An Evaluation of the Impact of Ecological Compensation on the Cross-Section Efficiency Using SFA and DEA: A Case Study of Xin’an River Basin

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Abstract: This paper aims to address the issue of evaluating watershed environmental efficiency with ecological compensation. One of the main objectives is the dynamic assessment of cross-section efficiency. The first transboundary watershed ecological compensation pilot of Xin’an river basin serves as the case study, and stochastic frontier analysis (SFA) is adopted as the main evaluation method. Furthermore, the efficiency is estimated by the data envelopment analysis (DEA) approach. The results validate that SFA can be used as an effective method on such issues by comparing it with the benchmark and the result of DEA, which proves the feasibility of our research methodology. The other purpose is to investigate the factors affecting environmental efficiency. This paper explores the relationship between environmental efficiency with 21 pollutant emission factors as well as the correlation between environmental efficiency and five macro factors of economic development, industrial structure, population density, degree of environmental protection, and natural environment. Finally, suggestions are provided for future improvement. This paper therefore presents a comprehensive reference analysis that contributes to facilitating balanced regional development and environmental conservation in the future.

Keywords: watershed ecological compensation; environmental efficiency; Xin’an river basin; stochastic frontier analysis; data envelopment analysis

1. Introduction

Over the last decades, the problem of environmental contamination has become progressively prominent all over the world. Securing ecosystem services is regarded as one of the fundamental challenges facing humanity [1]. The main reason for such phenomena is the side effects of rapid industrial development. As a country that has had remarkable development, China is no exception. In the past, China’s extensive economy mainly relied on resource utilization, which led to economic development accompanied by serious pollution problems. In response to this environmental challenge, policies and activities are implemented in various ways throughout the country. Ecological compensation, as a promising mechanism to coordinate economy and environment, is being rapidly employed in China.

Ecological compensation is also known as payment for ecosystem services (PES) internationally. To date, there is no unified definition worldwide. Engel et al. [2], Wunder [3], Muradian, et al. [4], and Tacconi [5], respectively, define PES based on Coase theory and Pigou theory. Ecological compensation in China is defined as a mechanism that aims to protect or improve the ecosystem by adopting economic means to align the interests of stakeholders [6]. The principle of ecological compensation is constructed on “who develops, who protects; who destroys, who restores; who benefits, who compensates; who pollutes, who pays” [7].
As one of the most concerning problems encountered by contemporary development of China, basin contamination attracts rising attention. This problem is in conflict with China’s inherent requirements for pursuing comprehensive, balanced, and sustainable development. In particular, watershed issue has its distinct feature, that is, pollutants in the upstream regions are easy to transfer to its downstream regions. Thus, water pollution is not a problem limited to one single administrative region but involves multiple administrative regions. Therefore, a watershed ecological compensation system is introduced to deal with watershed pollution, especially cross regional water pollution. This system is conductive to facilitating the cooperation among different regions in disposing cross regional water pollution, and at the same time helping to balance their economic development.

Xin’an river basin, covering Anhui province and Zhejiang province, is the first pilot to implement transboundary ecological compensation and is also an important example of environmental governance in China’s watershed that constitutes a belt for the coordinated development of ecological civilization construction. We therefore attempt to scientifically evaluate its environmental efficiency and provide reference and implication for future development. This paper has three main contributions. Firstly, we introduce and apply the feasible evaluation methods into an empirical case to assess the environment efficiency with ecological compensation. Stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are adopted as complementary methods to conduct dynamic assessment of cross-section efficiency analysis. Secondly, the results and relationship analysis in this paper highlight the trade-offs between environmental efficiency and different types of factors and enable us to clarify the underlying mechanism. Last but not least, the research outcomes could provide valuable information to support future policy development and the possibility of improving the effectiveness of environmental issues.

The rest of this paper is organized as follows. Section 2 provides a brief review of the literature on ecological compensation assessment and environmental efficiency evaluation. Section 3 presents the methodology of SFA and DEA. Section 4 introduces the case and reports the data and variables used in the empirical analysis. Section 5 discusses the results and analysis. Section 6 draws conclusions including implications and suggestions.

2. Literature Review

2.1. Ecological Compensation Assessment

After years of research on ecological compensation system design, compensation standards, compensation conditions, and compensation methods, ecological compensation assessment is becoming a new focus. Sonter, et al. [1] use spatial simulation models to quantify potential net impacts of alternative compensation policies on biodiversity and two ecosystem services and analyze two influencing factors of policy design and local conditions in four case studies. Adamowicz et al. [8] predict the market-clearing equilibrium to evaluate the potential of the Panama Canal Watershed PES programs, which often act as investment mechanisms for ecological infrastructure. Song et al. [9] study the program effects from the perspective of energy use and other factors by conducting the survey of households under Conversion of Croplands to Forest Program and Ecological Welfare Forest Program based on the PES. Blundo-Canto et al. [10] evaluate the impact of PES on the livelihood of 46 cases through a systematic literature review. Andersson et al. [11] test more than one thousand users of tropical forest in five countries to measure the effectiveness of PES strategy for tropical forest conservation and explore the impact of PES interventions and the role of trust. Alix-García et al. [12] apply a regression discontinuity method to determine the effects of the causal program and compare the results between PES participants and similar rejected applicants who are close to the cut-off score. Romulo et al. [13] first attempt to quantitatively analyze the enabling conditions for investments in watershed services programs across the world through assessing and comparing 416 largest cities and measure relative importance of ecological and social factors by employing random forest ensemble learning methods.
2.2. Environmental Efficiency Evaluation

Many studies on the efficiency evaluation method have been proposed. A common approach for measuring efficiency is the frontier analysis method, which can be divided into parametric methods and non-parametric methods. The former is represented by SFA, while the latter is by DEA. Through a bibliometric analysis, Lampe and Hilgers [14] illustrate that DEA and SFA are popularly adapted to the research of economy and management, especially in the last decade. These two instruments are also widely applied in the field of environment. Hoang and Nguyen [15] use DEA and SFA to analyze variation in materials’ balance-based environmental efficiency and establish a stochastic nutrient frontier and nutrient inefficiency model to analyze the determinants. Van Meensel et al. [16] assess the ability of SFA and DEA methods to analyze trade-offs between economy and environment with reference to a mechanistic frontier approach. Reinhard et al. [17] compare the differences between the SFA model and DEA model for the estimation of environmental efficiency and reveal their strengths and weaknesses. There are numerous studies using these two methods to measure environmental efficiency.

