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Can More Environmental Information Disclosure Lead to Higher Eco-Efficiency? Evidence from China

Yantuan Yu * [ID]**, Jianhuan Huang and Nengsheng Luo**

School of Economics and Trade, Hunan University, 109 Road Shijiachong, Yuelu District, Changsha 410079, China; jhhuang@hnu.edu.cn (J.H); lns1122@163.com (N.L.)
*   Correspondence: yantuanyu@163.com; Tel.: +86-183-7318-1348

Abstract: The present paper investigates the impact of pollution information transparency index (PITI) on eco-efficiency using a novel panel dataset covering 109 key environmental protection prefecture-level cities in China over the period 2008–2015. We apply an extended data envelopment analysis (DEA) model, simultaneously incorporating metafrontier, undesirable outputs and super efficiency into slack-based measure (Meta-US-SBM) to estimate eco-efficiency. Then, the bootstrap Granger causality approach is utilized to test the unidirectional Granger causal relationship running from PITI to eco-efficiency. Results of DEA model show that there exist significant spatiotemporal disparities of eco-efficiency, on average, the eco-efficiency in eastern region is relative higher than those of central/western region. Estimates of ordinary least square (OLS) method, quantile regression, and spatial Durbin model document that the evidence of an inverted-U-shaped relation between PITI and eco-efficiency is supported, and the turning points vary from 0.3370 to 0.4540 with different model specifications. Finally, supplementary analysis of panel threshold model also supports the robust findings. Policy implications are presented based on the empirical results.

Keywords: environmental information disclosure; eco-efficiency; Meta-US-SBM; quantile regression; spatial Durbin model

1. Introduction

In this study, we investigate how environmental information disclosure of Chinese prefecture-level cities relates to eco-efficiency [1]. More specifically, we examine the association between the pollution information transparency index (henceforth PITI, maximum value is 100) and eco-efficiency measured by an extended DEA model [2], simultaneously incorporating the presence of metafrontier technique, undesirable outputs, and super efficiency into slacks-based measure (henceforth Meta-US-SBM). (The World Business Council for Sustainable Development (WBCSD) defines eco-efficiency as the reducing environmental impact and resource intensity in the process of satisfying human needs and bringing quality of life [3]. Up to date, eco-efficiency has been widely utilized to measure sustainability for varied levels in existing literature [4–11]) We focus on the impact PITI exerts on eco-efficiency from both non-spatial and spatial model specifications.

Extensive studies have been devoted to studying environmental disclosure, which will impose either positive effect on sustainability performance [12,13], or negative effect on sustainability performance [14,15]. From the micro-level (e.g., enterprises, companies, and institutions), however, a multitude of studies on analyzing the environmental information disclosure has been conducted in the academic community [16–19]. If government information were more transparent, it would be more beneficial to the improvement of eco-efficiency [20]. Prior research has not yet established a consistent understanding regarding the relationship between environmental disclosure and eco-efficiency; rare studies have shown whether there exists unidirectional or bidirectional relation between environmental

information disclosure and eco-efficiency [21]. On the one hand, following the voluntary disclosure theory [22], a region/city with incentive to disclose information is conducive to reduce pollutant emissions, thus leading to promoting eco-efficiency. On the other hand, a region/city without incentive to disclose information is reluctant to reduce pollutant emissions, consequently resulting in lower eco-efficiency, as predicted by legitimacy theory [23,24]. However, the two theories are not necessarily contradictory but are instead two sides of the same coin [25]. Thus, we suppose that there may exist a tradeoff between PITI and eco-efficiency of prefecture-level cities in China. Specifically, environmental information disclosure has been advocated by the government; managers/policymakers believe that disclosing more environmental information can be fully detected by government, enabling them to access more such resource elements as technology and labor force, leading to improve eco-efficiency overall. With this scenario, the PITI is positively associated with eco-efficiency before the PITI reaches the threshold value. Otherwise, the PITI is negatively associated with eco-efficiency after the threshold value, which resulted from regulators having limited supervision of the vast amount of information with the increase of environmental information disclosure, along with the increase potential costs of litigation risk caused by environmental information disclosure.

The main contributions of this article are as follows. First, we use Meta-US-SBM model to evaluate eco-efficiency of prefecture-level cities in China. The strengths of Meta-US-SBM are its comparable treatment of efficiency of the same DMU in different years due to technological progress to consider the metafrontier [26]; its identifiable treatment of DMUs located on efficient frontier to consider super efficiency [27]; and its similar to the real production process when considering undesirable outputs. Second, we explore the impacts of PITI on eco-efficiency based on non-spatial and spatial econometric methods. Policy implications are provided based on the empirical results.

The remainder of this paper proceeds as follows. Section 2 outlines methodology and empirical strategy. Data sources and variable definitions are described in Section 3. Section 4 reports empirical results. Finally, Section 5 summarizes and concludes.

2. Methodology and Empirical Strategy

2.1. Measuring Environmental Information Disclosure in China

The major breakthroughs in Chinese environmental information disclosure occurred after 2007, but the first formal government initiatives on environmental information disclosure date to 1999–2000. Then, environmental information disclosure gradually expanded. The concepts of disclosure and public participation are included in the 2003 Environmental Impact Assessment (EIA) Law and the 2004 Administrative Licensing Law (ALL). Environmental regulators were the first to promulgate implementing rules pursuant to the State Council Regulation on Open Government Information, a signal of support for disclosure. In recent years, China has adopted several measures for information disclosure; more details can be found in the latest work of [28], which examines the emergence of environmental information disclosure in China. Since 2008, the Institute of Public & Environmental Affairs and Natural Resource Defense Council evaluate PITI for the periods of 2008–2016, providing the details of evaluation method and criteria, and alleviating the difficulties of measuring information disclosure in China. Figure 1 illustrates the total amount of pollution monitoring records during 2006–2016, indicating that the geometrical growth rate of pollution monitoring records is approximately 43%. Theoretically, for a region/city, more environmental information disclosure leads to desire to reduce pollutant emissions, thus improving eco-efficiency. Empirically, however, it is worth studying whether there exists a nonlinear relation between PITI and eco-efficiency; as a result, the impact PITI exerts on eco-efficiency may show a threshold effect or interval effect. In econometric models, the key explanation variable (PITI) is directly collected from Institute of Public & Environmental Affairs (IPE) and Natural Resource Defense Council (NRDC) and converted to the proportion form (maximum value is 1).
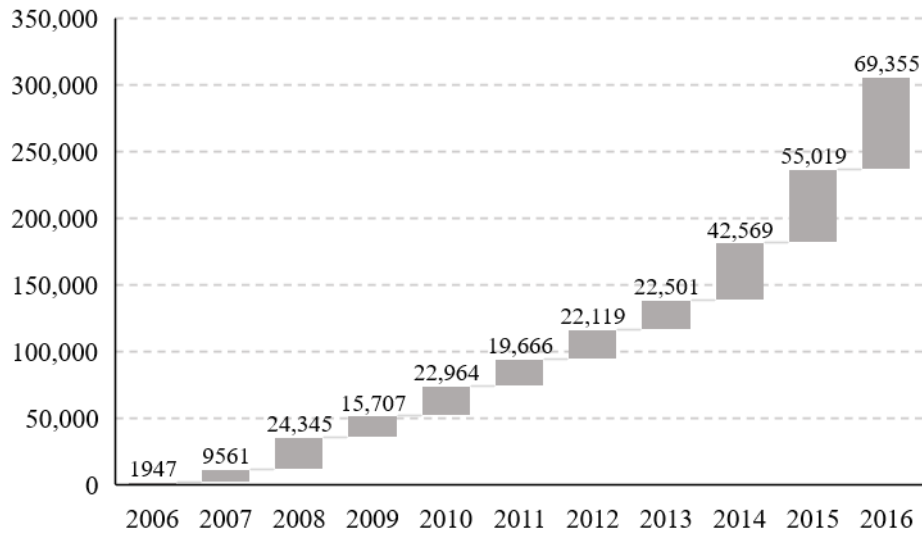
Figure 1. Total amount of pollution monitoring records, 2006–2016. Sources: Institute of Public & Environmental Affairs and Natural Resource Defense Council (2016–2017).

