic Zone (SREZ) in 2011–2020 and verifies the convergence of the environmental efficiency. The results show that the ten node cities had an overall low environmental efficiency and a large gap in environmental efficiency, highlighting the necessity of cross-regional cooperation in emission reduction and the promotion of environmental technologies between regions; the environmental efficiency gaps between node cities and between the three regions started to narrow in 2016 and 2018, respectively, showing a certain convergence trend. In addition, the Tobit model was called to analyze the factors affecting environmental efficiency, revealing that per-capita gross domestic product (GDP), foreign trade, and population density promote environmental efficiency, while the proportion of the secondary industry, number of authorized patents, and regional feature significantly suppresses environmental efficiency. Finally, several suggestions were provided to reduce regional pollution emissions and increase China's environmental efficiency, according to the results of empirical analysis.

## 1. Introduction

Since its conception in September 2013, Silk Road Economic Zone (SREZ) has gradually become a major national strategy for the Chinese government to reduce the economic gap between the eastern and western regions, fully promote opening-up, and guarantee energy security.

The implementation of this strategy, while driving the development of transport, energy, logistics, and emerging industries along the Silk Road, leads to lots of resource consumption and triggers the rapid decline in the regional ecoenvironment. As some node cities have not effectively controlled environmental pollution, environmental problems such as grassland desertification, water pollution, and air pollution have appeared, which directly affect the health of the people and seriously threaten the country's sustainable development plan.

In this paper, ten major cities are selected as the node cities in the Chinese section of the SREZ, namely, Xi'an,

Lanzhou, Urumqi, Xining, Yinchuan, Chongqing, Chengdu, Zhengzhou, Wuhan, and Shanghai. According to the principles of scale, representativeness, and comprehensiveness, we select these 10 big cities as the node central cities of the domestic section of the Silk Road Economic Belt for research. The reason is that since the Silk Road Economic Belt strategy was put forward, most of the 10 node central cities have put forward the strategic positioning of participating in the construction of the Silk Road Economic Belt according to their own geographical conditions and development status. Among them, Xi'an is positioned as a new starting point for the construction of the Silk Road Economic Belt; Lanzhou is positioned as the core node city of the Silk Road Economic Belt; Urumqi is positioned as a transportation hub center, business logistics center, financial service center, cultural, scientific and educational center, and medical service center on the "Silk Road Economic Belt"; Xining is positioned as an important growth pole of the Silk Road Economic Belt; Yinchuan is positioned as a major node

city of the Silk Road Economic Belt, a “bridgehead” of opening to the West and cooperation with Afghanistan; Chongqing is positioned as an important strategic fulcrum of the construction of the Silk Road Economic Belt and the industrial hinterland of the twenty-first century Maritime Silk Road; Zhengzhou is positioned as an important node city of the Silk Road Economic Belt; Chengdu and Wuhan are positioned as important node cities of the “Belt and Road”; Shanghai is positioned as the vanguard and main force in the construction of the “Belt and Road”, especially the twenty-first Century Maritime Silk Road. From the perspective of positioning, these 10 node central cities constitute the important fulcrum and space carrier of the domestic section of the Silk Road Economic Belt. It is necessary to strengthen industrial cooperation to form a joint force to build the Silk Road Economic Belt. These large cities can comprehensively represent the environmental situation in the Chinese section of the SREZ. To evaluate the environmental situation in that section, the authors adopted the environmental efficiency that fully considers economic factors like inputs and outputs.

Specifically, the environmental data envelopment analysis (DEA) model was employed to measure the environmental efficiencies of the node cities in 2011–2020; the factors affecting the environmental efficiency were examined by the Tobit model; the multiple regression model was used to analyze the influencing factors, and several suggestions were presented for the development of the node cities.

## 2. Theoretical Review

The concept of environmental efficiency was first formally proposed by the World Economic Council for Sustainable Development. It refers to the economic value of products

and services that meet human needs divided by the environmental load, that is, the economic value of a unit of environmental load. Since the model for evaluating environmental efficiency was formally proposed by Färe et al., there have been a large number of research results applied to environmental efficiency evaluation [1–4].