Lu et al. [18] apply the metafrontier–stochastic frontier analysis two-step estimate method into the measurement of environmental efficiency and impact analysis of local leadership’s characteristics. Qi and Choi [19] assess the feasibility of cooperation between Shanghai and Korea on the pilot emissions trading schemes by estimating the environmental efficiency and CO\textsubscript{2} marginal abatement cost of coal-fueled power plants through a directional distance function and SFA. Wang et al. [20] adopt SFA to evaluate the eco-efficiency of the coal industry ecosystem and the potential improvement in 28 typical Chinese coal-mining cities so as to promote their healthy development.

Zheng et al. [21] analyze the water efficiency performance and influencing factors of regions in China during 2000–2015 based on the Shephard water distance function and SFA. Bai et al. [22] employ a stochastic metafrontier approach to conduct quantitative measurement of the environmental performance and carbon emission reduction potential of 39 Chinese industrial sectors from 2005 to 2011. Robaina-Alves et al. [23] propose a new stochastic frontier model considering both the desirable output and the undesirable output to analyze the difference in European countries’ environmental and resource efficiency before and after the Kyoto Protocol. Zhou et al. [24] analyze the environmental efficiency of 30 provinces in China from the perspective of hog production in the period of 2004–2012 with the method of SFA production function.

Zhang et al. [25] use a DEA super slack-based measure to comprehensively analyze the environmental efficiency of 283 cities in China during the rapid economic development process. Long et al. [26] adopt a metafrontier directional slacks-based measure with consideration of heterogeneity to evaluate the environmental efficiency of 192 Chinese thermal power plants in Yangtze River Delta during 2009–2011. Martin-Gamboa et al. [27], Xing et al. [28], and Cecchini et al. [29] integrate DEA and life cycle assessment to measure the environmental efficiency for 20 natural gas combined cycle power plants in Spain, 26 economic sectors in China, and 10 dairy cattle farms in Umbria, respectively. Halkos and Polemis [30] analyze the impact of economic growth on the environmental efficiency of the US electricity sector based on window DEA. Wang et al. [31] assess environmental and emission reduction efficiency by combining DEA with the materials balance principle considering the laws of thermodynamics. Chen and Jia [32] analyze the environmental efficiency in different regions of China through a DEA slacks-based measure incorporating undesirable outputs. Sueyoshi and Yuan [33] conduct empirical research evaluating the regional performance in China by DEA that takes into account two undesirable outputs and two disposability concepts. Yang et al. [34] use a super-efficiency DEA model to deal with the environmental efficiency of 30 Chinese provinces in 2000–2010.

Taken together, as a promising mechanism to solve environmental problems, ecological compensation attracts increasing attention. Existing literature on ecological compensation assessment adopts various methods and analyzes from different aspects, whereas the ex-post assessment, especially the assessment of the environmental efficiency with ecological compensation, is still inadequate, and the factors that drive and explain their environmental performance are also relatively lacking [35]. With the wildly recognized effective and classic efficiency assessment tools in the field of environment,
this paper applies SFA and DEA as complementary approaches to the empirical issue of watershed ecological compensation.

3. Materials and Methods

3.1. Case Background

Xin’an River originates from Huangshan city and spans the Anhui and Zhejiang provinces. It is the third largest water system in Anhui Province and the largest river that inflows into Qiandao Lake in Zhejiang Province. The main stream of Xin’an River is about 359 km in length, including 242.3 km in Anhui Province. The total area of the river basin is about 11,452.5 km², including 6736.8 km² in Anhui Province, of which 5856.1 km² is within the territory of Huangshan City, accounting for 51.1% of the total. This case focuses on Huangshan city, in which the upstream is mainly located.

In December 2010, the central government allocated 50 million start-up funds for the ecological compensation pilot of Xin’an river basin. In 2011, the central government issued the implementation method and allocated 200 million funds. In 2012, the provincial governments of Anhui Province and Zhejiang Province officially signed Water Environment Compensation Agreement of Xin’an River Basin. The pilot work is divided into three rounds of implementation with each round lasting three years, including the first round of 2012–2014, the second round of 2015–2017, and the third round of 2018–2020. The payment of the first two rounds was jointly funded by the central and local governments. From the third round, the payment from the central government declined and mainly came from Anhui and Zhejiang provinces.

In the agreement, the compensation index is the basis for allocating ecological compensation funds. According to Environmental Quality Standard for Surface Water (GB3838-2002), the compensation index P is calculated based on the average of three-year annual concentration value of permanganate index, ammonia nitrogen, total phosphorus, and total nitrogen in the round. The threshold for water quality is quantitatively specified in advance to determine the direction of payment. If P is no less than threshold, Zhejiang Province will allocate its provincial compensation fund to Anhui Province; if P is greater than the threshold or a major water pollution accident has occurred in Xin’an river basin within the boundary of Anhui Province (subject to the definition of the Ministry of Environmental Protection), Anhui Province will allocate its provincial compensation fund to Zhejiang Province. In any case, all the central financial fund will be allocated to Anhui Province. The calculation equation for the compensation index is as follows in (1).

\[
P = d \times \sum_{i=1}^{n} e_i \frac{f_i}{f_{i0}}
\]

where \(P\) denotes the compensation index, \(d\) denotes the water quality stability coefficient, \(e_i\) denotes the weight allocating to indicator \(i\), \(f_i\) denotes annual average concentration value of indicator \(i\), and \(f_{i0}\) denotes the basic limit value of indicator \(i\). It should be noted that \(e_i\) and the threshold are set as different values in the first and second round.

Through the introduction of an ecological compensation mechanism, the first transboundary pilot work covering upstream and downstream regions is established in Xin’an river basin. Since its implementation, the water quality of the Xin’an river basin has greatly improved compared with the past.

