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Environmental information disclosure and firm production: evidence from the estimated efficiency of publicly listed firms in China

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Abstract
This study employs the recently developed conditional nonparametric frontier approach to assess the impact of environmental expenditures associated with environmental information disclosure (EID) on the production of China's listed manufacturing firms from 2010 to 2018. An inverted U-shaped relationship is found between environmental expenditures and firms' productive efficiency. Increasing expenditure on pollution control initially lowers the production efficiency at firm level, and indicates the negative impacts of regulatory costs attributable to the resources devoted to EID-related activities. However, a firm's production efficiency increases with environmental expenditure after a certain threshold, which implies that the regulatory costs can be fully offset by triggering innovation. The co-existence of the traditional view of the negative impacts of environmental regulation on production and the positive impacts of Porter-type innovation explains the mixed empirical evidence in the literature. Government subsidies help firms to cover the regulatory costs and support a smooth transition to a Porter-type innovation regime. We also find that continuous environmental investments beyond the threshold can narrow the efficiency gap between firms in the same industry, bringing about additional societal spillover impacts. Our findings thus deepen the understanding on how regulations such as EID affect the economic performance of public firms.

Keywords Environmental information disclosure · Efficiency · Nonparametric location-scale regression · Government subsidy · Porter hypothesis

JEL codes D24 · H23 · Q58

1 Introduction

Environmental information disclosure (EID) is widely used to encourage firms to undertake environmental protection activities (Brzeszczynski et al., 2019; Cohen et al., 2020). China launched its own staged EID program in 2008[1], and publicly listed firms are now required to disclose annually their environmental related activities, such as pollution control and environmental investment in Corporate Social Responsibility. Inevitably, firms have to allocate their capital resources and recruit additional employees to handle pollution control and environmental protection, which can increase firms' financial costs and also result in some productive input resources having to be allocated to EID

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[1] The Chinese Government launched a three-stage environmental information disclosure program for listed companies, i.e., voluntary disclosure, semi-mandatory disclosure and full-mandatory disclosure. More specifically, during the first stage to the end of 2017, listed companies could voluntarily disclose their environmental information, and semi-mandatory disclosure was introduced in 2018 during the second stage, whereby mandatory disclosure was required for listed companies in key heavy-pollution industries while other companies could follow the principle of "explain if not disclosure". The third stage began at the end of December 2020 and requires mandatory disclosure by all listed companies.

activities when budgets are constrained. Therefore, production performance is influenced. The extant literature, such as Kassinis and Vafeas (2002), Lewis et al. (2014) and Du et al. (2022), mainly focuses on the factors that drive EID-related efforts at firm level, and discussion on how and to what extent environmental expenditures on EID programs influence the production performance of listed firms is rare.

This paper studies the impact of using resources for EID-related pollution control on the production performance of publicly listed manufacturing firms in China by adopting a two-step approach. In the first step, as an exploratory tool for measuring firms' production performance, we employ conditional nonparametric frontier analysis (CNFA) to estimate both conditional and unconditional nonparametric efficiency (Cazals et al., 2002; Bădin et al., 2012). Compared with the traditional stochastic frontier approach, this approach does not introduce any specific parametric function for the production frontier or assumptions about the error term and inefficiency component distribution, and it can help to identify the nonlinear effects of external variables. As suggested by Huiban et al. (2018), the external variables are factors that are out of the producer's control, such as a firm's expenditure on pollution control.

Before proceeding to the second step, the 'separability condition' needs to be tested, as suggested by Daraio et al. (2018). Simar and Wilson (2007; 2011) point out that the separability condition suggests that the external variables have no effect on the boundary of the production possibility set and merely influence the efficiencies distribution. This test helps to determine whether unconditional or conditional efficiency can be used for the next step in the analysis. In the second step, according to Bădin et al. (2012), we apply the nonparametric location-scale regression model to further explore the potential nonlinear effects of environmental expenditures and time on firms' efficiency and the dispersion of firms' efficiency. To avoid ex ante determining the local polynomial order, following Hall and Racine (2015), we employ infinite order cross-validated local polynomial regression to detect the average effect of environmental expenditures and its variability across enterprises and over years.

The main result is that an inverted U-shaped relationship is found between environmental expenditures and firms' production efficiency. Increasing expenditure on pollution control first lowers the production efficiency at firm level, which indicates the negative impacts of the regulatory costs associated with EID-related activities. However, a firm's production efficiency increases with environmental expenditures over a certain threshold, which implies that the regulatory costs can be fully offset by triggering innovation, as indicated by the Porter hypothesis (Porter and Van der Linde, 1995). In addition, environmental expenditures present a nonlinear relationship with the dispersion of efficiency distribution. Variance of production efficiency increases with environmental expenditures at lower levels, and such dispersion declines with an increase in environmental expenditures after reaching the threshold. Enterprises in pollution-heavy industries are affected more than their peers in non-pollution-heavy industries.

Our findings have important implications for future policy design and assessment. The existence of a threshold suggests that firms have to allocate a certain share of resources to cover the regulatory costs and to stimulate Porter-type innovations. Therefore, when the firm's management makes financial decisions under these regulatory constraints, it should take into account the implicit threshold needed to achieve the positive impacts of environmental regulation. The government can help firms to reach the threshold more smoothly by providing financial assistance for the environment-related expenses. Beyond the threshold, environmental expenditures reduce the dispersion of firms' efficiency and thus narrow the efficiency gap between firms in the same industry, which will result in additional societal spillover impacts. However, in order for firms to reach a level of spending at which they can achieve benefits while ensuring authentic and reliable EID, it is necessary to be able to estimate this threshold level.

This paper makes two key contributions. First, this study strengthens the understanding of the impacts of EID on firms. Most previous studies have focused on the comprehensive effects of EID on firms' business or financial performance, like return on assets or annual income. For example, Hull and Rothenberg (2008) investigated to what extent corporate social performance can enhance firms' financial performance, and Dixon-Fowler et al. (2013) conducted a meta-analytic review of studies and found that environmental performance seems to be one of the key factors in determining market measures of financial performance. Matsumura et al. (2014) found that the median value of firms that disclose carbon emissions is much higher than that of non-disclosing firms, while the results from Aragon-Correa et al. (2016) show that although leading international firms record better environmental disclosure than their counterparts, they have worse environmental performance. Brzeszczynski et al. (2019) found that the market does not penalize or repay those energy and resource companies that have socially responsible investment practices, and Cohen et al. (2020) show that firms' decisions to install solar panels are an example of profit-motivated social responsibility. Wang et al. (2020) examined the impact of EID on financial performance and explored the mediating effects of visibility and liquidity for China's listed companies. However, these studies overlook the fact that resources that otherwise could have a productive use have to be used to mitigate pollution to comply with the regulations (Picazo-Tadeo et al., 2005), thus the input to pollution control and environmental protection can influence firms' production. This paper fills this gap by investigating the effects of environmental expenditures on EID activities on listed firms' production performance.