Environmental efficiency measures both actual and potential pollution emissions. In economics, environmental efficiency means the potential to reduce the pollution emissions from the current level, without changing inputs and outputs, in reference to the decision-making unit (DMU) on the efficiency frontier. It mainly measures the distance of the pollution emissions of an economy (region) to the minimum pollution emissions under fixed inputs and outputs [5].

Traditionally, the regional environment is evaluated by metrics like per-capita pollution emissions and pollution emissions per unit of gross domestic product (GDP). These traditional methods are easy to understand but severely limited [6]: When region environment is evaluated by environmental efficiency, the production process of an economy is treated as the conversion of a certain number of inputs into several good outputs and bad outputs (pollution); that is, the inputs, outputs, and pollution emissions are considered as a systemic whole to compare the regional difference in environmental performance under the same inputs and outputs.

Most studies on environmental efficiency measurement are based on the nonparametric method of DEA [7]. Proposed by You and Yan in 1978, DEA is a field integrating operations, management, and mathematical economy [8]. The traditional DEA model is called the Charnes–Cooper–Rhodes (CCR) model:

$$\begin{cases} \min & \theta \\ \text{s.t.} & \sum_{j=1}^n \eta_j x_{ij} + s^- = \theta x_0, \quad \sum_{j=1}^n \eta_j y_{rj} - s^+ = y_0, \quad s^-, s^+, \eta_j \geq 0, \quad j = 1, 2, \dots, n, \end{cases} \quad (1)$$

where  $x_{ij}$  and  $y_{rj}$  are input and output vectors, respectively;  $x_0$  and  $y_0$  are the input and output of a DMU, respectively;  $\theta$  is the scalar;  $\eta_j$  is the weight vector.

The CCR model assumes that the scale income of the DMU remains unchanged and measures the integrated efficiency of the DMU. Later, Banker et al. developed an efficiency evaluation model for DMUs with variable scale income by adding a constraint on the weight vector:  $\sum_{j=1}^n \eta_j = 1$ . Their model is generally referred to as the Banker–Charnes–Cooper (BCC) model, which measures the technical efficiency of the DMU [9].

In 1989, Färe et al. [10] presented a curve measure evaluation method for handling bad outputs: the good outputs of efficiency evaluation are increased and the pollutants are reduced by analyzing the good output efficiency with radial measure and weighing the pollutant efficiency with the reciprocal (curve). Hailu and Veeman [11] treated

bad outputs as inputs. However, this treatment does not reflect the actual production efficiency because pollutants are not necessarily proportional to resource inputs in specific production processes. Seaford and Zhu [12] developed a data conversion function that transforms the bad outputs, which should be minimized, into good outputs, which should be maximized, takes the transformed pollutants as common good outputs, and then calls the traditional DEA model for calculation. But the data conversion function cannot maintain the consistency of classification in the CCR model.

To overcome the defects of the previous efficiency evaluation models, Zou et al. [13] designed a novel model to handle bad outputs, the proportional model: Let  $y_{rj}$  and  $y_{lj}^b$ ,  $l = 1, \dots, t$  be the  $r$ -th good output and  $l$ th bad output of the  $j$ th DMU, respectively. Considering the relationship between different bad outputs, the loss function of  $y_{lj}^b$  is represented by  $\beta_b$ , and the total loss of  $DMU_j$  by

$\delta_j = \sum_{l=1}^t \beta_l y_{l,j}^b$ . In addition, the adjusted good output is denoted as a new variable  $o_{r,j} = (y_{r,j}^b / \delta_j)$ ,  $r = 1, \dots, s$ . Then, the new proportional model (with variable scale income) can be defined as follows:

$$\left\{ \begin{array}{l} \min \quad \theta \\ \sum_{j=1}^n \eta_j x_{ij} + s_i^- = \theta x_{ij_0}, \quad i = 1, \dots, m, \\ \text{s.t.} \quad \sum_{j=1}^n \eta_j o_{rj} - s_r^+ = o_{rj_0}, \quad r = 1, \dots, s, \\ \sum_{j=1}^n \eta_j = 1, \eta_j, s_i^-, s_r^+ \geq 0, \quad j = 1, \dots, n, \end{array} \right. \quad (2)$$

where  $s_i^-$  and  $s_r^+$  are both slack terms;  $\theta$  is the solution.