2.2. Measuring Eco-Efficiency with Meta-US-SBM Model

If there are N DMUs (prefecture-level cities in this study), H technology-heterogeneous groups (in China, we considered three regions: eastern, central and western) and N_h DMUs in Group h, we have $\sum_{h=1}^{H} N_h = N$. Each DMU uses inputs $\boldsymbol{x} = [x_1, x_2, \ldots, x_M] \in R_+^M$ to produce desirable (good) outputs $\boldsymbol{y} = [y_1, y_2, \ldots, y_R] \in R_+^R$ and undesirable (bad) outputs $\boldsymbol{b} = [b_1, b_2, \ldots, b_J] \in R_+^J$. The frontier production technology of Group h can be expressed as follows:

$$P^h = \left\{ \left(\boldsymbol{x}^h, \boldsymbol{y}^h, \boldsymbol{b}^h \right) : \sum_{n=1}^{N_h} \lambda_n^h x_n^h \leq x^h; \ \sum_{n=1}^{N_h} \lambda_n^h y_n^h \geq y^h; \ \sum_{n=1}^{N_h} \lambda_n^h b_n^h \leq b^h; n = 1, 2, \ldots N_h \right\} \tag{1}$$

where λ_n^h is a weighting vector of nth DMU in Group h with reference to the corresponding group frontier. By enveloping all group frontier technologies [26], we can also express the metafrontier production technology as follows:

$$P^{meta} = \Big\{ (\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}) : \sum_{h=1}^{H} \sum_{n=1}^{N_h} \xi_n^h x_n^h \leq x^h; \ \sum_{h=1}^{H} \sum_{n=1}^{N_h} \xi_n^h y_n^h \geq y^h; \ \sum_{h=1}^{H} \sum_{n=1}^{N_h} \xi_n^h b_n^h \leq b^h; \\ n = 1, 2, \ldots N_h; \ h = 1, 2, \ldots, H \Big\} \tag{2}$$

where $P^{meta} = \left\{ P^1 \cup P^2 \cup \ldots \cup P^H \right\}$ and ξ_n^h is a weighting vector of the nth DMU in Group h with reference to the metafrontier. With group frontier and metafrontier defined, we can now define non-oriented super efficiency SBMs for both frontiers. Assuming constant returns to scale (CRS), the optimal objective value for the oth DMU in Group k ($o = 1, 2, \cdots, N_k; k = 1, 2, \cdots, H$) with reference to the group frontier is estimated as:

$$\rho_{ko}^{group*} = \min \left(\frac{1 + \frac{1}{M} \sum_{m=1}^{M} \frac{s_{mko}^x}{x_{mko}}}{1 - \frac{1}{R+J} \left(\sum_{r=1}^{R} \frac{s_{rko}^y}{y_{rko}} + \sum_{j=1}^{J} \frac{s_{jko}^b}{b_{jko}} \right)} \right)$$

$$s.t. \ x_{mko} - \sum_{n=1, \neq o}^{N_k} \lambda_n^k x_{mkn} + s_{mko}^x \geq 0; \ \sum_{n=1, \neq o}^{N_k} \lambda_n^k y_{rkn} - y_{rko} + s_{rko}^y \geq 0;$$

$$b_{jko} - \sum_{n=1, \neq o}^{N_k} \lambda_n^k b_{jkn} + s_{jko}^b \geq 0; \ 1 - \frac{1}{R+J} \left(\sum_{r=1}^{R} \frac{s_{rko}^y}{y_{rko}} + \sum_{j=1}^{J} \frac{s_{jko}^b}{b_{jko}} \right) \geq \varepsilon;$$

$$\lambda_n^k, s_{mko}^x, s_{rko}^y, s_{jko}^b \geq 0; m = 1, 2, \ldots, M; r = 1, 2, \ldots, R; j = 1, 2, \ldots, J \tag{3}$$

and the same for the *o*th DMU in Group *k* ($o = 1, 2, \cdots, N_k$; $k = 1, 2, \cdots, H$) with reference to the metafrontier is estimated as:

$$\rho_{ko}^{meta*} = \min \left(\frac{1 + \frac{1}{M} \sum_{m=1}^{M} \frac{s_{mko}^x}{x_{mko}}}{1 - \frac{1}{R+J} \left(\sum_{r=1}^{R} \frac{s_{rko}^y}{y_{rko}} + \sum_{j=1}^{J} \frac{s_{jko}^b}{b_{jko}} \right)} \right)$$

$$s.t. \; x_{mko} - \sum_{h=1}^{H} \sum_{\substack{n = 1, \neq o \\ if \; h = k}}^{N_k} \xi_n^h x_{mhn} + s_{mko}^x \geq 0; \sum_{h=1}^{H} \sum_{\substack{n = 1, \neq o \\ if \; h = k}}^{N_k} \xi_n^h y_{rhn} - y_{rko} + s_{rko}^y \geq 0;$$

$$b_{jko} - \sum_{h=1}^{H} \sum_{\substack{n = 1, \neq o \\ if \; h = k}}^{N_k} \xi_n^h b_{jhn} + s_{jko}^b \geq 0; 1 - \frac{1}{R+J} \left(\sum_{r=1}^{R} \frac{s_{rko}^y}{y_{rko}} + \sum_{j=1}^{J} \frac{s_{jko}^b}{b_{jko}} \right) \geq \varepsilon;$$

$$\xi_n^h, s_{mko}^x, s_{rko}^y, s_{jko}^b \geq 0; m = 1, 2, \ldots, M; r = 1, 2, \ldots, R; j = 1, 2, \ldots, J \tag{4}$$

where λ in Model (3) and ξ in Model (4) are nonnegative weights, and s_{mko}^x, s_{rko}^y, and s_{jko}^b represent, respectively, the input, desirable output, and undesirable output slacks. The difference between the super efficiency model and the standard model is that DMU$_{ko}$ in the reference set in the super efficiency model is excluded [27], which is denoted by $n \neq o$. Adding the constraints $\sum_{n=1, \neq o}^{N_k} \lambda_n^k = 1$ to Equation (3) and $\sum_{h=1}^{H} \sum_{n=1, \neq o \; if \; h=k}^{N_k} \xi_n^k = 1$ to Equation (4) will impose the variable returns to scale (VRS) assumption. The term ε is non-Archimedean infinitely small and the corresponding constraint ensuring the denominator in objective function greater than zero.

2.3. Empirical Strategy

Empirical approaches such as ordinary least square (OLS) regression, quantile regression, and spatial econometric model are used throughout this paper. Firstly, for the sake of simplicity, to investigate the nonlinear relationship between PITI and eco-efficiency, we introduce the quadratic term of PITI into the baseline model, which is formally specified as follows:

$$EE_{it} = \alpha + \beta_1 PITI_{it} + \beta_2 PITI_{it}^2 + \gamma x_{it} + \mu_t + \delta_i + u_{it} \tag{5}$$

where EE_{it} represents eco-efficiency for city i at year t; $PITI_{it}$ is our explanatory variable of main interest and its quadratic term denoted as $PITI_{it}^2$; and β_1 and β_2 are the corresponding parameter vectors. x_{it} is the vector of control variables including scale effect, composition effect, and technique effect and γ represents the parameter vector. μ_t represents year fixed effects, δ_i captures unobserved heterogeneity and u_{it} is the normal distributed error term.

Secondly, to analyze the relationship between PITI and eco-efficiency in the presence of different eco-efficiency levels, we further adopt quantile regression as the empirical model [29]. With the advantages of being free from the strict assumptions for the data distribution hypothesis, along with effectively eliminating the interference of outliers and heavy-tailed distributions, quantile regression method is widely used in the existing literature [30–34]. A quantile regression approach may be more efficient than the OLS method when the residual series is non-normal [32]. Consequently, we also estimate a fixed effects version of the conditional quantile regression model with the nonlinear term as follows:

$$Q_{EE_{it}}(\tau | x_{it}, \delta_i) = \alpha + \beta_{1\tau} PITI_{it} + \beta_{2\tau} PITI_{it}^2 + \gamma_\tau x_{it} + \delta_i \tag{6}$$

where all variables are similar to the variables used in Equation (5), and τ is a parameter ($0 < \tau < 1$) which represents quantile level.