Second, this paper complements existing research that has analyzed the strong version of the Porter hypothesis; that is, that regulation could potentially enhance firms' competitiveness[2]. Although some theoretical studies show that the strong version can be verified based on specific firm behaviors, market and organizational failures and internalizing knowledge spillovers (see Ambec and Barla, 2002; Mohr, 2002; Greaker, 2006; André et al., 2009), many empirical studies provide rather mixed evidence (Kozluk and Zipperer, 2015; Dechezleprêtre and Sato, 2017; Lu and Zhang, 2022). For example, the early studies by Gray (1987), Barbera and McConnell (1990) and Dufour et al. (1998) show the negative impacts of environmental regulations on productivity. However, Rubashkina et al. (2015) found no significant effect of environmental regulations on productivity for the manufacturing sectors in seventeen European countries after taking into account potential endogeneity issues. Studies by Albrizio et al. (2017) and Franco and Marin (2017) found positive effects at the sectoral level for eight European countries and seventeen OECD countries. Recently, the results of Hille and Möbius (2019) study that investigated cross-country multi-sectors show no evidence to support the strong version of the hypothesis once simultaneity is controlled. Ambec et al. (2013) point out that the controversy around the strong version lies in whether or not the regulatory costs can be compensated for completely. Moreover, according to André (2015), the linearity and monotonicity relation may not be correct, as "it is not reasonable to assume that the effect of environmental regulation is monotonic".

Given these problems, Huiban et al. (2018) applied conditional nonparametric efficiency analysis combined with nonparametric regression to the French food processing industry to determine the nonlinear relation of pollution abatement capital and productive efficiency, and we further extend their analysis by considering the heterogeneity of industry. We do find a similar inverted U-shaped relationship between environmental expenditures and productive efficiency in China's listed manufacturing firms, but the threshold in non-pollution-heavy industries appears earlier than in pollution-heavy industries.

The remainder of the paper is organized as follows. Section 2 presents the literature review, and Section 3 provides relevant background information for this study. Section 4 presents the methodology, Section 5 presents the description of the data and variables, and Section 6 reports and discusses the results. Section 7 presents a heterogeneous analysis, and the last section concludes the paper and identifies some implications.

2 Literature review

In this section, we briefly review the existing advances in conditional measures and papers and apply the probabilistic framework of efficiency measurement. In the last decades, investigating the role of environmental factors in the production process has been a hot topic in the efficiency literature. Based on the probabilistic formulation of the production process introduced by Cazals et al. (2002), Daraio and Simar (2005; 2007) further extended this approach to include the presence of environmental factors, which led to conditional Debreu-Farrell efficiency estimators.[3] However, the conditional efficiency estimators generally require smoothing techniques for environmental factors. To overcome this difficulty, Bădin et al., (2012) provide a data-driven approach for optimal bandwidth selection. Bădin et al. (2014) developed the approach of Bădin et al. (2012) by using a procedure that allows researchers to make local inferences and provide confidence intervals for the impact of environmental factors on the process. Bădin et al. (2019) further introduced a new bootstrap approach for bandwidth selection when estimating conditional efficiency. In addition, Daraio et al. (2018) developed a test of the restrictive "separability" condition that is necessary for second-stage regressions of estimated efficiency on environmental factors. The recent study by Simar and Wilson (2020) developed a method that eliminates much of this ambiguity by repeating the random splits a large number of times in separability hypothesis testing.

On the other hand, conditional measures based on a probabilistic framework have been widely applied in evaluating the influence of external factors on the production process. The earlier studies by Daraio and Simar (2006) introduced the conditional efficiency measure to analyze mutual fund performance. By applying conditional efficiency measures, some following papers focused on public good provision for public libraries (De Witte and Geys, 2011), the impact of educational innovations on school performance (Haelermans and De Witte, 2012) and university rankings (Daraio et al., 2015), the effect of competition on the technical efficiency of Italian airports (D'Alfonso et al., 2015) and the cost efficiency of general hospitals (Mastromarco et al., 2019). The studies by Broadstock et al. (2019; 2020) investigated the impact of

[2] Both in theoretical studies and in empirical literature, the concept of competitiveness is general and can be represented as different measurements, including higher productivity, cost reduction, increased profits, etc.

[3] Some papers also discuss the directional distance estimators (Daraio and Simar 2014; Daraio et al., 2020).

ESG policy on firms' eco-performance and innovation capacity. Also, by using the latest advances in the conditional efficiency approach, Grant et al. (2020) explored how R&D expenditures affect firms' technical efficiency. Cordero et al. (2020; 2021) estimated the efficiency of municipalities in the presence of unobserved heterogeneity. The recent study by Daraio et al. (2021) modeled the performance of universities in the presence of observed and unobserved heterogeneity.

3 Institutional background

China has recently been focusing on the development of a green and sustainable economy. In the 12th Five-Year Plan (2011–2015) for Economic and Social Development, renewable energy and environmentally friendly industries such as wind power and photovoltaic energy were listed as emerging national strategic industries, and in the 13th Five-Year Plan (2016–2020) for Economic and Social Development, "green" was one of five development ideas aimed at sustainable growth. As part of this effort, the environmental information disclosure (EID) program has been further improved and effectively implemented since 2010, with an increasing number of listed companies being included in the EID program. Figure 8 compares the economic situation of EID-listed companies with all listed companies. Panel (a) shows the annual mean values of the operating costs of EID and all listed companies for the 2010–2018 period. Clearly, the listed companies involved in the EID program had much higher average operating costs than all listed companies, except for only a few years. Similar trends in annual average profit are also clear during the period, as shown in panel (b). Panel (c) shows the annual average asset-liability ratio. Except for 2010 and 2018, the EID-listed companies had a higher average asset-liability ratio compared with all listed companies. In terms of return on total assets (ROTA), EID-listed companies had higher average ROTA in some years and lower average ROTA in other years. These results suggest that the listed companies that disclose their environmental information demonstrated good business performance and strong anti-risk ability.

As a result, according to Greenstone et al. (2021), China made significant progress in pollution reduction by 2018. As shown in panel (a) in Fig. 9, all air pollutant concentrations except O_3 dropped dramatically during the 2013–2018 period. $PM_{2.5}$ decreased by 27.7 μg/m3 or nearly 41%, and SO2 fell the most, declining by over 65%. In terms of regional heterogeneity, panel (b) shows $PM_{2.5}$ trends across six regions by estimating the year-to-year changes in $PM_{2.5}$ separately for each region. Although the initial speed of the reduction in $PM_{2.5}$ in six regions was different, similar $PM_{2.5}$ reductions can be seen in all regions by the end of 2018. Panels (c) and (d) in Fig. 9 show surface water quality. The first measure of water quality is dissolved oxygen (DO) concentration, which shows the degree of oxygen saturation in water and is a measure of its suitability for aquatic life. The second measure is chemical oxygen demand (COD), which represents the degree of oxygen depletion in water as a result of bacterial action and is a measure of water pollution. Clearly, water quality gradually improved from 2008 to 2018 in all regions except the Yangtze River Basin, which initially had the highest water quality. Also, there is a clear trend of convergence in water quality in all river basins. The largest water quality improvement can be seen in the Huai and Yellow River basins, which initially had the lowest initial water quality.