Similar to the BCC model, the above model can obtain the efficiency of each DMU. Through the above transform, the efficiency can be evaluated more reasonably in light of the relationship between different good outputs. The superiority of the proportional model was fully demonstrated through the empirical analysis by Huang et al. [14].

### 3. Methodology and Data

The research data are mainly about the inputs and outputs of the node cities in the Chinese section of the SREZ in 2011–2020. The sources include *China urban statistical yearbook* [15], *China Statistics Yearbooks on Environment* [16], and *China statistical yearbook for the regional economy* [17] published in 2011–2020.

**3.1. Environmental DEA Model.** It is assumed that each DMU (node city) produces  $M$  good outputs  $y = (y_1, \dots, y_M) \in R_+^M$ , and  $I$  bad outputs  $b = (b_1, \dots, b_I) \in R_+^I$ , from  $N$  inputs  $x = (x_1, \dots, x_N) \in R_+^N$ . Then, the set of possible production scenarios can be expressed as follows:

$$P(x) = \{(y, b) : x \text{ can product } (y, b)\}, \quad x \in Y = R_+^M, \quad (3)$$

where  $P(x)$  is a set containing good outputs, bad outputs, and inputs. It was defined by Fare et al. (2004) as environmental output set. The environmental output set  $P(x)$  meets the following conditions:

- (1) Closed set and convex set;
- (2) Strong or free disposability for inputs and good outputs: if  $(y, b) \in P(x)$  and  $y' \leq y$  or  $x' \geq x$ , then  $(y', b) \in P(x)$ ,  $P(x) \subseteq P(x')$ ;
- (3) Jointly weak disposability: if  $(y, b) \in P(x)$  and  $0 \leq \theta \leq 1$ , then  $(\theta y, \theta b) \in P(x)$ ;
- (4) Null-jointness: if  $(y, b) \in P(x)$  and  $b = 0$ , then  $y = 0$ .

The jointly weak disposability indicates that the reduction of bad outputs incurs a cost. Under the given inputs, the reduction of bad outputs must consume some inputs originally used to produce good outputs, resulting in a decline in good outputs. The null-jointness means good outputs are always accompanied by bad outputs. Thus, the environmental output set  $P(x)$  can be described by the DEA.

Suppose the inputs and outputs of the  $K$ -th province in each period  $t = 1, \dots, T$  is  $(X^{k,t}, y^{k,t}, b^{k,t})$ . Based on these inputs, good outputs, and bad outputs, the following environmental DEA model can be constructed:

$$P^t(x^t) = \left\{ \begin{array}{l} (y^t, b^t): \sum_{k=1}^K Z_k^t y_{km}^t \geq y_m^t, \quad m = 1, \dots, M, \\ \sum_{k=1}^K Z_k^t x_{kn}^t \leq x_n^t, \quad n = 1, \dots, N, \\ \sum_{k=1}^K Z_k^t b_{ki}^t = b_i^t, \quad i = 1, \dots, I, Z_k^t \geq 0, \quad k = 1, \dots, K \end{array} \right\}. \quad (4)$$

**3.2. Environmental Efficiency.** Based on the above environmental DEA, the environmental efficiency (EE) DEA can be defined as follows:

$$\begin{aligned} EE = \text{Min} \quad & \theta \\ \text{s.t.} \quad & \sum_{k=1}^K Z_k^t x_{kn}^t \leq x_{kn}^t, \quad n = 1, \dots, N, \quad \sum_{k=1}^K Z_k^t y_{km}^t \geq y_{km}^t, \quad m = 1, \dots, M, \\ & \sum_{k=1}^K Z_k^t y_{ki}^t = \theta b_{ki}^t, \quad i = 1, \dots, I, \quad Z_k^t \geq 0, \quad k = 1, \dots, K, \end{aligned} \quad (5)$$

where  $\theta$  is the environmental efficiency of the  $K'$ -th DMU (node city) in year  $t$ . It measures the distance of the pollution emissions of a region to the minimum pollution emissions under fixed inputs and outputs. If  $\theta = 1$ , the DMU is on the efficiency frontier (with minimal pollution emissions); otherwise, the DMU is not on that frontier, and the environmental efficiency has a loss of  $1 - \theta$  (i.e., the space of improvement is  $1 - \theta$ ).