Finally, to ascertain the impacts of PITI on eco-efficiency when the spatial effects are considered, we estimate the empirical Model (5) with a spatial Durbin model (SDM) [35–37] specification as follows:

$$EE_{it} = \rho \sum_{j=1}^{N} w_{ij} EE_{jt} + \theta_1 PITI_{it} + \varphi_1 \sum_{j=1}^{N} w_{ij} PITI_{jt} + \theta_2 PITI_{it}^2 + $$
$$\varphi_2 \sum_{j=1}^{N} w_{ij} PITI_{jt}^2 + \theta_3 x_{it} + \varphi_3 \sum_{j=1}^{N} w_{ij} x_{jt} + \mu_t + \delta_i + u_{it} \tag{7}$$

where j represents the neighbor cities ($j \neq i$); ρ is the spatial autocorrelation coefficient; θ and φ are coefficients to be estimated; and u_{it} is the error term. w_{ij} are the elements in an $n \times n$ spatial weight matrix W describing the spatial arrangement of the prefecture-level cities. In this study, we construct four major types of spatial weights matrices, i.e., inverse distance matrix (W^1), economic-based matrix (W^2), inverse distance and economic-based matrix (W^3), and population-distance-based matrix (W^4), which defined as follows.

$$w_{ij}^1 = \begin{cases} 0, & \textit{if } i=j \\ \frac{1}{d_{ij}}, & \textit{if } i \neq j \end{cases} ; \quad w_{ij}^2 = \begin{cases} 0, & \textit{if } i=j \\ \frac{1}{|\overline{GDP_i} - \overline{GDP_j}|}, & \textit{if } i \neq j \end{cases} ;$$

$$w_{ij}^3 = w_{ij}^1 \times w_{ij}^2 ; \quad w_{ij}^4 = \begin{cases} 0, & \textit{if } i=j \\ \frac{\overline{pop_j}/d_{ij}}{\sum_{j \in J_i} (\overline{pop_j}/d_{ij})}, & \textit{if } i \neq j \end{cases} .$$

where d_{ij} measures the distance between city i and j; $\overline{GDP_i}$ and $\overline{GDP_j}$ present, respectively, the average GDP of city i and j during the study periods; $\overline{pop_j}$ denotes the average population of city j during the study periods; and $j \in J_i$ denotes all the cities adjacent to city i.

Indeed, the general form of W^1 is the "distance decay" function specified as $w_{ij}^1 = 1/d_{ij}^\kappa$, where κ is some positive parameter [38]. Our inverse distance matrix assumes that $\kappa = 1$. Following [39], we construct W^2 with $w_{ij}^2 = 1/|\Pi_i - \Pi_j|$, where Π is a relevant socioeconomic variable. We utilize the average GDP of each observation during the study period for Π. Considering both geographical and economic factors, we generate W^3 by combining W^1 and W^2. Following [40], we also use a population-distance-based matrix through adding distance terms and defined as W^4. We normalize the spatial weights matrices such that the elements of each row sum to unity. Other types of spatial weights will be investigated and compared in the future research, such as parameterize and time-varying spatial weights matrices, etc.

Because the spillover effects of the spatial error model are zero by construction, and the spatial autoregressive model and spatial autoregressive combined model suffer from the problem that the ratio between the spillover effect and the direct effect is the same for every explanatory variable, the general nesting spatial model is overparameterized, as a result of which the t-values of the coefficient estimates and the effects estimates have the tendency to go down, or its parameters cannot be reproduced using Monte Carlo simulation experiments. In sum, the SDM model produces acceptable results.

If the coefficient of $PITI_{it}$ is strictly greater than zero while the coefficient of $PITI_{it}^2$ is strictly smaller than zero, and the evidence of the inverted-U-shaped relationship between PITI and eco-efficiency is supported, then the turning point level of PITI is calculated as follows [41]:

$$PITI_{OLS}^* = -\frac{\beta_1}{2\beta_2}; \quad PITI_\tau^* = -\frac{\beta_{1\tau}}{2\beta_{2\tau}}; \quad PITI_{SDM}^* = -\frac{\theta_1}{2\theta_2}.$$

From the abovementioned methods, we use a flowchart diagram to explain all the methodological steps performed in the empirical analysis in a graphical way (Figure 2).
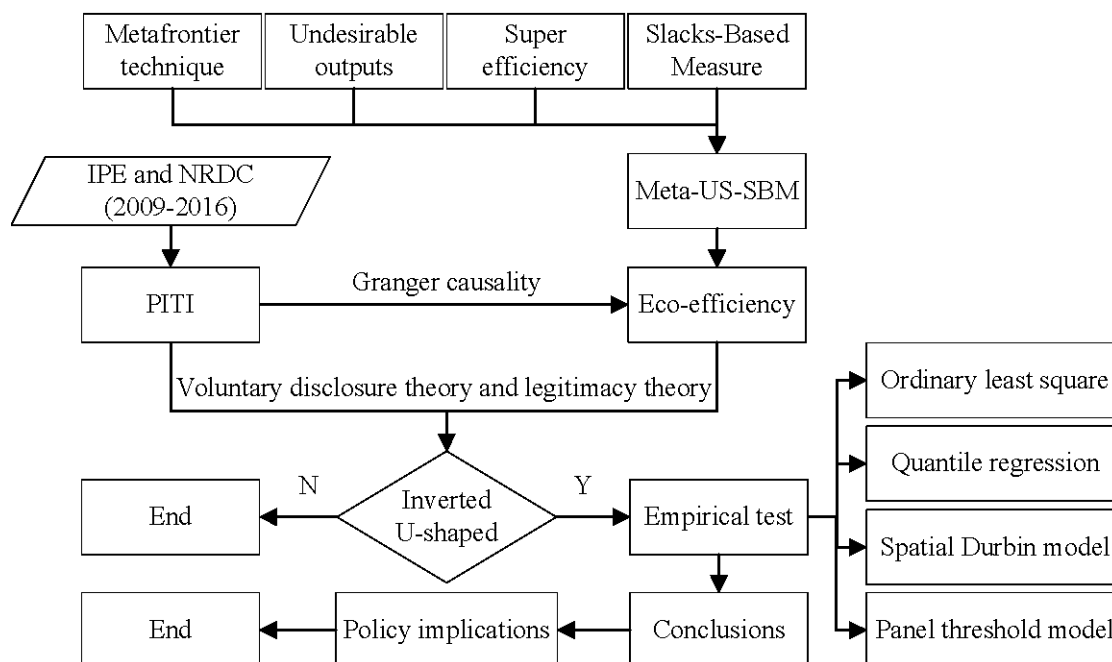
Figure 2. Methodological steps performed in the empirical analysis.

3. Data Sources and Variable Definitions

Our sample consists of panel 109 key environmental protection (KEP) prefecture-level cities in China over the period of 2008–2015. From the 113 and 120 cities listed as KEP during periods of 2008–2012 and 2013–2015, we select 109 of them as the research subject to conduct feasible comparison (see Appendix A). Taiwan, Hong Kong and Macau are excluded temporally due to unavailability of data. We collect data from many official sources, including China Environment Yearbook [42], China Energy Statistical Yearbook [43], China City Statistical Yearbook [44], etc.

To measure eco-efficiency comprehensively and accurately, all input and output variables relevant to economics, the environment, and resources should be considered as much as possible to the extent that the data are available. The input and output variables for measuring eco-efficiency are described as follows:

(1) Desirable output: The real gross domestic product (GDP) is chosen as good output with the data at constant 2008 prices, wherever applicable throughout this paper.

(2) Undesirable outputs: Like most existing literature, environmental pollutants are treated as the bad outputs. In this study, four variables are selected according to data availability, namely, carbon dioxide emission which is estimated using the procedure suggested by Huang et al. [45], volume of industrial waste water discharged, volume of sulfur dioxide emission, and volume of industrial soot-dust removed. A potentially unfortunate consequence of the conventional DEA is that extreme values of inputs or outputs result in extreme weights such that some DMUs become "efficient by default" [46]. A widely applied approach to address this issue is generate an entropy-weighted index of multiple factors [47,48]. Thus, to alleviate the influence of extreme value, we employed the entropy weight method to generate a composite environmental pollution index (EPI) of these pollutants. The calculation process is provided in Appendix B.

(3) Labor force: According to data availability, the total number of employees is used as proxy here.

(4) Capital input: The method used frequently to estimate capital input is the perpetual inventory method [49,50]. The capital stock can be calculated as $K_{i,t} = I_{i,t} + (1 - \sigma_{i,t})K_{i,t-1}$, where $K_{i,t}$ is the capital stock of city i in year t, and $\sigma_{i,t}$ is the depreciation rate of fixed assets of city i in year t. We estimate capital stock based on the procedure provided by Ke and Xiang [51].

(5)　Land input: This paper adopts the construction land area as the proxy for land-use due to the accessibility of data [7].

(6)　Energy input: The primary energy consumption of 2008–2013 is extracted from Huang et al. [45], the primary energy consumption of the following two years is estimated using the same method they provided. Primary energy consumption is converted to standard coal equivalent (SCE) units—the standard energy metric used in Chinese energy statistics.