4 Methodology

4.1 Theoretical background

We first provide a simple conceptual framework that has a focus on how EID can influence firms' production decisions and thereby change their production function. We assume that firms produce homogeneous goods, with a Hicks-neutral continuously differentiable production function $Q(K, L)$,[4] where K is capital and L is labor, assuming that the marginal output of capital $Q_k > 0$ and marginal output of labor $Q_l > 0$ and Q_{kk}, $Q_{ll} < 0$. One firm produces output Q with a by-product, i.e., pollution emissions E. In response to the EID program, one firm has to employ additional labor and capital to deal with environmental concerns, especially reducing its pollution emissions. Therefore, we have $E(Q, K_E, L_E)$, where K_E and L_E are additional (non-productive) capital and labor and $E_Q > 0$, $E_{KE} < 0$, $E_{LE} < 0$. In addition, once the firm's emissions are over the threshold $\overline{E}$, the regulator will impose a unit tax (fine), t, on the firm's excessive emissions (E-$\overline{E}$).

Hence, one firm maximizes its profit by setting K, L, K_E, L_E as follows:

$$\max \pi = p \cdot Q(K, L) - r \cdot (K + K_E) - w \cdot (L + L_E) - t \cdot \left(E(Q, K_E, L_E) - \overline{E}\right) \tag{1}$$

[4] The production function with Hicks-neutral technology is generally represented as $Q = AF(K, L)$. Here, to make it simple, we use $Q(K,L)$ instead. Note that this is a relatively restrictive assumption, especially in real-life settings. The recent work by Färe et al., (2021) characterizes the Hicks-neutral technical change and homothetic technology based on the radial expansions or contractions of the relevant isoquants.

where p is market output price, r is capital price or interest rate and w is wage. The first-order conditions for the firm's profit maximization problem are:

$$\frac{\partial \pi}{\partial K} = p \cdot Q_k - r - t \cdot E_Q \cdot Q_K = 0$$
$$\frac{\partial \pi}{\partial L} = p \cdot Q_L - w - t \cdot E_Q \cdot Q_L = 0$$
$$\frac{\partial \pi}{\partial K_E} = -r - t \cdot E_{k_E} = 0$$
$$\frac{\partial \pi}{\partial L_E} = -r - t \cdot E_{L_E} = 0 \tag{2}$$

By applying the implicit function theorem to the equations in (2), we can obtain the following results:

$$\frac{\partial K}{\partial t} < 0, \frac{\partial L}{\partial t} < 0; \frac{\partial K_E}{\partial t} > 0, \frac{\partial L_E}{\partial t} > 0 \tag{3}$$

From Eq. (3), we can observe that the variation in unit tax can largely change the firm's production decision, i.e., labor and capital inputs related to production and pollution treatment, and thus influence the firm's production function.

4.2 Production efficiency

Following the seminal work of Cazals et al. (2002) and Daraio and Simar (2005), the data-generating process (DGP) that characterizes a firm's production with environmental factors includes an input $X \in R_+^p$, an output $Y \in R_+^q$ and environmental factors $Z \in R_+^r$ that cannot be completely controlled by producers but may have an effect on the firm's production and efficiency performance. In this study these are referred to as environmental expenditures. In addition, following Mastromarco and Simar (2015), we further include the time dimension. Specifically, in this study the production process is represented as:

$$H^t_{X,Y|Z}(x, y|z) = \text{Prob}(X \leq x, Y \geq y|Z = z, T = t) \tag{4}$$

where $H^t_{X,Y|Z}(x, y|z)$ is the probability that an enterprise that operates at level (x, y) is dominated by peers experiencing the same level of environmental factors z at year t. The support of this conditional probability is formally characterized as Ψ_t^z. Further, we can define the conditional output-oriented technical efficiency of a production plan $(x, y) \in \Psi_t^z$ with conditions of z at time t as:

$$\lambda_t(x, y|z) = \sup\{\lambda|(x, \lambda y) \in \Psi_t^z\} = \sup\left\{\lambda|S^t_{Y|X,Z}(\lambda y|x, z) > 0\right\} \tag{5}$$

where $S^t_{Y|X,Z}(\lambda y|x, z) = \text{Prob}(Y \geq y|X \leq x, Z = z, T = t)$ is the conditional survival function of Y. Note that this is not a conventional conditional survival function as $X \leq x$ is introduced. If we have panel data $S_n = \left\{\left(X_{i,t}, Y_{i,t}, Z_{i,t}\right) |i = 1, \ldots, n; t = 1, \ldots, s\right\}$, then the conditional output-oriented free disposal hull (FDH) efficiency estimator is given by:

$$\lambda_t(x, y|z) = \max_{j \in \mathrm{I}(z,t)}\left(\min_{k=1,\ldots,q}\left(\frac{Y_j^k}{y^k}\right)\right) \tag{6}$$

where $I(z, t) = \{j = (i, \tau)|z - h_z < Z_{i,\tau} < z + h_z;\ t - h_t < \tau < t + h_t \cap X_i \leq x\}$, and h_z and h_t are the selected bandwidths for environmental expenditures and year. For the unconditional efficiency measures, the attainable set $\Psi = \left\{(x, y) \in R_+^{p+q}|x \text{ can produce } y\right\}$ is written as:

$$\Psi = \left\{(x, y)\middle|H_{X,Y}(x, y) > 0\right\} \tag{7}$$

where $H_{X,Y}\ (x, y) = \text{Prob}(X \leq x,\ Y \geq y)$, and we can further define the unconditional output-oriented technical efficiency of a production plan (x, y) as:

$$\lambda(x, y) = \sup\{\lambda|(x, \lambda y) \in \Psi\} = \sup\left\{\lambda|S_{Y|X}(\lambda y|x) > 0\right\}$$
$$\lambda(x, y) = \max_{i \in D_{x,y}}\left(\min_{k=1,\ldots,q}\left(\frac{Y_i^k}{y^k}\right)\right) \tag{8}$$

where $S_{Y|X}\ (\lambda y|x) = \text{Prob}(Y \geq y|X \leq x)$ is the conditional survival function of Y given that $X \leq x$), $D_{x,y} = \{i|(X_i, Y_i) \in S_n, X_i \leq x, Y_i \geq y\}$. The estimated efficiencies have the relations $1 \leq \lambda_t(x, y|z) \leq \lambda(x, y)$. If the efficiency score equals 1, then the unit is efficient; however, if the efficiency score is more than 1, then the unit is not efficient and the inefficiency is $\lambda_t(x, y|z) - 1$ or $\lambda(x, y) - 1$.