The above model can also be combined with a weighted nonradial efficiency model into an environmental nonradial efficiency model.

**3.3. Tobit Regression Analysis.** The efficiency measured by DEA falls between zero and one. To find the factors affecting the efficiency measured by DEA, the dependent variable of

the regression equation is limited in that range. If the least squares method is used directly, it would be impossible to fully present the data or avoid bias of estimation. To solve the problem, this paper adopts the Tobit model to regress the influencing factors of environmental efficiency [18]:

$$\begin{aligned} y_i^* &= \beta_0 + \sum_{j=1}^k \beta_j x_{ij} + \varepsilon_i, \\ y_i &= y_i^*, \quad \text{if } 0 < y_i^* \leq 1, \\ y_i &= 0, \quad \text{if } y_i^* < 0, \\ y_i &= 1, \quad \text{if } y_i^* > 1, \end{aligned} \quad (6)$$

where  $y_i^*$  is the latent dependent variable;  $y_i$  is the observed independent variable;  $x_{ij}$  is the vector of independent variable;  $\beta_j$  is the vector of correlation coefficient;  $\beta_0$  is a constant term;  $\varepsilon_i$  is independent and  $\varepsilon_i \sim N(0, \sigma^2)$ .

Combined with the above Tobit regression analysis, the input and output variables used in this article are defined as follows:

- (1) “Good” output: “Good” output is expressed by the GDP of each region. The GDP of all regions uses the 2021 constant price, and the deflation index is calculated based on the price index of each region.
- (2) “Bad” output: “Bad” output refers to the environmental pollutants produced by the company in the production process. It mainly includes three forms of wastewater, waste gas, and solid waste. The three pollutants also include many specific pollutants, considering data integrity and availability. Since the DEA model is a data-driven model, it is not necessary to require too many input-output indicators.
- (3) Labor input: labor input generally refers to the amount of labor actually invested in the production process. Developed countries generally use standard labor intensity labor hours to measure. Due to the lack of statistics on this aspect of relevant city data, existing studies have used the number of employees instead.
- (4) Capital investment: the estimation of capital stock is a very complicated process. Most studies have used the perpetual inventory method to estimate the fixed capital stock in various regions.

## 4. Empirical Analysis

**4.1. Variable Selection and Data Sources.** In the DEA model, income indices are usually treated as outputs and cost indices as inputs. Hence, this paper takes resource consumption as inputs, and economic values and environment pollution as outputs, creating an index system for environmental efficiency in the Chinese section of the SREZ (Table 1).

Based on the intercity panel data 2011–2020, this paper implements the environmental DEA model with fixed scale income. Table 2 presents the measured environmental efficiencies of the node cities in the Chinese section of the

SREZ in 2011–2020. This part focuses on the environmental efficiency and its convergence of node cities.

**4.2. Efficiency Frontier.** As shown in Table 2, Shanghai is the city with the highest environmental efficiency in China. It remained on the efficiency frontier in 2011–2020, providing a benchmark for evaluating the environmental efficiency of any other city.

Wuhan and Chengdu reached the efficiency frontier in 2011 and 2019, respectively, a sign of a marked increase in their respective environmental efficiency. This is probably related to the vigorous promotion of eco-city construction in Central China.

Xining and Yinchuan had the lowest environmental efficiencies ( $<0.2$ ), which gradually moved away from the efficiency frontier. Taking Shanghai as the reference, the two cities could at least cut down their pollution emissions by 80%.

The results show a significant gap in environmental efficiency between node cities and also a massive potential of emission reduction in backward cities.

**4.3. Distribution of Environmental Efficiency.** To compare their difference in environmental efficiency, the node cities were divided into three categories by the traditional classification standard for eastern, central, and western regions of China: Shanghai is the only eastern city; Zhengzhou and Wuhan are central cities; Xi’an, Lanzhou, Urumqi, Xining, Yinchuan, Chongqing, and Chengdu are western cities.