3.2. Data Description

The data in this paper consist of a panel data covering 8 monitoring sites of Jiekou stations for the cross section in Xin’an river basin within Huangshan city from 2011 to 2018. In the efficiency calculation, decision making units (DMUs) are defined as 8 monitoring sites, including Huangkou, Huangdun, Hengjiangdaqiao, Jiekou, Kengkou, Lvshuidaqiao, Pukou, and Xinguan. Taking each year of 2011–2018 as a period, the calculation is repeated 8 times, and the average value of the monitoring
stations is used as the efficiency score of the current year. Output is defined as dissolved oxygen (DO), which is usually a basis for measuring the degree of pollution and the self-purification ability of water. If the time required to return to the initial state after consuming the DO in the water is short, it means that the water body is not seriously polluted, or the water body has a strong self-purification ability. Otherwise, it means that the water body is seriously polluted, or the self-purification ability is weak and even lost. To a certain extent, it reflects the service value of watershed ecosystems for pollutant degradation and water purification. With regards to pollutants, there are different approaches to deal with undesirable outputs. This paper takes the undesirable outputs as an alternative indicator of environmental impact and uses them as inputs. In this way, inputs are defined as 21 pollutant emission factors, including permanganate index, biochemical oxygen demand, ammonia nitrogen, petroleum, volatile phenol, mercury, lead, chemical oxygen demand, total nitrogen, total phosphorus, copper, zinc, fluoride, selenium, arsenic, cadmium, hexavalent chromium, cyanide, anionic surfactant, sulfide, and fecal coliform.

3.3. Methodology

Efficiency is the relative concept that an effective DMU is relative to all other DMUs with comparison, and it can be judged by a simple requirement that lies on or below the frontier line. The DMU on the frontier is considered to be an efficient unit, and the DMU below the frontier is regarded as an inefficient unit. The parametric method and non-parametric method are two fundamental methodologies applied to measure the frontier. The frontier is composed of the best performing DMUs, which can produce the most output when input is given or using least input when output is fixed. Once the frontier is determined, the efficiency can be estimated by the distance between the frontier and the unit to be evaluated. The farther away from the frontier, the lower its performance.

SFA is the representative of the parametric method that uses econometric techniques, and DEA is the representative of the non-parametric method that is based on linear programming. They have different ways to construct the frontier. The basic idea of SFA is to use functions and random perturbation terms to build a stochastic frontier. DEA selects one or several DMUs as technically effective points according to the input–output data of DMUs, and then constitutes a frontier. The advantage of SFA is not only that exogenous variables can be directly integrated, but also that statistical noise that distorts most efficiency assessments is considered. Additionally, it can clearly calculate the efficiency of every decision unit without resulting in the same value, and the special points have less influence on its results [20]. The main disadvantage of SFA is the need to define a specific function with the error term composed of the inefficiency term and random error term, which causes specification and estimation problems. On the contrary, DEA does not need to establish a functional relationship between the explanatory variable and the dependent variable, thus avoiding erroneous conclusions due to the use of the wrong function form. At the same time, DEA has the disadvantages of the deterministic model that has no statistical characteristics and does not consider the effect of random errors on individual efficiency. These two methods are detailed in the following sections.

3.3.1. SFA

SFA method is firstly proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). Comprehensive reviews on SFA can be found in Forsund, et al. (1980), Schmidt (1986), Bauer (1990), and Greene (1993). Through comparing the evaluated DMU with the optimal frontier, SFA judges the efficiency and degree of effectiveness by the difference between them. This method is wildly adopted as an effective tool to measure efficiency, especially as an econometric method for multiple inputs and single output. SFA is a parametric method that has an error term consisting of two parts. One is $B \sim N(0, \sigma^2_v)$, which is used to reflect statistical noise (error), and the other is $C \geq 0$, which is used to reflect the controllable but does not reach the optimal part by DMU itself (low efficiency of x). It includes stochastic frontier production function and stochastic frontier cost function. Frontier production refers to the maximum output that can be achieved at a certain level of input, and frontier
cost refers to the minimum cost that can be achieved at a certain level of output. The former is adopted in this study and can be expressed as follows in (2).

\[ Y_i = a x_i + (B_i - C_i), \quad i = 1, \ldots, N \]  

where \( Y_i \) denotes the production output of DMU \( i \); \( x_i \) denotes a \( k \times 1 \) vector of input quantities of DMU \( i \); \( a \) denotes a vector of unknown parameters; and \( B_i \) denotes the random variable assumed to be independently and identically distributed as \( N(0, \sigma_v^2) \) and independent of \( C_i \). \( C_i \) denotes the non-negative random variable assumed to account for technical inefficiency in production, and is often assumed to be independently and identically distributed as \( N(0, \sigma_v^2) \).

3.3.2. DEA

The DEA method [36] is based on the previous work of Afriat (1972), Boles (1966), Bressler (1966), and Farrell (1957). DEA is a nonparametric method of measuring efficiency through linear programming. It does not need to know the specific form of production frontier, but only requires input and output data. It is a convenient method for DMUs with multiple inputs and multiple outputs. A number of comprehensive reviews are available, such as Charnes et al. (1995), Cooper et al. (2000), and Ray (2004). The first CCR model of DEA is proposed by Charnes, Cooper, and Rhodes (1978), which is the basis of other DEA models. This model considers constant return to scale (CRS); that is, outputs increase in the same proportion as inputs. It is an evaluation of the overall efficiency, including technical efficiency and scale efficiency. Banker, Charnes, and Cooper (1984) then propose the BCC model that relaxes the CRS assumption in the CCR model to variable return to scale (VRS), which means that the outputs of the BCC model will not increase by the same proportion as the inputs. It evaluates the pure technical efficiency. The BCC model can be expressed as mathematical programming in (3):

\[
\begin{align*}
&\min_{\varepsilon, \mu} \varepsilon \quad \text{s.t.} \\
&\quad \varepsilon x_i - \sum_{j=1}^{n} x_j \mu_j \geq 0 - y_i + \sum_{j=1}^{n} y_j \mu_j \geq 0 \sum_{j=1}^{n} \mu_j = 1 \mu_j \geq 0
\end{align*}
\]  

where \( \varepsilon \) is the efficiency score; \( x \) and \( y \) are the input and output variables, respectively; and \( \mu \) is the dual variable that identify the benchmark for inefficient unit.