We further use partial frontiers to determine the robust efficiency of some outliers and extreme observations. Specifically, for conditional and unconditional output-oriented efficiency, for any $\alpha \in (0,1)$, according to Daouia and Simar (2007), the order-α quantile efficiency can be defined as:

$$\lambda_{t,\alpha}(x, y|z) = \sup\left\{\lambda|S^t_{Y|X,Z}(\lambda y|x, z) > 1 - \alpha\right\}$$
$$\lambda_\alpha(x, y) = \sup\{\lambda|S_{Y|X}(\lambda y|x) > 1 - \alpha\} \tag{9}$$

It is worth mentioning that we use FDH estimators to calculate the conditional and unconditional efficiency employed in this paper, which does not impose the convexity assumption about the attainable set as is usual in data envelopment analysis (DEA).[5] To introduce the corresponding estimators for order-α unconditional and conditional efficiency, we first define

$$\gamma_i = \min_{k=1,\ldots,q} \frac{Y_i^k}{y^k},\ i = 1, \ldots, n \tag{10}$$

Let $N_x = n\widehat{F}_{X,n}(x) = \sum_{i=1}^{n} I(X_i \le x)$ be non null. For $j = 1,\ldots, N_x$, denote by $\gamma_{(j)}^x$ the jth order statistics of the observation γ_i. Then, we further characterize the empirical version of the survival function for unconditional efficiency:

$$\widehat{S}_{Y|X,n}(\lambda y|x) = \frac{\sum_{i|X_i \le x} I(Y_i \ge \lambda y)}{N_x} = \frac{\sum_{j=1}^{N_x} I(\lambda \le \gamma_{(j)}^x)}{N_x} \tag{11}$$

Therefore, the unconditional order-α FDH estimator can be written as:

$$\widehat{\lambda}_{\alpha,n}(x, y) = \begin{cases} \gamma_{\alpha N_x}^x \ \mathit{if}\ \alpha N_x \in N^* \\ \gamma_{([\alpha N_x]+1)}^x\ \mathit{otherwise} \end{cases} \tag{12}$$

where N^* represents the set of positive integers and $[\alpha N_x]$ represents the integral part of αN_x.

Similarly, if $N_{x'} = \sum_{j'=(i,\tau)} I(X_{j'} \le x)$ the corresponding empirical survival function for conditional efficiency is represented as:

$$S'_{Y|X,Z}(\lambda y|x, z) = \frac{\sum_{j'=(i,\tau)} I(x_{j'} \le x, y_{j'} \ge \lambda y) K\left((z - Z_{j'})/h_z\right) K((\tau - t)/h_t)}{\sum_{j'=(i,\tau)} I(x_{j'} \le x) K\left((z - Z_{j'})/h_z\right) K((\tau - t)/h_t)}$$

$$= \begin{cases} 1 \text{ if } \lambda \le \gamma_{(1)}^x \\ L_{k+1} \text{ if } \lambda_{(k)}^x < \lambda \le \gamma_{(k+1)}^x,\ k = 1, \ldots, N_{x'} - 1 \\ 0 \text{ if } \lambda > \gamma_{(N_{x'})}^x \end{cases} \tag{13}$$

where $K(\cdot)$ is the kernel and $z - h_z < z_{i,\tau} < z + h_z$; $t - h_t < \tau < t + h_t$, h_z and h_t are the chosen bandwidths for environmental variables and time[6], $L_{k+1} = \frac{\sum_{j'=k+1}^{N_{x'}} K\left((z - Z_{j'})/h_z\right) K((\tau - t)/h_t)}{\sum_{j'=(i,\tau)} I(x_{j'} \le x) K\left((z - Z_{j'})/h_z\right) K((\tau - t)/h_t)}$. Therefore the conditional order-α FDH estimator is computed as:

$$\widehat{\lambda}_{t,\propto}(x, y|z) = \begin{cases} \gamma_{(k)}^x\ \mathit{if}\ L_{k+1} \le 1 - \alpha < L_k,\ k = 1, \ldots, N_{x'} - 1 \\ \gamma_{(N_{x'})}^x\ \mathit{if}\ 0 \le 1 - \alpha \le L_{N_{x'}} \end{cases} \tag{14}$$

In addition, according to Bădin et al. (2010)[7], we apply the least squares cross-validation method to obtain the optimal bandwidths. As Mastromarco and Simar (2015) point out, assumptions that are not empirically verified should be avoided when analyzing the boundary.

4.3 Estimation of the effects of environmental expenses on production

4.3.1 Exploratory analysis

Following Bădin et al. (2012) and Mastromarco and Simar (2015), we investigate how environmental variables and time influence the boundary by computing the ratios of the conditional to unconditional efficiency measures:

$$R_o(x, y|z, t) = \frac{\lambda_t(x, y|z)}{\lambda(x, y)} \tag{15}$$

where R_o $(x, y|z) \le 1$ for any (x, y, z, t) in the attainable set. R_o $(x, y|z, t) \le 1$ means the conditional efficient boundary is below the unconditional boundary, and R_o $(x, y|z, t) \le 1$ indicates no shift of the efficient boundary of the two attainable sets. A global tendency of the ratios to increase with the variables represents a favorable effect of conditioning variables on the boundary and unfavorable effects in the opposite case. Accordingly, we can detect the effect of the conditioning variables (z and t) on the distribution of inefficiencies by using the order-α counterparts of Eq. (15), i.e., partial frontier ratio:

$$R_{o,\alpha}(x, y|z, t) = \frac{\lambda_{t,\alpha}(x, y|z)}{\lambda_\alpha(x, y)} \tag{16}$$

Where $R_{o,\alpha}$ $(x, y|z, t)$ is not bounded by 1, the ratios can be smaller than 1 or greater than 1. Note that when α→1, $R_{o,\alpha}$

[5] Some studies show the superiority of the FDH estimator over the DEA estimator. Tulkens (2006) demonstrated that compared with the DEA estimator, the FDH estimator possesses goodness of fit to the data, has more simple computational requirements and provides a more convincing comparison of efficiency estimates. Cherchye et al., (2000) show that Thrall's (1999) argument against the FDH estimator builds on an inappropriate criterion and discusses non-trivial economic conditions (imperfect competition and price uncertainty) under which FDH may even become economically more meaningful without introducing the assumption of the convex production set, which is often a restrictive assumption (Daraio and Simar 2007). Note that we do not test for convexity before using the FDH estimators to compute the conditional and unconditional efficiency estimates. For further details of testing the convexity of the production set, please see Simar and Wilson (2020).

[6] It requires smoothing through bandwidths using kernels with compact support (Bădin et al., 2010), which is based on least squares cross-validation (LSCV) criterion (Hall et al., 2004; Li and Racine 2007). We obtain the optimal bandwidth by using Epanechnikov kernel for z and t based on the approach proposed by Bădin et al., (2010) in the empirical setting.

[7] For details of FDH estimator, see Daraio and Simar (2007).

$(x, y|z, t) \rightarrow R_o(x,y|z, t)$. Similarly, a tendency of $R_{o,\alpha}$ $(x, y|z, t)$ to increase with the conditioning variables represents a favorable effect of these variables on the distribution of the efficiencies, i.e., the conditional distribution is more concentrated at its upper boundary when the variables increase. $R_{o,\alpha}$ $(x, y|z, t)$ shows the opposite pattern in the case of an unfavorable effect.

4.3.2 Separability condition

We can further analyze the effects of time and environmental expenditures using a nonparametric regression model, but this approach requires the 'separability condition', i.e., neither time nor environmental expenditures will affect the boundary of the attainable set. According to Simar and Wilson (2007; 2011), the assumption of "separability" refers to when the frontier of the attainable set does not depend on the values of Z.[8] Under the "separability" condition, $\Psi_t^z \equiv \Psi$ for all (z, t). If this condition is rejected, according to Bădin et al. (2012), conditional efficiency scores λ_t $(x, y|z)$ rather than unconditional efficiency scores $\lambda(x, y)$ should be used as a dependent variable in the second stage.