As shown in Table 3, the environmental efficiency of the eastern city was far higher than that of central and western cities. In 2011–2020, the annual mean environmental efficiencies of eastern, central, and western cities stood at 0.80, 0.47, and 0.30, respectively. If central and western cities could reach the average level of environmental efficiency of the eastern city, the pollution emissions of central and western regions could be reduced by 33% and 50%, respectively, from the current levels, even if the inputs and outputs remain unchanged. Thus, central and western cities have a great potential of reducing pollution emissions.

In general, from 2011 to 2020, the eastern region saw a wavy increase in environmental efficiency, and the central region witnessed a clear decline in that efficiency. Meanwhile, the western region’s environmental efficiency basically followed the inverted *U*-shaped trend: the environmental efficiency continuously decreased before 2013 and slowly rebounded since then. To this end, the government should make central and western cities the focus of emission reduction, aiming to reverse the falling environmental efficiency in these regions. Some preliminary conclusions can be drawn out through empirical analysis: environmental pollution has significantly reduced the mean environmental, economic efficiency of the node cities. Besides, the government should encourage environmental technology exchanges between regions. Improving the vulnerable ecoenvironment of the western region is critical to the sustainable development of the national economy.

TABLE 1: Index system for environmental efficiency in Chinese section of the SREZ.

Category	Type	Name and meaning	
Inputs	Resource consumption	Energy consumption	Total energy consumption
		Water consumption	Total water consumption
		Land consumption	Construction land area
		Human resource consumption	Number of employees
		Capital consumption	Fixed asset depreciation
Outputs	Environmental pollution	Wastewater emissions	Industrial wastewater emissions
		Waste gas emissions	Industrial waste gas emissions
		Solid waste emissions	Industrial solid waste emissions
	Economic output	Economic aggregate	Regional GDP

TABLE 2: Environmental efficiencies of some node cities in Chinese section of the SREZ in 2011–2020.

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Xi'an	0.274	0.268	0.264	0.271	0.269	0.261	0.256	0.237	0.249	0.247
Lanzhou	0.285	0.300	0.270	0.248	0.228	0.198	0.207	0.183	0.183	0.185
Urumqi	0.377	0.363	0.386	0.351	0.334	0.294	0.253	0.219	0.205	0.196
Xining	0.139	0.142	0.134	0.130	0.126	0.126	0.116	0.095	0.096	0.094
Yinchuan	0.120	0.109	0.087	0.089	0.082	0.078	0.094	0.085	0.083	0.086
Chongqing	0.327	0.314	0.356	0.390	0.322	0.356	0.366	0.378	0.378	0.484
Chengdu	0.384	0.462	0.356	0.350	0.358	0.379	0.404	0.384	0.459	0.506
Zhengzhou	0.546	0.483	0.481	0.467	0.442	0.474	0.472	0.373	0.401	0.425
Wuhan	0.659	0.654	0.611	0.618	0.584	0.618	0.613	0.438	0.429	0.474
Shanghai	0.901	0.890	0.889	0.845	0.811	0.823	0.722	0.621	0.688	0.724

TABLE 3: Regional distribution of mean environmental efficiencies of node cities in the Chinese section of the SREZ in 2011–2020.

Year	Eastern city	Central city	Western city
2011	0.776	0.461	0.329
2012	0.787	0.521	0.337
2013	0.768	0.503	0.308
2014	0.769	0.475	0.304
2015	0.775	0.473	0.298
2016	0.828	0.470	0.282
2017	0.845	0.472	0.283
2018	0.812	0.456	0.276
2019	0.819	0.417	0.289
2020	0.825	1.419	0.296

4.4. *Convergence Test.* The above analysis shows that the node cities differed greatly in environmental efficiency. The distribution of environmental efficiency carries strong regional features. To clarify the evolution of the intercity gap, it is necessary to test the convergence of environmental efficiency.

Convergence can be generally divided into sigma convergence and beta convergence. The sigma value measures how much a variable varies between regions. If the value attenuates over time, then the variable converges. Beta convergence describes the negative correlation between economic variables and their initial economic levels. By the traditional Barro regression, the test of beta convergence might suffer from Galton’s fallacy. Many scholars are doubtful about the results of the beta convergence test [19–21]. Therefore, this paper relies on the coefficient of variation to test the sigma convergence of environmental efficiency.