Key variables and controls used in econometric models are presented as follows. To control for the characteristics of each KEP prefecture-level cities, five control variables are included in the econometric estimation: (1) population density (POPD), the ratios of total population in construction land area; (2) FDI (SFDI), the shares of foreign direct investment (FDI) in GDP; (3) industrial structure (SIND), the shares of total output of the secondary industry in GDP; (4) wage level of employees (WAGE), which calculated by the logarithm form of the average wage of employed staff and workers; and (5) technology level (TECH), we use the shares of employees associated with scientific and technical sector (scientific research, technical service and geologic prospecting) in the total number of employees as the proxy due to the accessibility of data. Table 1 reports descriptive statistics of the variables for both DEA and econometric models. Appendix C reports the data sources of relevant variables used in this paper.

Table 1. Descriptive statistics.

	Variable	Obs.	Unit	Mean	Std. Dev.	Min	Max
DEA model	Labor	872	10,000 persons	88.9464	107.8553	6.7070	986.8700
	Capital	872	100 million RMB	2660.0000	2740.0000	63.6000	22,000.0000
	Land	872	km^2	13,820.4800	13,256.3700	1573.0000	90,659.0000
	Energy	872	Tons of SCE	2561.7100	1978.5020	147.6930	11,719.5000
	GDP	872	100 million RMB	3180.0000	3350.0000	130.0000	25,000.0000
	EPI	872	-	1.1468	1.0351	0.0993	16.8606
Econometric model	EE	872	-	0.4834	0.1999	0.2210	1.1630
	PITI	872	-	0.3680	0.1553	0.0830	0.8530
	PITI2	872	-	0.1595	0.1309	0.0069	0.7276
	POPD	872	1000 persons/km^2	0.5456	0.3919	0.0388	2.6481
	SFDI	872	-	0.2002	0.2302	0.0000	1.4432
	SIND	872	-	0.5183	0.1012	0.1974	0.9097
	WAGE	872	-	10.6216	0.3189	9.6542	11.6358
	TECH	872	-	0.0202	0.0159	0.0016	0.0986

The correlation coefficients presented in Table 2 suggest positive and significant correlation between PITI and EE, indicating the benefit of PITI in promoting eco-efficiency.

Table 2. Correlation coefficients for regression variables.

	EE	PITI	PITI2	POPD	SFDI	SIND	WAGE	TECH
EE	1.0000							
PITI	0.0760 **	1.0000						
PITI2	0.0530	0.9770 ***	1.0000					
POPD	0.3380 ***	0.0320	0.035	1.0000				
SFDI	0.3480 ***	0.0200	0.035	0.4620 ***	1.0000			
SIND	0.0240	0.0330	0.033	−0.1450 ***	−0.0760 **	1.0000		
WAGE	0.1250 ***	−0.0440	−0.042	0.2060 ***	0.2620 ***	−0.1550 ***	1.0000	
TECH	−0.1320 ***	−0.0780 **	−0.081 **	−0.0310	−0.0650 *	−0.2740 ***	0.2420 ***	1.0000

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

4. Empirical Results

4.1. Measuring Eco-Efficiency

Incorporating metafrontier technique, undesirable outputs and super efficiency into SBM simultaneously, the eco-efficiency is evaluated across each prefecture-level city in China and for each year. We calculate the average change rates of eco-efficiency and PITI over the analyzed period using the geometrical mean, as depicted in Figure 3, indicating that higher growth rate of PITI is not always accompany with higher growth rate of eco-efficiency. On average, the eco-efficiency of the eastern region is the highest (0.5178), followed by western (0.4617) and that of the central is the lowest (0.4491). One possible explanation is that, the industrial structure in central/western region is mainly based on heavy industry; along with the large consumption of coal, energy and other resources, more industrial pollutants will also be produced, resulting in lower eco-efficiency in central/western region. Consequently, the efficiency gap between the eastern and central regions is far greater than that of the central and western regions.
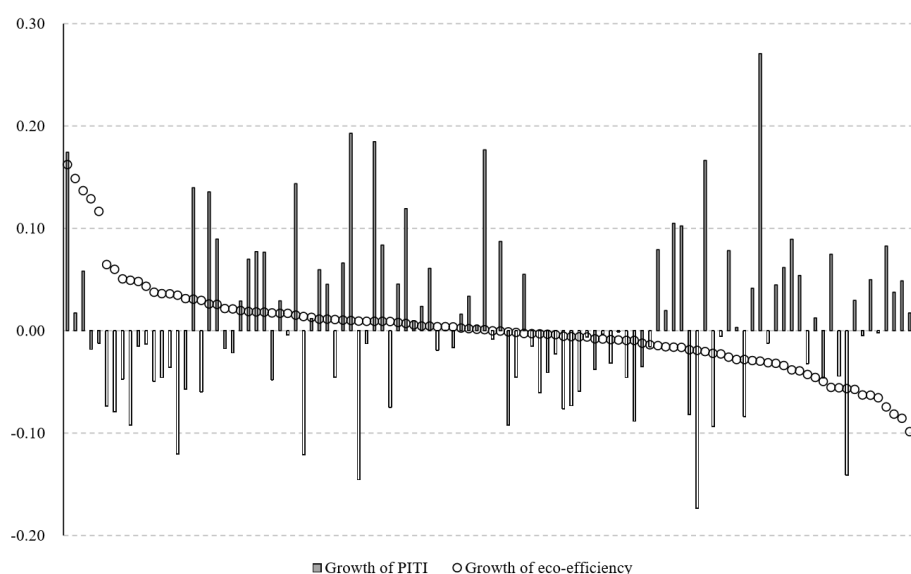

Figure 3. Prefecture-level cities sorting by growth rate of eco-efficiency, 2008–2015.

The time evolution of eco-efficiency scores in different regions are illustrated in Figure 4. As shown in the graph, we can conclude that the distribution layout of eco-efficiency for three regions is similar to that of national level, following left skewed distributions as well as having a cluster around 0.4. The vertical lines in Figure 4 show the average eco-efficiency in the corresponding years, indicating that the mean of eco-efficiency for western region decreased significantly from 2008 to 2015. Moreover, the kernel density curves have obviously moved upward over time; as a result, the eco-efficiency gap among eastern region, central region, and western region has decreased. Besides, the kernel density of eco-efficiency scores has two peaks, located at around 0.4 and 1, respectively. It should be noted that the eco-efficiency of prefecture-level cities in China was relatively high but deteriorated slightly from 2008 to 2015 derived from the kernel density curve shifts from right to left. Despite the similar distribution shapes, eco-efficiency scores of different regions are mainly distributed in [0.2, 1.0] in the selected year.

The non-parametric analysis of convergence shows the evolution over time (from time t to time $t + k$) of eco-efficiency distribution. Figure 5 reports the evolution of eco-efficiency dynamics from 2008 to 2015. The stochastic kernels are calculated by means of a Matlab routine developed by Magrini [52]. The surface plot shows a clear tendency towards a single ridge; moreover, a prominent peak at approximately 1.0577, which lies on the 45° line, can be detected around the middle of the

distribution. The stochastic kernel referring to the whole period 2008–2015 shows a strong persistence of eco-efficiency because the kernel is significantly concentrated along the main diagonal, as shown in Figure 5b.
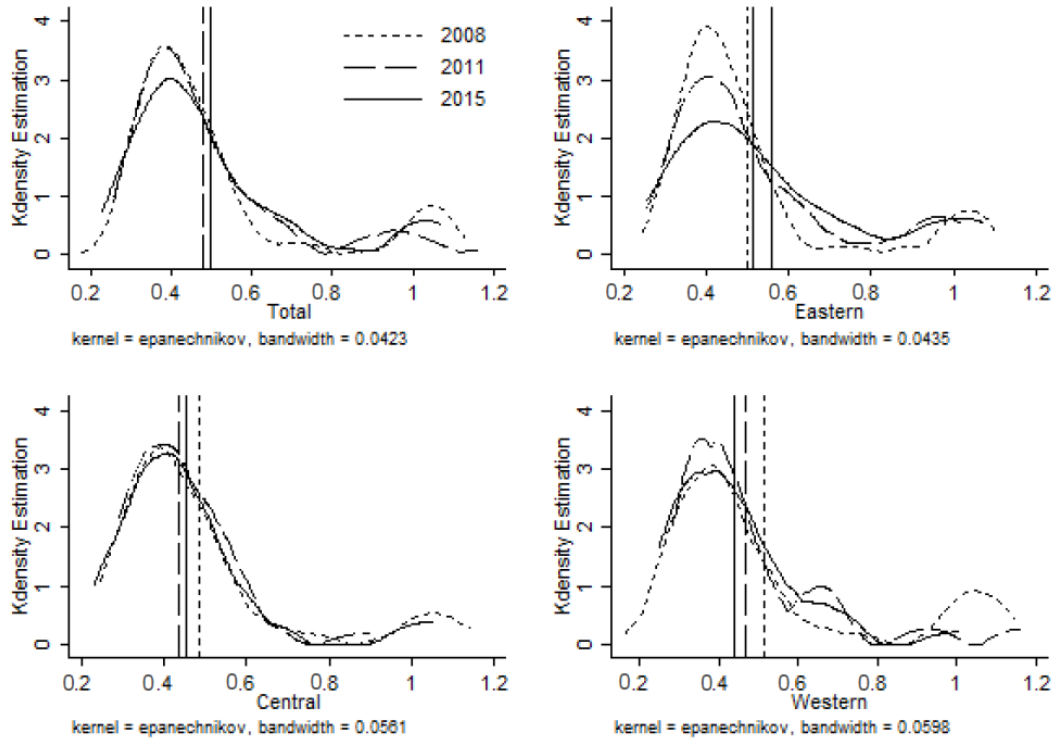