Formally, we employ the test proposed by Daraio et al. (2018) to examine the separability condition under the null hypothesis of separability versus the alternative of non-separability. Specifically, the data sample S_n firstly should be randomly split into two independent subsamples, S_{n_1} and S_{n_2}, such that $n_1 = [n/2]$, $n_2 = n\text{-}n_1$. We can then calculate the unconditional estimates using the n_1 observations in S_{n_1} and the conditional estimates using the n_2 observations in S_{n_2}:

$$\widehat{\mu}_{n_1} = \frac{1}{n_1}\sum_{i=1}^{n_1}\widehat{\lambda}(X_i, Y_i)$$
$$\widehat{\mu}_{n_{2,h}} = \frac{1}{n_{2,h}}\sum_{i=1}^{n_{2,h}}\widehat{\lambda}_t(X_i, Y_i|Z_i) \tag{17}$$

where $n_{2,h} = \min\ (n_2,\ n_2 h^r)$[9], r is the dimension of environmental variables Z and h is the bandwidth for Z. The corresponding variances are given by:

$$\widehat{\sigma}^2_{n_1} = \frac{1}{n_1}\sum_{i=1}^{n_1}\left(\widehat{\lambda}(X_i, Y_i) - \widehat{\mu}_{n_1}\right)^2$$
$$\widehat{\sigma}^2_{n_2} = \frac{1}{n_2}\sum_{i=1}^{n_2}\left(\widehat{\lambda}_t(X_i, Y_i|Z_i) - \widehat{\mu}_{n_2}\right)^2 \tag{18}$$

where these two subsamples are used to compute these two variances. Further, we need to calculate the bias for the unconditional $\widehat{B}_{n_1}$ and conditional cases $\widehat{B}_{n_{2,h}}$, as shown in Daraio et al. (2018). Finally, the test statistic is given by:

$$\frac{(\widehat{\mu}_{n_1} - \widehat{\mu}_{n_{2,h}}) - (\widehat{B}_{n_1} - \widehat{B}_{n_{2,h}})}{\sqrt{\frac{\widehat{\sigma}^2_{n_1}}{n_1} + \frac{\widehat{\sigma}^2_{n_2}}{n_{2,h}}}} \xrightarrow{\mathcal{L}} N(0,\ 1) \tag{19}$$

where the test statistic is asymptotically distributed as a standard normal distribution under the null hypothesis of non-separability.

4.3.3 Nonparametric location-scale regression of efficiency

If the separability condition test shows that the separability condition is rejected, conditional efficiency λ_t $(x, y|z)$ should be used as the dependent variable in the following nonparametric location-scale regression[10]:

$$\lambda_t(x, y|z) = \mu(z, t) + \sigma(z, t)\varepsilon \tag{20}$$

where ε is the error term such that $\mathbb{E}(\varepsilon|z, t) = 0$ and $\mathbb{V}(\varepsilon|z, t) = 1$. We use this model to further detect the location effect, i.e., the average effects of environmental expenditures and time on efficiency, $\mu(z, t) = \mathbb{E}[\lambda_t(X, Y|Z = z)|Z = z, T = t]$ and the scale effect, i.e., the impact of environmental expenditures and time on dispersion of the efficiency distribution, $\sigma^2(z, t) = \mathbb{V}[\lambda_t(X, Y|Z = z)|Z = z, T = t]$.

To estimate this model, we employ the "infinite order cross-validated local polynomial regression approach" (Hall and Racine 2015)[11], which can jointly determine the polynomial order and the value of the bandwidth using a data-driven cross-validation procedure to avoid ex ante determining the polynomial order. As the order of the polynomial can determine the quality of the resulting approximation, our

[8] The separability condition refers to when the environmental factors influence neither the shape nor the level of the boundary of the attainable set and the potential effect of Z on the production process is only through the distribution of the inefficiencies. If the separability condition holds, it is meaningful to analyze the behavior of $\lambda(x, y)$ as a function of Z using appropriate regressions. However, most previous studies analyzed the effect of Z on $\lambda(x, y)$ by estimating second-stage regressions without testing the separability condition, leading to invalid results for the effect of Z on the production process.

[9] All bandwidths are assumed to be the same. For details, see Daraio et al., (2018).

[10] The nonparametric location-scale regression model is a basic model in nonparametric econometrics. A classical location-scale regression model can be written as $Y = m(X) + \sigma(X)\varepsilon$, where $m(X) = E(Y|X = x)$ and $\sigma^2\ (X) = V(Y|X = x)$ are some unknown but smooth location and scale functions, $m(X)$ measures the average effect of X on the dependent variable Y, and $\sigma(X)$ shows additional information on the dispersion of Y as a function of X. For details, see for example Fan and Gijbels (1996).

[11] The computations are completed by the npglpreg function from the crs library in R (Nie and Racine 2012).

Table 1 Summary statistics of listed manufacturing firms

Group	N. Obs.	Output (10^6 USD)	Labor (10^3 person)	Capital (10^6 USD)	Environmental expenditures (10^3 USD)
Pollution-heavy	846	2019.76 (4357.408)	7.20 (10.12)	779.773 (1472.356)	1714.708 (2252.893)
(a) With subsidy	513	1371.757 (2012.813)	5.88 (4.90)	536.234 (628.111)	1598.453 (1934.065)
(b) Without subsidy	333	3018.034 (6358.380)	9.25 (14.72)	1154.954 (2162.468)	1893.804 (2663.912)
Non-pollution-heavy	180	1133.855 (370.509)	5.98 (7.22)	295.042 (370.509)	627.532 (994.431)
Total	1026	1864.338 (4008.957)	6989.66 (9680.18)	694.732 (1358.358)	1523.975 (2127.923)

The table reports the mean values with standard deviations in parentheses

regression model can improve the performance of the finite sample efficiency and convergence rate.

5 Data

The data used in this paper were obtained from the Chinese A-share stock markets. We focus on publicly listed manufacturing firms as they are the major contributors to environmental pollution in China (Zhang, 2017).[12] The usual inputs and outputs of each firm can be acquired from the China Stock Market and Accounting Research database (CSMAR) database. We use the annual number of employees of each firm as a measurement for labor, and we use fixed assets deflated by the annual price index for capital goods as a measurement for capital.[13] Although we do not have data on the added value for firms' output, following Giannetti et al. (2015) and Chen et al. (2020), we use the sales of goods and services as an alternative measurement for output. Data on environmental expenditures are manually collected from listed firms' annual reports on environment and sustainability. Environmental expenditures include the expenditures related to pollution control and environmental protection, such as desulfurization, denitration, sewage treatment, waste gas treatment, dust removal and energy conservation.

Our initial sample consisted of the listed manufacturing firms that reported their expenditures on the EID program for the period from 2010 to 2018. To ensure the sample was stable and valid, we further excluded firms with special treatment (ST-stock) and also excluded firms with incomplete or missing data.[14] Finally, we obtained a balanced panel of 114 firms for the period 2010–2018, including 94 firms from pollution-heavy industries and 20 firms from non-pollution-heavy industries.[15] Moreover, to measure variations between firms that receive a government subsidy related to pollution reduction and environmental protection and those that do not,[16] we divided the pollution-heavy industry firms into two groups—one group with government subsidy (57 firms) and the other without government subsidy (37 firms).