As shown in Figure 1, the coefficient of variation for environmental efficiency between node cities slowly increased before 2018 and then gradually decreased. On the nationwide scale, the environmental efficiency gap between the 10 cities narrowed after 2018, showing a weak sigma convergence. However, the sigma convergence was very prominent between the eastern, central, and western regions: from 2016, the coefficient of variation for environmental efficiency decreased at a rapid speed. Therefore, the environmental efficiencies of the three regions tended to converge, and the regional difference gradually diminished. 2016 and 2018 are two obvious turning points, which might be the result of China’s enhancement of environmental protection.

## 5. Analysis on Influencing Factors

5.1. *Variable Selection.* There are many factors that affect environmental efficiency. Drawing on the relevant results [22–26], this paper decomposes environmental effect into economic scale, industrial structure, technological progress, environmental policy and control, international trade, and regional feature and predicts how each independent variable acts on environmental efficiency (Table 4).

5.1.1. *Economic Scale.* Economic scale can be characterized by two variables. The first variable is per-capita GDP. The theory on the environmental Kuznets curve (EKC) holds that, with the improvement of living standards, people would raise higher demand for the environment. Compared with employment and income, people are willing to divert

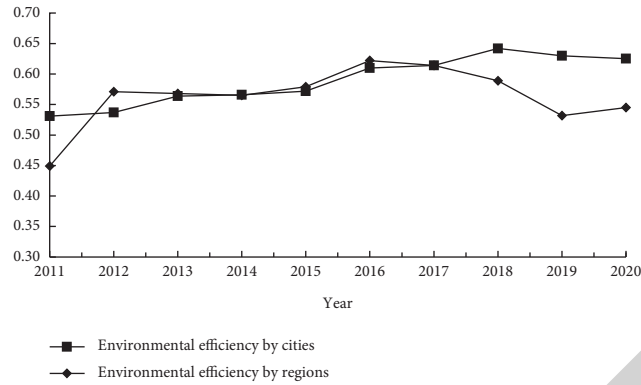


FIGURE 1: Coefficient of variation for environmental efficiency between cities (2011–2020).

TABLE 4: Details about independent variables.

Name	Symbol	Meaning and unit	Predicted sign
Economic scale	Ln (GP)	Per-capita GDP (yuan/person)	Positive
	GR	Regional GDP as a proportion of national GDP (%)	Positive
Industrial structure	PI	Secondary industry output as a proportion of regional GDP (%)	Unknown
Government regulation	FI	Regional industrial pollution management investment as a proportion of regional GDP (%)	Unknown
Opening-up	DT	Trade dependence: total value of import and export as a proportion of GDP (%)	Positive
	DC	Foreign fund dependence: actually utilized foreign direct investment as a proportion of GDP (%)	Unknown
Technological progress	Ln (TI)	Number of authorized patents	Positive
Regional feature	Ln (PD)	Population density: ratio of the year-end total population to the regional area (persons/km <sup>2</sup> )	Unknown

more resources to improve the environment and increase environmental efficiency.

The second variable is regional GDP as a proportion of national GDP. The existing research has found that this variable does not significantly affect environmental efficiency. The proportion merely reflects the economic status of a region in the country; a better economic state does not necessarily bring a higher environmental efficiency. Hence, this variable is not adopted here.

**5.1.2. Industrial Structure.** This paper characterizes industrial structures with secondary industry output as a proportion of regional GDP. It is generally believed that, as the industry takes up a growing portion of the national economy, more and more resources are developed and utilized. The resource consumption rate begins to exceed the speed of resource regeneration and surpass the environmental carrying capacity. As a result, the pollution would increase significantly, while the environment efficiency would nosedive. However, China is still in high-speed development, and most of its regions rely on the secondary industry to elevate the GDP. Thus, the development of the secondary industry might also improve environmental efficiency. Overall, this paper holds that the impact of this variable is to be determined by empirical tests.