The measurement resulting from the above two models often shows multiple effective DMUs under some situations such as when the quantity of DMUs is small; that is, their efficiency scores are all 1. The efficiency level of these effective DMUs thus cannot be further compared. Andersen and Petersen (1993) propose a super-efficiency model that addresses such problems to a certain extent. Compared with the classic CCR and BCC models, this model recalculates the efficiency of the DMU with an efficiency score of 1 in those models, and finally distinguishes the efficiency level of the DMU that was originally on the frontier. It can be expressed as mathematical programming in (4):

\[
\begin{align*}
&\min_{\varepsilon, \mu} \varepsilon \quad \text{s.t.} \\
&\quad \varepsilon x_i - \sum_{i=1, i \neq 1}^{n} x_j \mu_j \geq 0 - y_i + \sum_{i=1, i \neq 1}^{n} y_j \mu_j \geq 0 \sum_{j=1}^{n} \mu_j = 1 \mu \geq 0
\end{align*}
\]  

The selection of estimation method is always a controversial issue. In general, SFA and DEA both have their own strengths and weaknesses, respectively. Aiming at the concerns of this paper, we attempt to use both SFA and DEA methods to measure the environmental efficiency with ecological compensation of Xin’an river basin. Taking SFA as the main method, DEA, BCC model, and super BCC model are used for comparison and verification.
4. Results

4.1. Data Processing

For each calculation, there are 8 DMUs and 22 variables. There are far more variables than DMUs, which makes it impossible to process and compute the efficiency score in SFA. We set the number of DMUs to n and the number of variables to m. After testing, we found that m must be less than n − 1. In other words, m ≤ n − 2; the maximum quantity of variables is n − 2. Therefore, this paper uses Principal Component Analysis (PCA) to conduct dimensionality reduction, which can compress data while minimizing information loss. PCA can be used for data compression and data preprocessing by combining potentially high-dimensional variables into linearly independent low-dimensional variables, which are called principal components. The new set of low-dimensional variables will retain the features of the original data as much as possible. The purpose of PCA is to reconstruct new features on the basis of these original features. The new features remove the redundant information of the original features, so they are more distinguishable. The PCA result obtains new features rather than simply discarding some features from the original. Its formula is as follows in (5).

\[
\hat{Y}_k = Y - \sum_{p=1}^{k} Y w(p) w^T(p) w(k) = \arg \max_{\|w\|=1} \left\{ \|\hat{Y}_k w\|^2 \right\} = \arg \max \left\{ \frac{w^T \hat{Y}_k^T \hat{Y}_k w}{w^T w} \right\}
\]

where \(w(p)\) is the multiplier in the \(p\)-th orthogonal projection, \(t\) is transpose, and \(k\) is used to index component.

The Kaiser–Meyer–Olkin measure of sampling adequacy is 0.825 > 0.5, indicating that PCA is feasible for dimensionality reduction in this case. Since there are 8 DMUs, the maximum quantity of variables should not exceed 6. Excluding 1 output variable, 21 input variables are compressed into 5 so as to retain the features of the original data as much as possible. As shown in Table 1, these 5 components can explain 92.4% of the original data. Hereafter, the inputs are redefined as fac 1–5, which are also known as regressor variables in SFA.

| Component | Initial Eigenvalues | Extraction Sums of Squared Loadings |
|-----------|---------------------|-------------------------------------|
|           | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1         | 10.8  | 51.5         | 51.5         | 10.8  | 51.5         | 51.5         |
| 2         | 3.7   | 17.4         | 68.9         | 3.7   | 17.4         | 68.9         |
| 3         | 2.9   | 13.9         | 82.8         | 2.9   | 13.9         | 82.8         |
| 4         | 1.3   | 6.0          | 88.8         | 1.3   | 6.0          | 88.8         |
| 5         | 0.7   | 3.6          | 92.4         | 0.7   | 3.6          | 92.4         |
| 6         | 0.5   | 2.4          | 94.8         |       |              |              |
| 7         | 0.3   | 1.5          | 96.2         |       |              |              |
| 8         | 0.3   | 1.3          | 97.6         |       |              |              |
| 9         | 0.2   | 1.0          | 98.5         |       |              |              |
| 10        | 0.1   | 0.6          | 99.1         |       |              |              |
| 11        | 0.1   | 0.3          | 99.4         |       |              |              |
| 12        | 0.1   | 0.3          | 99.7         |       |              |              |
| 13        | 0.0   | 0.1          | 99.8         |       |              |              |
| 14        | 0.0   | 0.1          | 99.9         |       |              |              |
| 15        | 0.0   | 0.1          | 100.0        |       |              |              |
| 16        | 0.0   | 0.0          | 100.0        |       |              |              |
| 17        | 0.0   | 0.0          | 100.0        |       |              |              |
| 18        | 0.0   | 0.0          | 100.0        |       |              |              |
| 19        | 0.0   | 0.0          | 100.0        |       |              |              |
| 20        | 0.0   | 0.0          | 100.0        |       |              |              |
| 21        | 0.0   | 0.0          | 100.0        |       |              |              |

Note: Fac 1–5 refer to the new variables compressed by PCA dimensionality reduction from 21 original input variables.
Since data after dimensionality reduction may have negative values while the input variables are pollutant emission factors that cannot be negative, normalization is needed. In addition, when computing efficiency score by SFA, if the input is positive and the output is 0, the efficiency score will be negative, which is unreasonable. In order to ensure the reliability of the results, the following formula as in (6) is used for dimensionless processing and eliminates negative numbers and zero values in the data.

\[ x_i^* = \phi + \frac{x_i - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \times (1 - \phi) \]  

(6)

where \( x_{\text{max}} \) and \( x_{\text{min}} \) are the maximum and minimum data in \( x_i \), respectively. \( \phi \) is determined according to the normalized data range, which is set to 0.5 to convert original data \( x_i \) to normalized \( x_i^* \) that falls into [0.5, 1] in this case. Table 2 shows the descriptive statistics for each variable of the processed data.