Table 1 reports the summary statistics of our sample. On average, the listed manufacturing firms in pollution-heavy industries put many more financial resources into pollution control and environmental protection than their counterparts in non-pollution-heavy industries. We observe a large variation in environmental expenditures in both the pollution-heavy group and the non-pollution-heavy group and larger variations and bigger average environmental expenditures in firms without a government subsidy. In addition, we use the continuous variables with logarithm transformations in the following analysis.

6 Results and discussion

6.1 Conditional and unconditional efficiency

Table 2 summarizes the distributions of the bandwidths h_t for year and h_{ee} for environmental expenditures. The median value for h_t is about 3, thus the conditional survival function

[12] Guidelines on Industry Classification of Listed Companies (Revised in 2012) shows that the listed manufacturing firms can be further divided into different industries including computers and other electronic equipment, meta products; wood processing, printing/packaging/paper producing, general machinery/special equipment manufacturing, leather, fur, feather and their products and footwear, Rubber and plastic products, pharmaceutical industry, petroleum processing, etc.

[13] The outputs and environmental expenditures are therefore deflated. In addition, as the listed companies in China do not report their intermediate inputs in the financial statements, we do not take the intermediate inputs into account in this study.

[14] According to the regulations of Shanghai Stock Exchange and Shenzhen Stock Exchange, these stocks should be labeled as ST-stock in case of financial issues or other abnormal conditions.

[15] As shown in the Guideline on Industry Classification of Listed Companies, pollution-heavy industry includes thermal power, iron and steel, cement, electrolytic aluminum, coal, metallurgy, chemical industry, petrochemical industry, building materials, papermaking, brewing, pharmaceutical, fermentation, textile, leather and mining industries. According to the CSMAR database, among these 1026 (114*9) observations, 385 observations were key pollution monitoring units, 535observations passed ISO14001 and 378 observations passed ISO9001. Only 4 observations failed to reach the pollution emission standard.

[16] Government subsidy includes many categories, such as R&D subsidy, and tax rebates.

Table 2 Distributions of the bandwidths h_t for year and h_{ee} for environmental expenditures

h_j	$\min(h_j)$	$Q_1(h_j)$	$Q_2(h_j)$	$Q_3(h_j)$	$\max(h_j)$
h_t	0.302	2.277	3.147	3.591	89.535
h_{ee}	0.038	0.218	0.312	0.456	157.300

Table 3 Summary statistics of the estimated production efficiency

Group	N. Obs.	Mean	SD	Min	Max
Unconditional efficiency					
Pollution-heavy	846	1.188	0.0986	1	1.597
(a) With subsidy	513	1.192	0.093	1	1.597
(b) Without subsidy	333	1.180	0.106	1	1.413
Non-pollution-heavy	180	1.197	0.095	1	1.405
Overall	1026	1.189	0.098	1	1.597
Conditional efficiency					
Pollution-heavy	846	1.116	0.102	1	1.597
(a) With subsidy	513	1.121	0.103	1	1.597
(b) Without subsidy	333	1.107	0.100	1	1.374
Non-pollution-heavy	180	1.110	0.103	1	1.401
Overall	1026	1.115	0.102	1	1.597

(and the conditional efficiency scores) were evaluated across a period of about six years around the current year. As the sample covers nine years, we can expect some effect of time on a firm's production process. The same is true for environmental expenditures, as the mean and standard deviation of environmental expenditures in terms of logarithms is around 3.6 and 0.6, respectively, whereas the median bandwidth for h_{ee} is around 0.3. Thus, localizing the year and environmental expenditures really matters.

Table 3 reports the summary statistics of estimated production efficiency. As shown in the table, the mean unconditional efficiency value for all firms is 1.189, which suggests that if all firms were to operate as efficiently as the leading performers, the efficiency could increase on average by 18.9%. On average, the pollution-heavy group performs better than their peers in the non-pollution-heavy group, and the firms without a government subsidy outperform their counterparts. When we further include the environmental variables, the overall mean inefficiency (1.115) is less than the means of unconditional efficiency.

To further investigate the robustness to alternative bandwidth selection, we use the bootstrap approach introduced by Bădin et al. (2019) to estimate conditional efficiency measures. The selected optimal bandwidth is 0.318 for environmental expenditures and 4.011 for year. We thus obtain the corresponding conditional efficiency and compare it with the conditional efficiency based on Bădin et al. (2010). The mean value and variance of conditional efficiency is 1.121 and 0.102, respectively, as shown in Table 4, which is similar to the corresponding values in Table 2. As a further analysis of the difference between the two results, we resort to commonly used nonparametric tests (Kolmogorov-Smirnov test and Mann-Whitney test). Table 5 reports the results from two tests for the distributions of two estimates. The values do not reject the null hypothesis that the two samples do not have a significant difference, which suggests that there is no significant difference between the two estimated conditional efficiency results. This shows that the approach for selecting bandwidth is not a concern for estimating conditional efficiency in this context.

6.2 Results of exploratory analysis

We then show the full and partial ratios of unconditional and conditional efficiency measures. According to Bădin et al. (2012), we can identify the possible effects of these environmental variables (z and t) on the boundary (shift of the frontier) by using the full frontier ratio $Ro(x, y|z, t)$. A global tendency of the ratios to increase with the variables represents a favorable effect of the conditioning variables on the boundary and an unfavorable effect in the opposite case. In Fig. 1, the top two panels present the full ratios from the marginal effects of environmental expenditures and time. The figure shows no clear effect of environmental expenditures and time on the frontier. To ensure that the result is robust and to investigate whether the effect is hidden by the observations with extreme values, we also estimate the partial frontier ratios with $\alpha = 0.99$, and find that the results are quite similar, as shown in Fig. 10 in the Appendix.

Next, we turn to the partial frontier ratios. If the pattern with the partial frontier ratios is similar to that shown for the full frontier ratios as a function of conditioning variables, we can draw the conclusion that the variables only have an effect on the boundary. If the effect with the partial frontier ratios (e.g., $\alpha = 0.5$) is greater than the effect with the full frontier ratios, this means that the conditioning variables not only influence the boundary but also affect the distribution of efficiencies. The bottom two panels in Fig. 1 show the marginal effect of environmental expenditures and time on the ratios $\widehat{R}_{o,\alpha}(\mathrm{x}, \mathrm{y}|\mathrm{z}, \mathrm{t})$ for $\alpha = 0.5$, which shows the effects of environmental expenditures and time on the median of distribution of median efficiencies, as shown in Bădin et al., (2012) and Mastromarco and Simar (2015). We find a clear positive relationship between environmental expenditures and $\widehat{R}_{o,\alpha}(\mathrm{x}, \mathrm{y}|\mathrm{z}, \mathrm{t})$ in the bottom left panel. This implies a favorable effect of environmental expenditures on the distribution of the efficiencies. In other words, given $X \le x$, the distribution of Y is more concentrated at its upper boundary when environmental expenditures increase. Moreover, the bottom right panel of Fig. 1 shows that the distribution of the ratio changes little over time. The above results show that the main effect of environmental