**5.1.3. Technological Progress.** Technological progress was characterized by the number of authorized patents, reflecting how much a region invests in technology. Technological progress could drive industry upgrading and environmental protection, help to improve production methods, and optimize the extensive model of economic growth from the source. This is obviously beneficial to environmental efficiency. Therefore, technological progress was expected to promote environmental efficiency.

**5.1.4. Environmental Policy and Control.** Environmental policy and control were characterized by regional industrial pollution management investment as a proportion of regional GDP. During the development of the market economy, the government should solve the environmental problems arising from the blind and irrational development of the market, as well as the one-sided pursuit of economic benefits. The possible instruments include laws, administrative orders, and economic means. Therefore, this variable was expected to promote environmental efficiency.

**5.1.5. International Trade.** International trade was characterized by trade dependence (total value of import and export as a proportion of GDP), i.e., opening-up. The greater the opening-up, the more the need for local industries to achieve a high degree of the international division of labor.

The resulting increase in the degree of specialization will bring continuous economic growth and efficiency improvement. Therefore, trade dependence was expected to promote environmental efficiency.

**5.1.6. Regional Feature.** The regional feature was characterized by population density, i.e., the ratio of the year-end total population to the regional area. A high population density increases the level of living and boosts education level and environmental awareness. With the increase of population density, people continue to call for adaptive changes in urban functions and spatial layouts, which will promote environmental efficiency. Meanwhile, a dense population brings more pressure to the ecoenvironment and

pushes up resource consumption, both of which are not conducive to environmental efficiency. Therefore, the impact of the regional feature on environmental efficiency remains uncertain.

**5.2. Establishment of Regression Model.** The DEA results show that environment efficiency always falls between zero and one (the maximum). The calculation results are truncated or censored. Thus, this paper chooses the Tobit model to regress the influencing factors of environmental efficiency. The relationship between the environmental efficiency of every node city and each influencing factor can be expressed as follows [27]:

$$EEI = \beta_0 + \beta_1 GR + \beta_2 \ln(GP) + \beta_3 PI + \beta_4 DT + \beta_5 DC + \beta_6 FI + \beta_7 \ln(PD) + \beta_8 \ln(TI) + \varepsilon, \quad (7)$$

where  $EEI$  is the environmental efficiency; the right terms are the influencing factors;  $\ln(GP)$  is Logarithm of per-capita GDP;  $GR$  is regional GDP as a proportion of national GDP;  $PI$  is secondary industry output as a proportion of regional GDP;  $FI$  is regional industrial pollution management investment as a proportion of regional GDP;  $DT$  is trade dependence;  $DC$  is foreign fund dependence;  $\ln(TI)$  is technological progress;  $\ln(PD)$  is the logarithm of population density;  $\beta_i$  ( $i = 0, 1, 2, \dots, 8$ ) are the coefficients to be estimated;  $\varepsilon$  is a random error term.

**5.3. Results Analysis.** The truncated data of the Tobit model were processed by the maximum likelihood estimation program of EViews 3.1. Table 5 shows the Tobit regression results of the panel data.

**5.3.1. Economic Scale Greatly Promotes Environmental Efficiency.** The impact coefficient of per-capita GDP on environmental efficiency was 0.144, passing the significance test on 1% level. This result verifies our expectations. Note that regional GDP as a proportion of national GDP ( $GR$ ), another index of the economic scale, does not significantly affect environmental efficiency. For environmental efficiency, per-capita GDP is the better indicator of the economic scale.

**5.3.2. Industrial Structure Has No Significant Effect on Environmental Efficiency.** The secondary industry output as a proportion of regional GDP ( $PI$ ) did not pass the significant test. This result verifies the uncertain effect of this proportion on environmental efficiency. On the one hand, a growing proportion of secondary industry can increase regional GDP, thereby improving environmental efficiency. On the other hand, more pollutants will be emitted due to the rising proportion of the secondary industry, which suppresses environmental efficiency [28]. But the environmental efficiency will gradually improve with the changes of industrial

structures. The proportion of secondary industry should be negatively correlated with environmental efficiency.