Figure 4. Kernel density estimation of eco-efficiency for different regions.
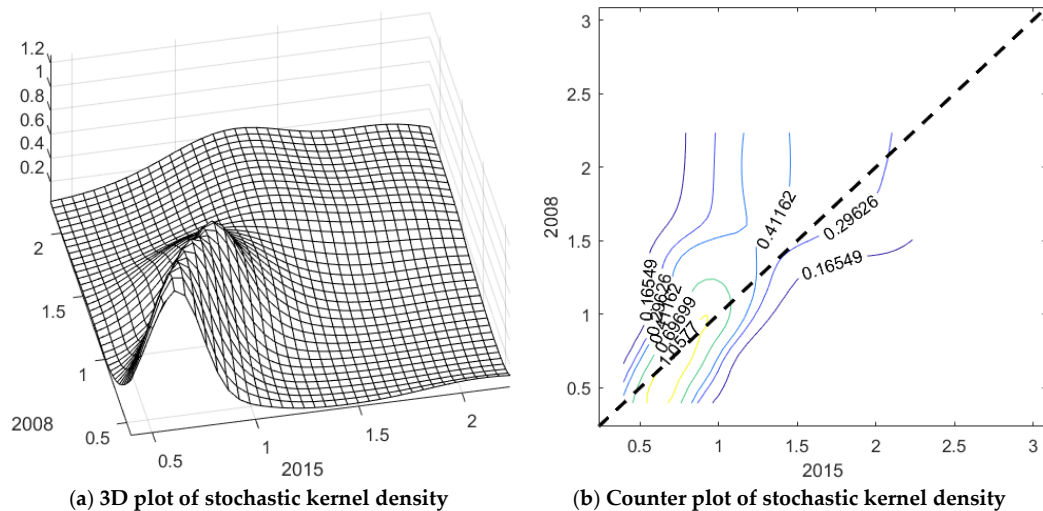

(a) **3D plot of stochastic kernel density**　　　(b) **Counter plot of stochastic kernel density**

Figure 5. 3D and counter plots of stochastic kernel densities of eco-efficiency from initial period to final period.

The above findings show that there exist significant regional differences of eco-efficiency in China; exploring the driving forces that impact on eco-efficiency is of importance for policymakers to implement pollution control polices and resource allocation from both theoretical and practical aspects. Thus, it is necessary to investigate the influence factors exert on eco-efficiency using the econometric tools discussed in Section 2.3, and the estimation results are presented in next subsection.

4.2. Estimation Results

4.2.1. Statistical Tests of Unit Root and Granger Causality

　　To examine the stationarity of the panel data and avoid spurious regressions, along with ensuring the effectiveness of the estimated results, we conduct the panel unit root test on each variable with the Levin–Lin–Chiu (LLC) approach [53]. Table 3 presents the LLC statistics for all the variables at levels. Two model specifications, one with only the intercept and the other with both the intercept and trend, are considered. Results show that all the variables are found to be stationary at levels. Additionally, results of both panel Granger causality [54] and bootstrap Granger causality [55,56] implied that Granger causal relationships run from PITI and PITI2 to EE rather than bi-directionally among PITI, PITI2 and EE in China. Thus, it is rational to further investigate the impact of PITI on eco-efficiency.

Table 3. Panel unit root test results.

	Level			
	Intercept		**Intercept and Trend**	
EE	−0.6969 ***	(−14.2660)	−1.5904 ***	(−59.1930)
PITI	−1.1365 ***	(−25.8790)	−1.7020 ***	(−42.6810)
PITI2	−1.1487 ***	(−25.3460)	−1.8994 ***	(−45.2540)
POPD	−0.2337 ***	(−13.0780)	−1.3823 ***	(−39.5360)
SFDI	−0.3729 ***	(−10.7740)	−1.4691 ***	(−65.3220)
SIND	−0.4174 ***	(−22.7920)	−0.6354 ***	(−28.7230)
TECH	−0.7564 ***	(−18.9200)	−1.4770 ***	(−38.8110)

Notes: The maximum lag length to be included in the model is set to 1; *** denotes statistical significance at the 1% significance level; *t*-statistics are given in the parentheses.

4.2.2. Estimation Results of OLS and Quantile Regression

　　In this section, we investigate the relationship between PITI and eco-efficiency and discuss the estimation results of the present study. First, Figure 6 shows the scatter plot of PITI and eco-efficiency during 2008–2015, along with the nonlinear fitted curve and the confidence interval with confidence level at 95%, illustrating the significant inverted-U-shaped relationship between PITI and eco-efficiency. Then, before the empirical estimates, we perform the Hausman test to select between fixed and random effects models. The significant test statistics and small *p*-value suggest that fixed effects are more suitable for our empirical models.

　　Estimation results of OLS and quantile regression in Table 4 show that PITI is significantly and positively associated with eco-efficiency, while PITI2 is significantly and negatively associated with eco-efficiency. In line with our theoretical predictions, there exist an inverted-U-shaped relation between PITI and eco-efficiency. Furthermore, we found that POPD exerts significant and positive impact on eco-efficiency, e.g., a unit increase in POPD would results in an increase in eco-efficiency score by 0.4364 for FE model, reducing to 0.1129 in pool OLS model, ceteris paribus. As suggested by Ciccone and Hall [57], compared to market scale and urban size, population density is more suitable for measuring regional economic agglomeration. That is, the improvement of eco-efficiency benefits from the promotion of economic agglomeration. Both the linear and quadratic terms of PITI are significant at the 10th, 75th, and 90th quantiles, implying that the inverted-U relationship is only significant around the low and high level of the distribution. Further insights into this result can be obtained by calculating the turning points. In Table 5, we find that the turning points obtained from quantile regression are generally greater than those obtained from FE model which shows that the eco-efficiency will continually increase until PITI reaches its scale of 0.3505.
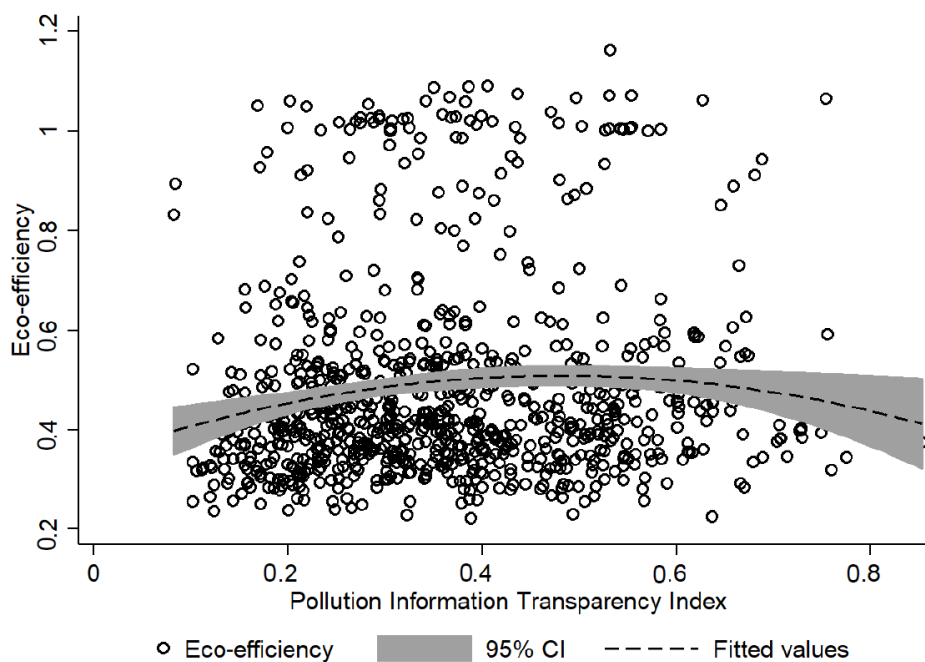
Figure 6. Inverted-U-shaped relationship between PITI and eco-efficiency (2008–2015).