### Table 2. Descriptive statistics of fac 1–5.

| Year | Statistics | DO | Fac 1 | Fac 2 | Fac 3 | Fac 4 | Fac 5 |
|------|------------|----|-------|-------|-------|-------|-------|
|      |            |    |       |       |       |       |       |
| 2011 | Mean       | 0.6774 | 0.9123 | 0.6229 | 0.8495 | 0.8983 | 0.8342 |
|      | S.D.       | 0.0676 | 0.1667 | 0.0661 | 0.0655 | 0.0841 | 0.0400 |
|      | Max        | 0.7630 | 0.9795 | 0.6863 | 0.9007 | 1.0000 | 0.8881 |
|      | Min        | 0.5417 | 0.5000 | 0.5000 | 0.7445 | 0.7322 | 0.7679 |
| 2012 | Mean       | 0.7307 | 0.9830 | 0.7157 | 0.8828 | 0.7993 | 0.7713 |
|      | S.D.       | 0.0708 | 0.0050 | 0.0691 | 0.0792 | 0.0640 | 0.0430 |
|      | Max        | 0.8306 | 0.9922 | 0.7998 | 1.0000 | 0.9204 | 0.8318 |
|      | Min        | 0.6380 | 0.9752 | 0.6044 | 0.7475 | 0.7178 | 0.6969 |
| 2013 | Mean       | 0.6748 | 0.9892 | 0.7068 | 0.8419 | 0.7914 | 0.6867 |
|      | S.D.       | 0.1297 | 0.0049 | 0.0729 | 0.0873 | 0.0646 | 0.1232 |
|      | Max        | 0.8278 | 1.0000 | 0.8199 | 0.9772 | 0.9042 | 0.8744 |
|      | Min        | 0.5000 | 0.9835 | 0.6020 | 0.6997 | 0.7124 | 0.5000 |
| 2014 | Mean       | 0.7913 | 0.9823 | 0.6872 | 0.8160 | 0.6852 | 0.7456 |
|      | S.D.       | 0.0844 | 0.0030 | 0.0675 | 0.0761 | 0.0492 | 0.0893 |
|      | Max        | 0.8972 | 0.9664 | 0.8010 | 0.9388 | 0.7607 | 0.9277 |
|      | Min        | 0.6722 | 0.9777 | 0.5756 | 0.6769 | 0.6184 | 0.6191 |
| 2015 | Mean       | 0.8192 | 0.9747 | 0.7361 | 0.8607 | 0.6047 | 0.8271 |
|      | S.D.       | 0.1185 | 0.0033 | 0.0608 | 0.0769 | 0.0644 | 0.0869 |
|      | Max        | 1.0000 | 0.9812 | 0.8296 | 0.9681 | 0.7022 | 0.9578 |
|      | Min        | 0.7204 | 0.9717 | 0.6160 | 0.7066 | 0.5000 | 0.6957 |
| 2016 | Mean       | 0.7945 | 0.9756 | 0.8118 | 0.7605 | 0.7109 | 0.8378 |
|      | S.D.       | 0.1081 | 0.0096 | 0.1014 | 0.1194 | 0.0756 | 0.0900 |
|      | Max        | 0.9685 | 0.9849 | 1.0000 | 0.8752 | 0.8447 | 1.0000 |
|      | Min        | 0.6815 | 0.9590 | 0.7060 | 0.5257 | 0.6152 | 0.7107 |
| 2017 | Mean       | 0.7341 | 0.9743 | 0.8667 | 0.7652 | 0.7937 | 0.8611 |
|      | S.D.       | 0.0679 | 0.0081 | 0.0867 | 0.1078 | 0.0801 | 0.0701 |
|      | Max        | 0.8593 | 0.9852 | 0.9980 | 0.8651 | 0.9122 | 0.9545 |
|      | Min        | 0.6750 | 0.9621 | 0.7681 | 0.5268 | 0.6670 | 0.7925 |
| 2018 | Mean       | 0.7244 | 0.9758 | 0.8265 | 0.7281 | 0.7973 | 0.8216 |
|      | S.D.       | 0.0683 | 0.0082 | 0.0868 | 0.1023 | 0.0782 | 0.0731 |
|      | Max        | 0.8111 | 0.9860 | 0.9676 | 0.8005 | 0.8994 | 0.9326 |
|      | Min        | 0.6204 | 0.9623 | 0.7376 | 0.5000 | 0.6323 | 0.7172 |

Note: Fac 1–5 refer to the new variables compressed by principle component analysis (PCA) dimensionality reduction from 21 original input variables.
4.2. SFA Efficiency Calculation

The efficiency score calculated by SFA (SFA ES) is as follows in Figure 1. The highest score is 0.999 in 2016, and the lowest is 0.9747 in 2011. According to the agreement, 2010–2011 is the start-up phase. The efficiency in the first round of implementing ecological compensation increases from 0.9965 in 2012 to 0.997 in 2014. The efficiency in the second round of implementing ecological compensation increases from 0.9976 in 2015 to 0.9999 in 2016, and then decreases to 0.9826 in 2017. 2018 is the first year of the third round, with an efficiency score of 0.9842. The overall trend shows the alternation between progress and decline.

![Figure 1. Combined line chart of SFA ES and RP. Note: SFA ES refers to SFA efficiency score, and RP refers to the reciprocal of compensation index P.](image)

As mentioned before, compensation index P is the basic index for the ecological compensation of the pilot. It should be noted that the higher the compensation index P, the more serious the pollution, and the worse the effect of the pilot work. SFA assesses the performance by efficiency score. Conversely, the higher the efficiency score, the better the effect of pilot work. In view of the fact that the SFA efficiency score and the compensation index P are calculated by different methods, the overall trend and ranking of the reciprocal of compensation index P (RP) in every round could serve as the benchmark to measure the availability and accuracy of SFA ES. Figure 1 also incorporates the reversed line chart of compensation index P by using the reciprocal for the convenience of easily understanding the comparison. Different coordinate axes are used due to the relatively weak discriminating power in ranking and comparing values. As shown in Figure 1, these two lines appear as very similar trends in the whole as well as in each round. The ranks of ES are also in coordinate with the ranks of RP in every round.