**5.3.3. Opening-Up Significantly Promotes Environmental Efficiency.** The impact coefficient of trade dependence ( $DT$ ) on environmental efficiency was 0.312, passing the significance test on 1% level. This means trade dependence can better promote environmental efficiency than per-capita GDP. Every 1% growth of trade dependence will lead to 0.31% increase in environmental efficiency. Meanwhile, foreign fund dependence ( $DC$ ), the other indicator of opening-up, does not significantly affect environmental efficiency. After all, foreign fund dependence only reflects the foreign fund attraction by a region. It does not have a fixed relationship with environmental efficiency.

**5.3.4. Government Regulation Has No Significant Effect on Environmental Efficiency.** The coefficient of regional industrial pollution management investment as a proportion of regional GDP ( $FI$ ) was  $-7.986$ , failing to pass the significance test on 1~10%. Hence, the investment in industrial pollution management in China has not effectively lowered pollution emissions.

**5.3.5. Population Density Significantly Promotes Environmental Efficiency.** The impact coefficient of population density ( $PD$ ) on environmental efficiency was 0.06, smaller than that of economic scale and opening-up. This agrees with our expectation, indicating that population density has a slightly higher positive effect on environmental efficiency than its negative effect. In other words, the negative impact of growing ecoenvironment pressure is offset by the positive effects like improved living standard, education level, and environmental awareness.

**5.3.6. Technological Progress Suppresses Environmental Efficiency.** The impact coefficient of technological progress



TABLE 5: Tobit regression results.

Independent variables	Meaning	Coefficient	Standard error	Z-score	Significance
Ln (GP)	Logarithm of per-capita GDP	0.144	0.037	3.835	***
GR	Regional GDP as a proportion of national GDP	-0.015	0.719	-0.021	—
PI	Secondary industry output as a proportion of regional GDP	-0.210	0.204	-1.030	—
FI	Regional industrial pollution management investment as a proportion of regional GDP	-7.869	6.156	-1.283	—
DT	Trade dependence	0.312	0.055	5.674	***
DC	Foreign fund dependence	-0.357	0.698	-0.512	—
Ln (TI)	Technological progress	-0.126	0.020	-6.257	***
Ln (PD)	Logarithm of population density	0.057	0.013	4.253	***
C	Constant	1.042966	0.09519	10.95632	***

on environmental efficiency was negative, passing the significance test on 1% level. Contrary to what was expected, technological progress suppresses environmental efficiency. A possible reason is that the number of authorized patents is not a good measure of technological progress [29], despite its popularity among Chinese scholars. The defect of measuring technological progress with the number of authorized patents mainly lies in the fact that most research and development (R&D) activities in China are carried out by government agencies, i.e., the technological R&D is not directly related with the market applications [30].

## 6. Conclusions

Based on the data of node cities in the Chinese section of the SREZ in 2011–2010, this paper relies on the DEA proportional model to measure environmental efficiency. The main findings are as follows:

- (1) Compared to traditional pollutant treatment methods, the DEA model can effectively deal with the efficiency evaluation problem involving bad outputs.
- (2) Environmental pollution has significantly reduced the mean environmental economic efficiency of the node cities. Environmental pollution incurred serious efficiency loss on regional economic growth and resulted in a low overall environmental efficiency, calling for continuous improvement.
- (3) Environmental efficiency is significantly promoted by economic scale, trade dependence, and population density, significantly suppressed by industrial structure, technological progress, and regional feature, and insignificantly promoted by the investment in industrial pollution management.

Our conclusions shed light on the development of the cities in the Chinese section of the SREZ:

- (1) Eastern cities should further deepen reforms, promote industrial transfer and industrial upgrading, and improve economic efficiency.
- (2) Central cities should consider both economic benefits and environmental benefits in industrial transfer. Never pursue economic development at the

expense of the environment and step up environmental governance to curb the further deterioration of the environment.

- (3) Despite their relatively high environmental efficiency, western cities must further strengthen environmental pollution control, owing to their low overall environmental efficiency.
- (4) Besides further development of the economy and opening-up, all regions should speed up the upgrading of the industrial structure, reduce the proportion of the secondary industry, and improve environmental governance, aiming to reduce environmental pollution and improve environmental efficiency.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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