Table 4. OLS and quantile regression results of model (dependent variable: EE).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Quantile Regression				
Variable	Pool OLS	FE	10th	25th	50th	75th	90th
PITI	0.7895 ***	0.1974 **	0.1975 ***	0.0624	0.1320	0.1915 ***	1.3186 ***
	(4.8492)	(2.0427)	(4.7273)	(1.5918)	(1.1037)	(6.7093)	(2.9324)
PITI2	−0.8701 ***	−0.2816 **	−0.2633 ***	−0.0937 **	−0.1389	−0.2109 ***	−1.6194 ***
	(−4.5736)	(−2.3647)	(−3.1906)	(−2.0697)	(−0.9986)	(−5.8970)	(−3.0553)
POPD	0.1129 ***	0.4364 ***	0.0776 ***	0.0526 ***	0.1500 ***	0.0719 ***	0.1049 ***
	(5.5408)	(2.7121)	(9.3876)	(4.4373)	(5.7884)	(13.3616)	(3.3808)
SFDI	0.2051 ***	−0.1866 **	0.0625 ***	0.1769 ***	0.1330 ***	0.3902 ***	−0.0867
	(5.3410)	(−2.2589)	(3.3452)	(23.1193)	(4.2489)	(55.3353)	(−0.6546)
SIND	0.1025	−0.1461	−0.0323 **	0.1634 ***	0.1303 ***	0.2738 ***	−0.2644
	(1.0763)	(−1.0325)	(−2.1717)	(10.0562)	(8.8133)	(11.3106)	(−1.4661)
WAGE	0.0347	0.1563 **	−0.0016	−0.0421 ***	0.0713 ***	0.0583 ***	0.3859 **
	(1.5854)	(2.5749)	(−0.2175)	(−4.7291)	(3.6603)	(17.6245)	(2.3921)
TECH	−1.3456 ***	0.8168	−0.7918 ***	−0.0686	−0.9622 ***	−1.3632 ***	−4.6986 ***
	(−3.1873)	(0.6997)	(−4.2873)	(−1.0968)	(−19.6825)	(−19.6231)	(−5.7829)

Notes: Robust *t*-statistics are in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Table 5. Turning points.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Quantile Regression				
Variable	Pool OLS	FE	10th	25th	50th	75th	90th
PITI *	0.4537	0.3505	0.3750	NA	NA	0.4540	0.4071

Note: NA denotes that the results are not available. Superscript * denotes the interested independent variable: pollution information transparency index

Figure 7 illustrates the coefficients and bootstrap confidence intervals (draws = 2000) of quantile regression model, indicating that the key interest explanatory variables PITI and PITI2 are positively and negatively associated with eco-efficiency across different quantiles we considered, respectively.
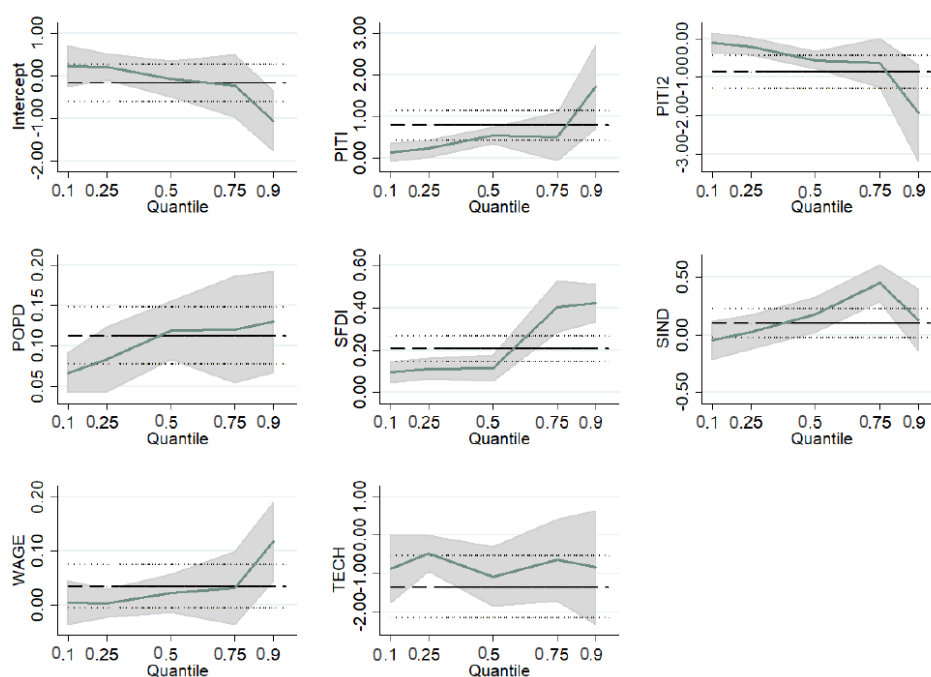
Figure 7. Coefficients and bootstrap confidence intervals (draws = 2000) of quantile regression.

4.2.3. Estimation Results of Spatial Durbin Model

Besides the non-spatial econometric evidence, we investigate the spatial dependence of the regression variables with two standard spatial autocorrelation tests of Moran's I [58] and Geary's C [59]. Regarding the ID-EB (inverse distance and economic-based) matrix, for example, the Moran's I statistic shows that, except for SIND, all variables are spatially autocorrelated at 5% significance while Geary's C rejects the null hypothesis of spatial independence for most variables, indicating the necessity to use spatial econometric models for further analysis. We then use Lagrange multiplier (LM) tests and their robust versions [37] to choose the most proper spatial econometric model to describe the quantitative relationship among data, along with the SDM generalizes both the spatial lag and the spatial error model, we estimate the SDM finally.

As can be seen in Table 6, with different spatial weight matrix, the coefficients of PITI and PITI2 are significantly positively and negatively associated with eco-efficiency, respectively. Hence, we can argue that there is strong evidence of inverted-U relation between PITI and eco-efficiency of study sample in China. In addition, the spatial coefficients (ρ) are also highly significant, which indicates a strong evidence of spatiality. In Table 6, we use Akaike Information Criterion and Bayesian Information Criterion (AIC and BIC, respectively) to compare goodness of fit for the models, although criteria are mainly aimed at selecting a parsimonious model rather than the model with the most support from the data [60]. Moreover, the coefficients of POPD and WAGE in spatial models are also significantly and positively associated with eco-efficiency, while the coefficients of SFDI are significantly and negatively associated with eco-efficiency. Our results are consistent with [61] and indicate the specification of the spatial weights matrices should have no effect on the estimation results.

Table 7 reports the direct, indirect, and total effects of corresponding models estimated in Table 6. The direct effects of PITI and PITI2 are significantly positive and negative, indicating the beneficial effects of PITI to promote eco-efficiency of host region. In terms of magnitude, a 1% increase in PITI results in an approximate 0.2% increase in eco-efficiency, while a 1% increase in PITI2 results in an approximate 0.3% decrease in eco-efficiency. The indirect effects of PITI and PITI2 are negative and positive, implying the increase in PITI of adjacent cities will lead to reduce eco-efficiency of local city. Among all control variables, POPD and WAGE have significantly positive direct effects on

eco-efficiency, hinting that a higher population density and wage level may result in high eco-efficiency to local cities, implying the existence of agglomeration effect and technique effect. In contrast, SFDI and SIND generate negative direct effects on eco-efficiency, implying the existence of composition effect. In Table 8, we find that the turning points obtained from the SDM are generally smaller than those obtained from FE and quantile regression models, showing that the eco-efficiency will continually increase till PITI approximately reaches its scale of 0.34.

Table 6. Estimation results of Spatial Durbin Model (dependent variable: EE).