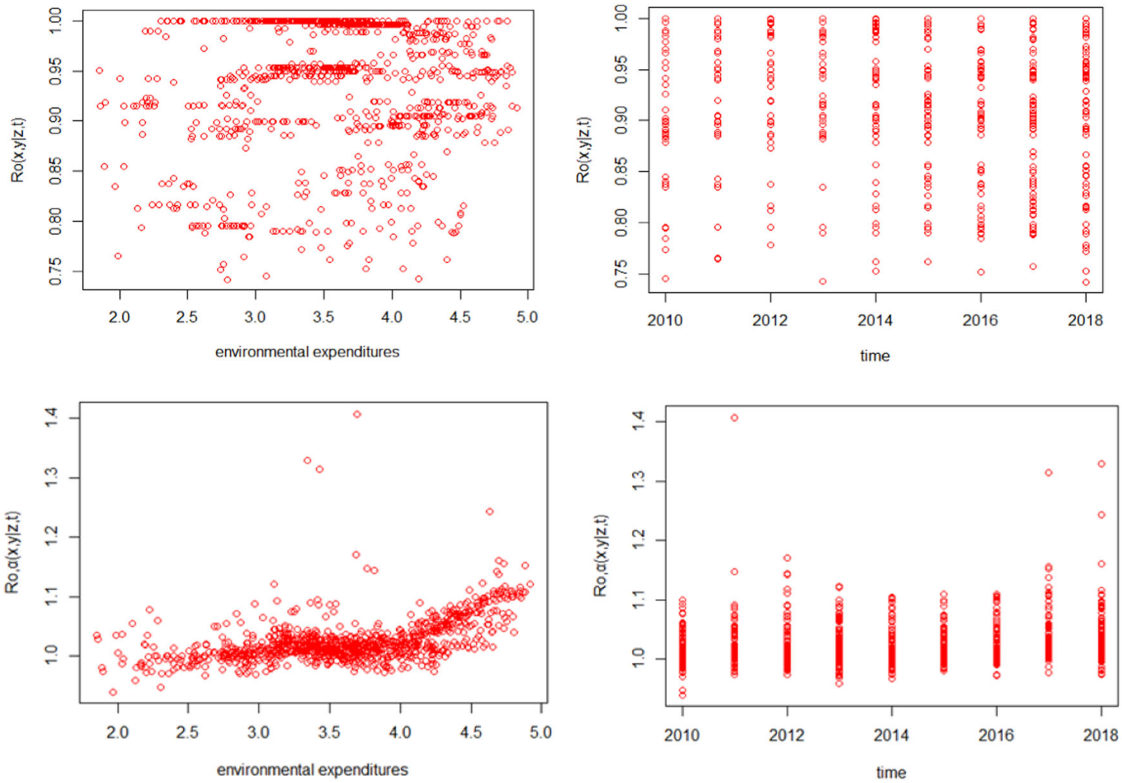


Fig. 1 Marginal effect of environmental expenditures (in logs) and time on the ratios $\widehat{R}_o(x, y|z, t)$ and $\widehat{R}_{o,\alpha}(x, y|z, t)$. The top two panels report the full frontier ratios $\widehat{R}_o(x, y|z, t)$ as a marginal function of environmental expenditures and time, and the vertical axis represents the full ratios $\widehat{R}_o(x, y|z, t)$. The bottom two panels show the partial frontier ratios $\widehat{R}_{o,\alpha}(x, y)$ for $\alpha = 0.5$ as a marginal function of environmental expenditures and time, and the vertical axis represents the partial ratios $\widehat{R}_{o,\alpha}(x, y|z, t)$

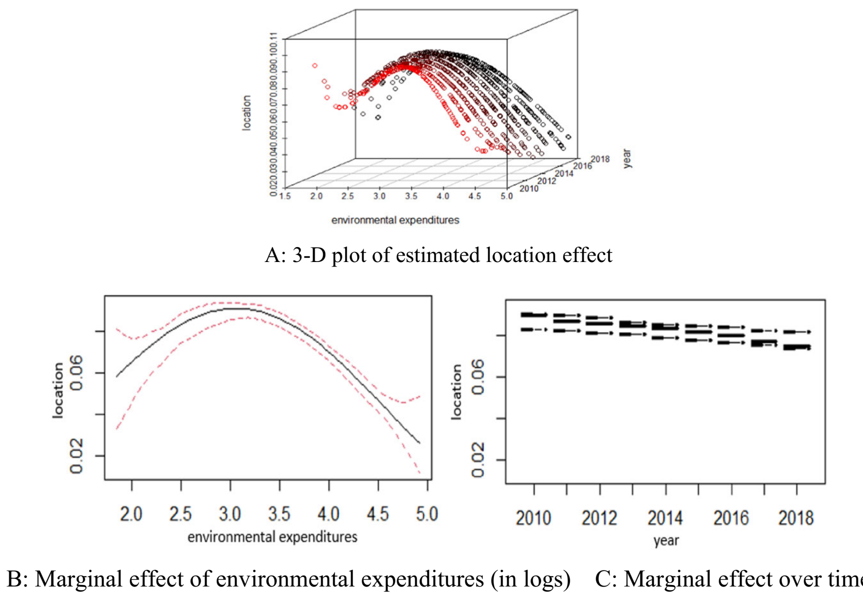
expenditures is on the distribution of efficiencies rather than the shift of the frontier. That is, environmental expenditures play an important role in determining technical catching-up (efficiencies distribution) and may not influence technical change (movements of the frontier). Nevertheless, as explained in Bădin et al., (2012) and Huiban et al., (2018), the above analyses should be regarded as exploratory.

6.3 Nonparametric location-scale regression

Before we proceed to the location-scale regression, we need to verify the separability condition formally, i.e., $\Psi_t^z \equiv \Psi$, where Ψ is the union of Ψ_t^z. We employ the test proposed by Daraio et al. (2018). Specifically, we use output-oriented free disposal hull (FDH) estimators and two randomly selected subsamples with bandwidths derived from least-squares cross-validation. Due to the panel data used in this paper, following Toma (2020), we compute the test for each year. The results show that the null hypothesis – that the environmental variables Z have no influence on the attainable set – cannot be rejected because the p-value is, on average, 0.11, which further supports the results of the exploratory analysis. When a test is conducted for the entire period, the corresponding p-value is 0.108. We further employ the newest test introduced by Simar and Wilson (2020), which removes the ambiguity or uncertainty due to a single split of the original sample. Given that we have over 1000 observations with 2 inputs, 1 output and 2 environmental variables, the computation burden forced us to limit our analysis to 2 sample splits and 1000 bootstrap replications repeated 1000 times.[17] The results show that the rejection rate for separability is about 47% based on the averaged statistic and 43% based on the Kolmogorov-Smirnov statistic, with p-values that are less than 0.1 among 1000 repetitions. Given the simulation results from Simar and Wilson (2020), the test statistics suggest that the departure from the null hypothesis is relatively small. Certainly, failure to reject the null does not imply that the null is true. One would expect to reject in about 10% of the tests at the 0.1 level, which can give us more confidence in the null hypothesis of separability. In fact, it is also supported by the

[17] The computations can be completed by the function test.sep.cont in the FEAR package in R. An effective way to reduce the computational burden is to approach the sample using clusters of different types of DMUs (i.e., heavily polluting ones and non-heavily polluting ones), which allows us to use more sample splits, the computation can be easier and the results will be much better. We thank one anonymous reviewer for pointing this out.