Compared with similar studies mentioned in Section 2, the combination of PCA and the frontier analysis method incorporates more variables with comprehensive features. Instead of new equation derivation and modelling, the classic mature methods have strong universality, which are more convenient and easier to apply. The results obtained show a high degree of similarity with the benchmark, which verify its feasibility and enable further analysis in the next step.
5. Discussion

5.1. The First-Round Analysis

The first round of implementing ecological compensation is from 2012 to 2014 that appears as an upward trend both in ES and RP. In order to eliminate magnitude difference between ES and RP, Figure 2 normalizes the data of the first round to the $[0, 1]$ range. It can be seen that the lines of ES and RP appear to have a high degree of fitting in the first round. Not only are the trends and ranks consistent, but the values are similar. This paper also uses Kendall Rank Correlation Coefficient (KRCC) to measure the degree of consistency between two ranks of SFA ES and RP, and to assess the significance of their consistency. Its calculation equation is as follows in (7). The value of KRCC ranges from −1 to 1. The larger the value, the more similar the two ranks. The consistency value calculated between the ranks of ES and RP within the first round is 1, which statistically supports our SFA; ES as the rank is largely in consistent with that of RP.

$$KRCC_{p,q} = \frac{\sum(N_{p,q}-1) \cdot f(r_{ij}-r_{jp})(r_{ij}-r_{jq})}{N_{p,q}(N_{p,q}-1)}$$

where $N_{p,q}$ denotes the number of items; $(r_{ij}-r_{jp})$ denotes the difference between two random items in rank $p$; $(r_{iq}-r_{jq})$ denotes the difference between two corresponding random items in rank $q$; and $f(x)$ denotes a binary threshold function.

![Figure 2](image)

**Figure 2.** Combined line chart of normalized SFA, ES and RP. Note: SFA ES refers to SFA efficiency score, and RP refers to the reciprocal of compensation index $P$.

5.2. The Second-Round Analysis

The second round of implementing ecological compensation is from 2015 to 2017. Both the trends and ranks of SFA and RP are consistent that appear first rising and then decreasing. Their values every year show big differences due to the change in the weight coefficient of indicator $i$ in the formula for calculating compensation index $P$ in the second round. In order to compare the changes of the compensation index $P$ in the second round of the pilot, $P$ of the second round is recalculated with reference to the formula and the weight coefficient for calculating $P$ of the first round. Figure 3 presents the normalized data of ES and RP with old calculating way (ORP) as same as in the first round that fall...
into $[0, 1]$. The highest both appear in 2016, and 2016 and 2017 have similar values and highly fitted lines. In addition, the consistency value is 1 within the second round, not only between ES and RP, but also between ES and ORP. These consistency values prove the rationality of the SFA method for environmental efficiency evaluation in this case.

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5.3. Comparison with DEA
This section compares SFA results with DEA results. Similar to SFA calculation, we employ DO as output, PCA-based 5 factors as inputs, 8 monitoring sites as DMUs, and use the annual average value of 2011–2018 as the efficiency score for DEA. The classic BCC model and super BCC model are adopted, respectively. Figure 4 presents the comparison among SFA ES and DEA ESs of these 2 models. Three insights can be found in the figure. First, apart from the value, there is not much difference between the two models on this issue. They are similar in the trend of 2011–2014, 2015–2016, and 2017–2018, and only obviously different in 2016. Second, DEA ES of the super BCC model has comparatively more similarities with SFA ES than DEA ES of BCC model in terms of trend, rank, and degree of fitting. In the BCC model, KRCC value between DEA ES and SFA ES is 1 within the first round and 0.3333 within the second round. In the super BCC model, KRCC value between DEA ES and SFA ES is 1 within both the first round and the second round. Third, as a whole, SFA ES and DEA ES are inconsistent at first, and then tend to be consistent. The reason why may be the scale efficiency of the ecological compensation funds that is gradually appearing by degrees. BCC model assumes that variable return to scale. There is no scale efficiency in the beginning due to relatively small fund investment, and the scale efficiency is reflected later because of the stable growth of additional fund investment in the second stage. Therefore, these two ESs are becoming more and more consistent. Overall, SFA and DEA are both applicable to this case, and they are generally consistent and can support each other.

5.4. Influencing Factors Analysis
To a large extent, the purpose of evaluating environmental efficiency is not only to estimate the efficiency scores, but also to propose practical policies to improve environmental efficiency. Thus, it is necessary to study the determinants and underlying influencing factors of environmental efficiency, which would be helpful for formulating more comprehensive policies to improve environmental efficiency.
with great biological toxicity to environmental pollution and also one of the most toxic heavy metals by the World Health Organization, and 1.5 mg/L for fluoride and selenium is 1 mg/L set by the Standards for Drinking Water Quality (4th edition) in China (GB 5749-2006). The 2011–2018 monitoring data shows that their concentrations in Xin’an river are far below the limit, with the highest fluoride concentration of 0.4092 mg/L and 0.01 mg/L, respectively, set by the Guidelines for Drinking-Water Quality (4th edition) by the World Health Organization, and 1.5 mg/L and 0.04 mg/L, respectively, set by Standards for Drinking Water in China (GB 5749-2006). The 2011–2018 monitoring data shows that their concentrations in Xin’an river are far below the limit, with the highest fluoride concentration of 0.4092 mg/L and selenium of 0.001 mg/L set by the World Health Organization.