Variable	(1) Inverse Distance Matrix W^1		(2) Economic-Based Matrix W^2		(3) Inverse Distance and Economic-Based Matrix W^3		(4) Population-Distance-Based Matrix W^4	
PITI	0.1685 *	(1.9046)	0.2108 **	(2.4150)	0.1915 **	(2.1882)	0.1691 *	(1.9040)
PITI2	−0.2500 **	(−2.4171)	−0.2976 ***	(−2.9256)	−0.2748 ***	(−2.6943)	−0.2491 **	(−2.3989)
POPD	0.4658 ***	(5.5019)	0.3797 ***	(4.5812)	0.4106 ***	(4.7467)	0.4798 ***	(5.6465)
SFDI	−0.1813 ***	(−3.2755)	−0.1582 ***	(−2.8477)	−0.1473 ***	(−2.6019)	−0.1818 ***	(−3.2685)
SIND	−0.0553	(−0.4570)	−0.0884	(−0.8185)	−0.0193	(−0.1712)	−0.0516	(−0.4259)
WAGE	0.1757 ***	(4.1175)	0.1572 ***	(3.7600)	0.1671 ***	(3.9253)	0.1753 ***	(4.0813)
TECH	1.4093 *	(1.9363)	0.6506	(0.9260)	0.8236	(1.1602)	1.4065*	(1.9320)
W*PITI	−1.0690	(−1.3788)	−0.2906	(−1.0696)	−0.2466	(−1.0178)	−1.0073	(−1.2991)
W*PITI2	1.2897	(1.3785)	0.3217	(0.9725)	0.2850	(0.9861)	1.2622	(1.3485)
W*POPD	−1.8345 ***	(−3.5051)	0.9066 ***	(2.8570)	0.1937	(0.7843)	−1.6461 ***	(−3.2014)
W*SFDI	−1.1522 ***	(−3.0795)	−0.1416	(−1.1196)	−0.0606	(−0.4617)	−1.0277 ***	(−2.8493)
W*SIND	−0.4715	(−0.6836)	−0.4337	(−1.4829)	−0.7373 ***	(−2.7542)	−0.6766	(−0.9785)
W*WAGE	−0.0255	(−0.0793)	−0.0056	(−0.0385)	0.0480	(0.3938)	0.1046	(0.3300)
W*TECH	5.1552	(0.8568)	3.1770	(1.2561)	−1.9314	(−0.9205)	4.5939	(0.7712)
ρ	−0.3483 *	(−1.9563)	0.1666 **	(2.2582)	0.1375 **	(2.1791)	−0.2645	(−1.5302)
R-squared	0.0191		0.0423		0.0869		0.0099	
Log L	1033.5962		1033.4107		1029.4746		1031.9667	
AIC	−2035.1920		−2034.8210		−2026.9490		−2031.9330	
BIC	−1958.8600		−1958.4890		−1950.6170		−1955.6010	

Notes: The *z*-statistics are given in the parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively; Log L: Log likelihood; individual and time fixed effects are included in every model.

Table 7. Direct, indirect, and total effects of SDM estimation (dependent variable: EE).

	(1) Inverse Distance Matrix W^1		(2) Economic-Based Matrix W^2		(3) Inverse Distance and Economic-Based Matrix W^3		(4) Population-Distance-Based Matrix W^4	
Panel A: Direct effect								
PITI	0.1800 **	(1.9871)	0.2082 **	(2.3097)	0.1899 **	(2.1024)	0.1783 **	(1.9622)
PITI2	−0.2649 **	(−2.5028)	−0.2959 ***	(−2.8088)	−0.2741 ***	(−2.5963)	−0.2616 **	(−2.4611)
POPD	0.4883 ***	(5.9892)	0.4090 ***	(5.1280)	0.4239 ***	(5.1619)	0.4980 ***	(6.0934)
SFDI	−0.1730 ***	(−3.1495)	−0.1614 ***	(−2.9429)	−0.1488 ***	(−2.6799)	−0.1758 ***	(−3.1944)
SIND	−0.0507	(−0.4244)	−0.0969	(−0.9266)	−0.0335	(−0.3095)	−0.0465	(−0.3910)
WAGE	0.1786 ***	(4.2069)	0.1596 ***	(3.8088)	0.1704 ***	(4.0470)	0.1771 ***	(4.1551)
TECH	1.3781*	(1.8308)	0.7295	(0.9827)	0.7914	(1.0570)	1.3854 *	(1.8366)
Panel B: Indirect effect								
PITI	−0.8717	(−1.5727)	−0.3108	(−1.0134)	−0.2591	(−0.9751)	−0.8677	(−1.4686)
PITI2	1.0767	(1.5856)	0.3398	(0.9003)	0.2974	(0.9307)	1.1072	(1.5275)
POPD	−1.4978 ***	(−3.4695)	1.1562 ***	(3.0592)	0.2873	(1.0544)	−1.4168 ***	(−3.1491)
SFDI	−0.8237 ***	(−2.8677)	−0.2014	(−1.4019)	−0.0942	(−0.6542)	−0.7901 ***	(−2.6734)
SIND	−0.3080	(−0.5611)	−0.4978	(−1.3436)	−0.8190 **	(−2.5141)	−0.4961	(−0.8515)
WAGE	−0.0809	(−0.3491)	0.0109	(0.0652)	0.0703	(0.5358)	0.0307	(0.1265)
TECH	3.5203	(0.8003)	4.0135	(1.3125)	−2.0145	(−0.8245)	3.4081	(0.7318)
Panel C: Total effect								
PITI	−0.6918	(−1.2231)	−0.1026	(−0.3102)	−0.0693	(−0.2376)	−0.6894	(−1.1409)
PITI2	0.8118	(1.1691)	0.0439	(0.1080)	0.0234	(0.0666)	0.8456	(1.1385)
POPD	−1.0095 **	(−2.4073)	1.5652 ***	(4.0387)	0.7112 ***	(2.6432)	−0.9189 **	(−2.1030)
SFDI	−0.9967 ***	(−3.5217)	−0.3628 **	(−2.3770)	−0.2429	(−1.6374)	−0.9659 ***	(−3.2980)
SIND	−0.3588	(−0.7073)	−0.5947	(−1.5275)	−0.8525 ***	(−2.6199)	−0.5426	(−1.0005)
WAGE	0.0977	(0.4248)	0.1705	(0.9478)	0.2407 *	(1.7108)	0.2079	(0.8618)
TECH	4.8984	(1.0756)	4.7430	(1.4442)	−1.2231	(−0.4537)	4.7935	(0.9945)

Notes: The *z*-statistics are given in the parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Table 8. Estimation results of Spatial Durbin Model (dependent variable: EE).

Variable	(1) Inverse Distance Matrix W^1	(2) Economic-Based Matrix W^2	(3) Inverse Distance and Economic-Based Matrix W^3	(4) Population-Distance-Based Matrix W^4
PITI *	0.3370	0.3542	0.3484	0.3394

Note: Superscript * represents the interested independent variable: pollution information transparency index

4.2.4. Supplementary Analysis: Panel Threshold Model

Given the presumed thresholds in a nonlinear relation, the pollution information transparency index (PITI) for a city may have different influences on eco-efficiency in that city above and below those thresholds. For supplementary analysis, we built a threshold model [62] as follows:

$$EE_{it} = \alpha + \beta' PITI_{it}I(PITI_{it} \leq \sigma) + \beta'' PITI_{it}I(PITI_{it} > \sigma) + \gamma x_{it} + \delta_i + u_{it} \tag{8}$$

where σ is the assumed specific threshold value and $I(\cdot)$ is defined as an indicator function.

Table 9 reports the testing for both single and double threshold effects. The *F*-statistics and *p*-values tested indicated an extremely insignificant relation between the two threshold values assumed, indicating the 100% rejection of the hypothesis that there are no two-threshold values. Figure 8 illustrates the LR statistics for testing single threshold effects. According to the threshold test results, there is a nonlinear relation between PITI and eco-efficiency, instead of a linear and positive assumption between PITI and eco-efficiency; particularly, the eco-efficiency will continually increase until PITI reaches its scale of 0.5850.
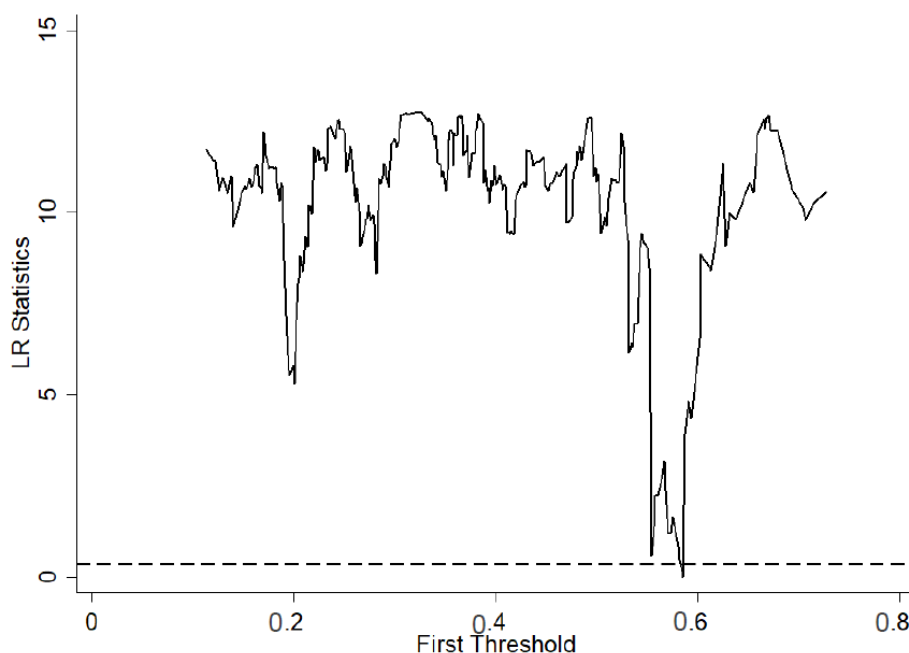

Figure 8. Testing for the single threshold effect.