5.4.1. Determinants

This paper uses regression analysis to identify significant determinants of environmental efficiency by setting SFA ES as a dependent variable and 21 pollution emission factors as independent variables. In multiple linear regression, the t test can test the significance of each variable coefficient in the regression equation. The regression analysis model is as follows in (8). From the results, $R^2$ being 0.669 means that the fitting effect is good, and the significance being $0.000 < 0.05$ means that the regression is significant. The significance levels of four independent variables are less than 0.05, which can be considered as highly explanatory to the dependent variable $y_1$.

$$y_1 = g_0 + g_1x_1 + g_2x_2 + \ldots + g_21x_{21}$$

As shown in Table 3, lead, total phosphorus, fluoride, and selenium have significant effects on SFA ES. Among them, total phosphorus is also an indicator in the calculation equation for the compensation index P. It mainly comes from domestic sewage, chemical fertilizers, organic phosphorus pesticides, and phosphate builders used in modern detergents. Excessive phosphorus is the main cause of water pollution, odor and eutrophication of lakes, and red tides in bays. Mercury is one of the heavy metals with great biological toxicity to environmental pollution and also one of the most toxic heavy metals to human beings. It cannot be decomposed in water, and its toxicity will be amplified after drinking and combined with other toxins in water to form more toxic organic matter. Appropriate fluorine and selenium are necessary for the human body, while excessive fluorine and selenium are harmful. In order to control the harm to human health caused by overdose, related standards are formulated to strictly regulate the concentration of fluoride and selenium in drinking water. The limited value for fluoride and selenium is 1 mg/L and 0.01 mg/L, respectively, set by Guidelines for Drinking-Water Quality (4th edition) by the World Health Organization, and 1.5 mg/L and 0.04 mg/L, respectively, set by Standards for Drinking Water in China (GB 5749-2006). The 2011–2018 monitoring data shows that their concentrations in Xin’an river are far below the limit, with the highest fluoride concentration of 0.4092 mg/L and selenium of 0.001 mg/L set by the World Health Organization.

![Figure 4. Combined line chart of SFA ES and DEA ESs. Note: SFA ES refers to SFA efficiency score, and DEA ES refers to DEA efficiency score.](image-url)
### Table 3. Descriptive statistics and coefficients of regression.

| Variable                  | Mean   | Std. Deviation | t stat | Sig.  |
|---------------------------|--------|----------------|--------|-------|
| Permanganate Index        | 0.790  | 0.118          | −1.662 | 0.104 |
| Biochemical Oxygen Demand | 0.951  | 0.063          | −1.669 | 0.102 |
| Ammonia Nitrogen          | 0.949  | 0.066          | 0.251  | 0.803 |
| Petro                     | 0.913  | 0.074          | 1.020  | 0.313 |
| Volatile Phenol           | 0.990  | 0.062          | −0.856 | 0.397 |
| Mercury                   | 0.992  | 0.063          | 0.631  | 0.531 |
| Lead                      | 0.979  | 0.061          | −2.870 | 0.006 |
| Chemical Oxygen Demand    | 0.682  | 0.093          | −0.395 | 0.695 |
| Total Nitrogen            | 0.776  | 0.075          | −0.416 | 0.679 |
| Total Phosphorus          | 0.759  | 0.100          | 2.398  | 0.021 |
| Copper                    | 0.992  | 0.063          | 0.661  | 0.512 |
| Zinc                      | 0.988  | 0.062          | 1.972  | 0.055 |
| Fluoride                  | 0.832  | 0.117          | 2.201  | 0.033 |
| Selenium                  | 0.879  | 0.082          | 2.628  | 0.012 |
| Arsenic                   | 0.972  | 0.061          | −0.495 | 0.623 |
| Cadmium                   | 0.992  | 0.063          | −1.686 | 0.099 |
| Hexavalent Chromium       | 0.568  | 0.110          | 0.604  | 0.549 |
| Cyanide                   | 0.568  | 0.133          | −0.784 | 0.437 |
| Anionic Surfactant        | 0.608  | 0.100          | 0.554  | 0.582 |
| Sulfide                   | 0.665  | 0.215          | 0.706  | 0.484 |
| Fecal Coliform            | 0.720  | 0.132          | −1.004 | 0.321 |

5.4.2. Influencing Factors

According to the Environmental Kuznets Curve (EKC) hypothesis, economic scale, structural change, technical progress, and government regulations are usually considered to be closely related to environmental performance [37–40]. In addition, regional factors, including population and resource endowment, may also affect environmental efficiency [41]. Combining the existing research and data availability, GDP per capita is adopted to demonstrate the economic scales. Industrial structure is employed to measure the structural changes. The degree of environmental protection illustrated by capital investment stands for government regulations. Population density and annual precipitation are used as the surrogate metrics for the regional factors. The regression analysis model is built as follows in (9) to check their impact on SFA ES. From the results, $R^2$ being 0.938 means that this model has high goodness of fit, and the significance being 0.000 < 0.05 means that the regression is significant. The coefficients of independent variables are presented as follows in Table 4.

$$y_2 = h_0 + h_1 GP + h_2 TI + h_3 PD + h_4 CI + h_5 NE$$  (9)

where $y_2$ is SFA ES; $h_0$ is constant term; $h_i$ (i = 1, 2, ..., 5) is the estimation parameter; GP is GDP per capita denoting the economic development level; TI is tertiary industry increasement index, to demonstrate industrial structure to some extent; PD is population density, expressed by the resident population per square kilometer; CI is capital investment on environmental protection, referring to the ecological compensation investment fund of this pilot; and NE is natural resource endowment, represented by annual precipitation.

As displayed in Table 4, five independent variables whose significance is less than 0.05 all have significant effects on SFA ES. GP takes an important positive position on environmental efficiency in this case. According to the Environmental Kuznets Curve theory [37,42], there is an inverted U-shaped curve between pollution emission and economic growth. The degree of environmental pollution is relatively light when a country’s economic development level is low, and then tends from low to high as social income increases. However, when the economic development reaches a critical point or “turning point”, the environment will improve with further increase of social income. Empirical analysis has confirmed the relationship between the level of environmental pollution and the level of
economic development, and the turning point generally occurs when the GDP per capita reaches about 6000–8000 USDs. With the issue of Responsibility statement for total emission reduction target of major pollutants in the 12th Five Year Plan for 2011–2015, the proposal of high-quality economic development at the 19th National Congress of the Communist Party of China in 2017 and other environmental conditioning polices, China’s economy is gradually changing from high-speed extensive growth to high-quality intensive development. In Huangshan city, the ecological compensation pilot work of Xin’an river basin officially initiated in 2011, and the GDP per capita exceeded 6000 USDs in 2017 (with annual average exchange rate: 6.7518), which may indicate the stage of meeting the turning point.

This can be further analyzed with the industrial structure. In accordance with GP, TI has a positive correlation with environmental efficiency. The proportion of three industries’ GDP in Huangshan city is presented in Figure 5. Compared with the decrease in primary industry and secondary industry, the proportion of tertiary industry increases from 42.0% to 56.7% by a growth rate of 35.0%. The GDP is mainly driven by tertiary industry. As shown in Figure 5, the GDP as well as its proportion of tertiary industry both show the increasing trend in 2011–2018, which is in a critical period of transformation of development mode, optimization of economic structure, and transition of growth power. Following the pace of the country, the impact of economic development on the environmental efficiency of Xin’an river basin in Huangshan city is affected by the strengthening of environmental regulations and the adjustment of industrial structure, the environmental pollution tends from high to low, and the environmental quality is gradually improving.

Table 4. Coefficients of regression.

| Variable | Unstandardized Coefficients | Standardized Coefficients Beta | t stat | Sig. |
|----------|-----------------------------|--------------------------------|--------|------|
| Constant | 2.387                        | /                              | 5.575  | 0    |
| GP       | 1.03 × 10^{-6}              | 0.72                           | 5.099  | 0    |
| TI       | 0.002                        | 0.377                          | 2.611  | 0.026|
| PD       | −0.011                       | −0.583                         | −4.091 | 0.002|
| CI       | 4.88 × 10^{-8}              | 0.444                          | 3.88   | 0.003|
| NE       | 2.36 × 10^{-5}              | 0.64                           | 6.55   | 0    |

Note: GP refers to GDP per capita, TI refers to tertiary industry increasement index, PD refers to population density, CI refers to capital investment, and NE refers to natural environment factor.

Figure 5. Three industries’ GDP in Huangshan from 2011 to 2018.
PD shows a negative impact on environmental efficiency. The average PD of Huangshan city in 2011–2018 is 150.865, exceeding the national average PD of 144.3 in 2017. Suitable population could be an advantage for regional development while the overloaded population needs to consume more ecosystem services and produce more emissions, which may exert additional pressure on the environment. CI that is represented by the ecological compensation investment fund in Xin’an river pilot work plays a positive role in environmental efficiency. Normally, investment in environmental protection and pollution control and treatment is helpful to curb the pollutants and improve environmental quality. To further explore the relationship between CI and SFA ES, their trendline is stimulated. As displayed in Figure 6, the environmental effectiveness is positively correlated with the amount of ecological compensation investment in general. However, the effect has good performance when the amount of compensation is within a certain range, rather than always being the higher the better. In this view, it is necessary to monitor the payment activities [35].

Figure 6. Relationship between ecological compensation investment and SFA ES.

NE expressed by annual precipitation has a positive link with the environmental efficiency. Precipitation results in different river runoff. On the one hand, the load of pollutants entering the river is relatively large in the year with large runoff. Once the pollutants in the soil are washed by the rain, they easily enter the river together with rainwater, which will affect the water quality. On the other hand, the concentrations of pollutants in runoff rainwater could decrease with rainfall duration. The total load of non-point source pollutants brought by rainfall is limited, but the river flow will increase greatly after heavy rain, thus resulting in a reduction of pollutant concentration. Therefore, the reason for the possible increase in pollutants caused by rainfall is not the precipitation itself, it should be considered from the source. Considering the complexity of pollution transport mechanisms and different local conditions, it should be further tested in combination with other environmental factors. For the purpose of accurately measuring the performance of such ecological compensation programs or other environmental policies, the natural environment factors beyond human control should be eliminated first.

6. Conclusions

With regards to the ecological compensation mechanism in China, the pilot work of Xin’an river basin has key theoretical and practical research value. In order to evaluate the performance of such programs, the SFA model is primarily treated as a tool for measuring environmental efficiency with ecological compensation. The estimated efficiency appears as an upward trend in the first four years and then alternates between progress and decline. The final rank of yearly efficiency is
obtained to provide dynamic city-level information and then compared with the rank of the benchmark index. This paper further compares the results of SFA and DEA methodology to prove the accuracy of estimation. As aligning with the benchmark index and DEA efficiency score to a great extent, our empirical results of SFA should be reliable. In addition, the relationship between environmental efficiency and pollutant emission factors and macro factors are analyzed separately, and four significant pollutants, four positive factors, and one negative factor are identified. Based on the analysis in Section 5, suggestions are provided as follows.

First, governmental environmental goals are important motivation for implementation. To better improve environmental quality and the effectiveness of ecological compensation, more pollutant emission factors should be considered in the official environmental quality assessment. Accompanying more importance being attached and more policy and fund being invested, the criteria of assessment should be stricter, and the scope of assessment indicators should be wider, so as to comprehensively improve water quality. Second, compensation funds should be raised through multiple channels and diversified compensation systems and compensation activities should be encouraged. It is important to establish an investment and financing system for ecological compensation that is based on government input and supported by the whole society. In accordance with the principle of “whoever invests, benefits”, it is necessary to broaden the channels for market-oriented and socialized operation of ecological compensation. At the same time, considering the usage efficiency and marginal utility of the investment fund, it requires more challenging policy decisions about the rational allocation of compensation funds and supervision of actual implementation for achieving environmental outcomes, which would improve the clarity on how compensation activities contribute to environmental conservation. The last suggestion is to give full play to the leading role of the government in combination with China’s characteristics, pay more attention to the balance between ecological services and social development, and strive to find a reasonable way of harmonious coexistence on the basis of considering environment, humanity, economy, and other factors in all-round regard. Relevant central departments should assume responsibility for the coordination and supervision of ecological compensation and promote relevant legislation.

The ecological compensation pilot of Xin’an river basin has achieved remarkable results over the period between 2011 and 2018, while the pressure for subsequent advancement is enormous, such as financial problems, social conflict, rights, and obligation. There is still a lot to be done in order to achieve the goal of harmonious development. Additionally, the mechanisms of environment as well as ecological compensation are complicated, and more variables should be incorporated. The impact of the influencing factors on environmental efficiency also vary under different circumstances. For a more comprehensive understanding of the environmental efficiency and effect of ecological compensation, future studies should be possible for more precise and valuable results when more data is available to us.

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