Table 9. Testing for the threshold effect of PITI on eco-efficiency.

Test for Single Threshold Effects			Test for Double Threshold Effects			
Threshold Values	*F*	*p*-Value	Double Threshold Values		*F*	*p*-Value
0.5850	12.8600	0.0495	0.5710	0.6030	0.2200	1.0000

Note: The *F*-statistics and *p*-value have generated from bootstrap method using 2000 replications.

5. Conclusions

We explore empirically the effect of environmental disclosure measured by pollution information transparency index (PITI) on eco-efficiency using a dataset for 109 key environmental protection (KEP) prefecture-level cities in China during 2008–2015. Meta-US-SBM model, quantile regression, and the SDM are applied throughout the paper. The main conclusions and corresponding policy implications are summarized as follows:

(1) Results of DEA model shows that there exist significant spatiotemporal disparities of eco-efficiency; on average, the eco-efficiency in eastern region is relatively higher than central/western region. To reduce the efficiency gap, the links between different regions should be strengthened so the eco-efficiency can be promoted in a coordinated way by improving industrial agglomeration and optimizing the resources allocation.

(2) Bootstrap Granger causality test implied that there exist unidirectional Granger causal relationships running from PITI and PITI2 to EE rather than bidirectional relationships among PITI, PITI2 and EE in China. Thus, it is of importance to pay high attention to environmental information disclosure in the process of ecological civilization in China.

(3) Both OLS and quantile regression show that the evidence of an inverted-U-shaped relation between PITI and eco-efficiency is supported, and the turning points range from 0.3505 to 0.4540. Estimation results of the SDM also support this finding, and the turning points become relatively smaller after considering spatial effects, varying from 0.3370 to 0.3542 based on different specifications of spatial weights matrices. Furthermore, improving and upgrading the levels of agglomeration, wages and technology will contribute to the promotion of eco-efficiency, while the industrial structure should be readjusted and optimized energetically.

(4) Panel threshold model also shows that the existence threshold effect between PITI and eco-efficiency, providing evidence that the eco-efficiency will continually increase until PITI reaches its threshold value.

Due to data restrictions, the period covered in this study was only eight years. Therefore, future studies can be conducted from three aspects. First, the time span can be increased to cover a longer period, and more information and data can be used to analyze the eco-efficiency of China, such as convergence analysis. Second, more precise measurement of environmental disclosure can be aggregated by micro-level datum. Third, the proposed DEA model can be extended to measure and compare productivity changes for prefecture-level cities in different groups under the framework of the Malmquist–Luenberger productivity indicator. With the same metafrontier, these indicators are comparable and can provide insightful information. Furthermore, to relax the assumption of a linear relationship on both sides of the threshold, panel smooth transition regression (PSTR) model should be adopted to empirically study the nonlinear relationship between PITI and eco-efficiency.

Author Contributions: Yantuan Yu and Jianhuan Huang had the initial idea for the study. Yantuan Yu is responsible for the data collection and econometric analysis. Nengsheng Luo proofread the paper. All authors have read and approved the final manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. List of 109 KEP Cities Included into the Sample

Table A1. The 109 KEP cities.

Region	City	Region	City	Region	City
Eastern (49)			Jining		Changsha
	Beijing Municipality		Tai'an		Zhuzhou
	Tianjin Municipality		Rizhao		Xiangtan
	Shijiazhuang		Guangzhou		Yueyang
	Tangshan		Shaoguan		Changde
	Qinhuangdao		Shenzhen		Zhangjiajie
	Handan		Zhuhai	**Western (29)**	
	Baoding		Shantou		Hohhot
	Shenyang		Foshan		Baotou
	Dalian		Zhanjiang		Chifeng
	Anshan		Dongguan		Nanning
	Fushun		Zhongshan		Liuzhou
	Benxi	**Central (31)**			Guilin
	Shanghai Municipality		Taiyuan		Beihai
	Nanjing		Datong		Chongqing Municipality
	Wuxi		Yangquan		Chengdu
	Xuzhou		Changzhi		Panzhihua
	Changzhou		Linfen		Luzhou
	Suzhou		Changchun		Mianyang
	Nantong		Jilin		Yibin
	Lianyungang		Harbin		Guiyang
	Yangzhou		Qiqihar		Zunyi
	Hangzhou		Daqing		Kunming
	Ningbo		Mudanjiang		Qujing
	Wenzhou		Hefei		Xi'an
	Jiaxing		Wuhu		Tongchuan
	Huzhou		Maanshan		Baoji
	Shaoxing		Nanchang		Xianyang
	Taizhou		Jiujiang		Yan'an
	Fuzhou		Zhengzhou		Lanzhou
	Xiamen		Kaifeng		Jinchang
	Quanzhou		Luoyang		Xi'ning
	Jinan		Pingdingshan		Yichuan
	Qingdao		Anyang		Shizuishan
	Zibo		Jiaozuo		Urumqi
	Zaozhuang		Wuhan		Karamay
	Yantai		Yichang		
	Weifang		Jingzhou		

Appendix B. Computation of Environmental Pollution Index

Following Bian and Yang [47] and Ludovisi [48], we construct a composite environmental pollution index (EPI) using the entropy to measure the weights of each pollutants, which helps to alleviate the influence of extreme values of individual factors. The calculation process involves four steps.

Let V_{iqt} denote the emission volume of pollutant $q(q = 1, 2, \cdots, Q)$ at region $i(i = 1, 2, \cdots, K)$ in year $t(i = 1, 2, \cdots, T)$. This is first normalized over entire sample:

$$P_{iqt} = \frac{V_{iqt}}{\sum_{i=1}^{K} \sum_{t=1}^{T} V_{iqt}} \tag{A1}$$

The entropy of pollutant q at region i is defined as:

$$e_{iqt} = -\frac{1}{LN(K \times T)} \sum_{t=1}^{T} \left(P_{iqt} \times LN(P_{iqt}) \right) \tag{A2}$$

Next, we calculate the weight of pollutant q at region i as:

$$w_{iqt} = \frac{1 - e_{iqt}}{\sum_{q=1}^{Q} \left(1 - e_{iqt} \right)} \tag{A3}$$

The composite environmental pollution index (EPI) covering four pollutants of region i in year t is given by:

$$\text{EPI}_{it} = \sum_{q=1}^{Q} \left(P_{iqt} \times w_{iqt} \right) \tag{A4}$$

Higher EPI indicates higher level of environmental pollution.

Appendix C. Data Sources

Table A2. Data sources of DEA model and econometric model.

	Variable	Sources
DEA model	Labor	China City Statistical Yearbook
	Capital	China City Statistical Yearbook and China Statistical Yearbook
	Land	China City Statistical Yearbook
	Energy	GDP energy intensity (manually collected from various official documents) multiplied by GDP, China Energy Statistical Yearbook
	GDP	China City Statistical Yearbook
	EPI	China City Statistical Yearbook and China Environment Yearbook
Econometric model	EE	Measured by Model (4)
	PITI	Institute of Public & Environmental Affairs and Natural Resource Defense Council (2008–2016)
	PITI2	Quadratic term of PITI
	POPD	China City Statistical Yearbook
	SFDI	China City Statistical Yearbook
	SIND	China City Statistical Yearbook
	WAGE	China City Statistical Yearbook
	TECH	China City Statistical Yearbook

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