Fig. 2 Estimated location of unconditional efficiency and corresponding two marginal views. Log $\lambda(x, y)$ is used as the dependent variable, and the vertical axis represents the estimated location $\widehat{\mu}(z_{i,t}, t)$, i.e., the conditional mean of unconditional efficiency, $\mathbb{E}[\lambda(X, Y)|Z = z, T = t]$, capturing the average effects of environmental expenditures and time on efficiency; 95% bootstrapped confidence bands are also shown in the two marginal views



following regression of conditional efficiency and results using Algorithm #2 introduced by Simar and Wilson (2007), which suggests that there should be no large difference between unconditional efficiency and conditional efficiency and external variables do not significantly influence the frontiers. Thus, unconditional efficiency $\lambda(x, y)$ is used as a dependent variable in the following main analysis.

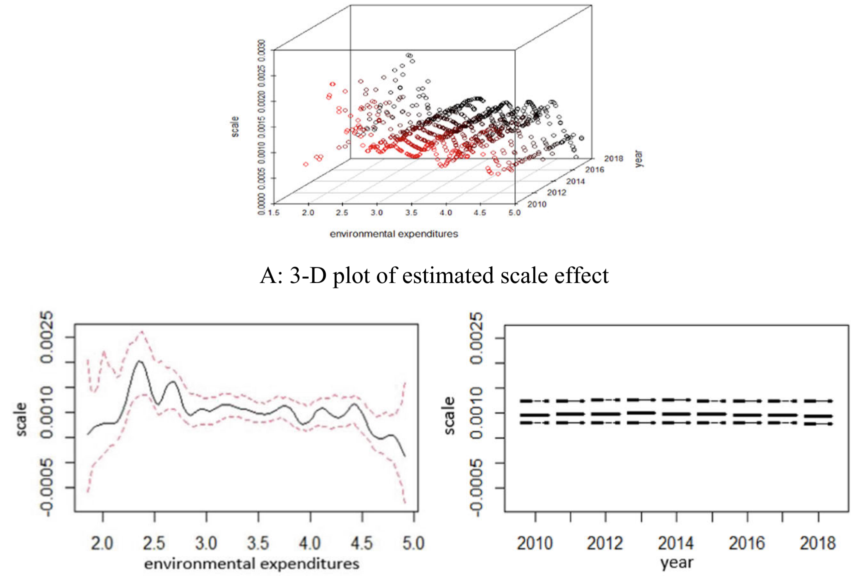
We then estimate the location-scale regression using the approach proposed by Hall and Racine (2015). Specifically, we regress unconditional efficiency (log) as a function of environmental expenditures (log) and time. In this nonparametric regression, we use Bernstein polynomials and a Gaussian kernel with second order for the continuous variable and environmental expenditures and the kernel introduced by Li and Racine (2007) for the ordered variable, time.

Firstly, we report the results of the location effect. Figure 2 shows the results of the estimated location effect for the whole sample. The 3D plot in the top panel and marginal effect of environmental expenditures clearly show a nonlinear effect of environmental expenditures on the efficiencies, and a typically inverted-U relation can be observed. The turning point is around 1000 thousand yuan in our case. Specifically, for low levels of environmental expenditures, the unconditional efficiency-environmental expenditures relation shows a flat pattern, indicating that it is necessary to have a minimum level of capital used for environmental protection and pollution control to have an effect. Note that an increase of log $\lambda(x, y)$ means a decrease in efficiencies, with the optimum being zero. Thus, we can observe a negative effect before the threshold and then a positive effect after reaching the threshold, indicating that environmental expenditures need to reach a certain level to obtain a positive effect.

This finding is relevant to traditional wisdom about the effect of environmental regulation. A firm's mitigation efforts may not negatively or positively influence its performance all the time, as André (2015) points out that the non-monotonic effect may exist. In addition, we can observe the positive effect of time on unconditional efficiency in both the 3D plot and the marginal effect over time. As the capital is mainly used to buy treatment facilities, to introduce green production technology or to upgrade production technology, our results may suggest that the spillover effects of these expenditures need a certain level of investment and time to be fully exploited and offset the 'crowding out' effect of resources put into pollution reduction.

We also present the results of the location effect of conditional efficiency, as shown in Fig. 12 in the Appendix. We find similar results. The 3D plot in the top panel and marginal effect of environmental expenditures also show a similar inverted-U relation. In addition, we observe the positive effect of time on conditional efficiency in the 3D plot and marginal effect over time. This similar finding is not surprising as the separability test shows that there should be no large difference between the unconditional efficiency and conditional efficiency results.

Next, we turn to the scale effect. In Fig. 3, a nonlinear relation between environmental expenditures and the scale effect is clearly presented, and the shape is similar to an inverted U, with more peaks in the low levels of environmental expenditures, followed by relatively flat ups and downs, thus indicating that low levels of expenditure on pollution control can increase the efficiency gaps among firms. After reaching the threshold, such dispersion abruptly declines with an increase in environmental expenditures. Therefore, to reduce the dispersion and narrow the



A: 3-D plot of estimated scale effect

B: Marginal effect of environmental expenditure (in logs) C: Marginal effect over time

Fig. 3 Estimated scale effect and corresponding two marginal views. *Notes:* Log $\lambda(x, y)$ is used as the dependent variable, and the vertical axis represents the estimated scale $\widehat{\sigma}(z_{i,t}, t)$, i.e., the conditional variance of unconditional efficiency, $\sigma^2(z, t) = \mathbb{V}[\lambda(X, Y)|Z = z, T = t]$, capturing the impact of environmental expenditures and time on the dispersion of efficiency distribution; 95% bootstrapped confidence bands are also shown in the two marginal views

efficiency gaps, a certain level of expenditure is also needed. Moreover, the marginal effect over time perspective indicates that the dispersion of performance changes little over time.

In addition, following Bădin et al. (2012) and Mastromarco and Simar (2015), we further investigate the residuals, i.e., unexplained part of the conditional efficiency measures, $\varepsilon_i = \frac{\lambda_t(x, y|z) - \mu(z, t)}{\sigma(z, t)}$. It can be interpreted as the idiosyncratic part of the efficiency, i.e., an efficiency score cleaned by the external effects (here environmental expenditures and time). Figure 12 shows idiosyncratic efficiencies. The histogram of the "idiosyncratic efficiencies" ε (top panel) looks like a normal distribution. The bottom panels display residuals ε against environmental expenditures and time. We do not observe a clear remaining dependence, suggesting that the location scale model in Fig. 12 has cleaned most of the effects of time and environmental expenditures on conditional efficiencies. This is confirmed by the very small correlation coefficients between ε and environmental expenditures and time, as shown in Table 5.

Last, we also perform Algorithm #2 introduced by Simar and Wilson (2007) to investigate the influence of time and environmental expenditures.[18] In addition to the environmental expenditures and time variables, we include the square of environmental expenditures and time and a term for the interaction of the two variables. Table 6 in the Appendix reports the results, including the estimated coefficients and corresponding 95% confidence intervals.

The coefficients of environmental expenditures (0.144), its square term (−0.037) and the confidence intervals clearly suggest that there still exists an inverted-U relation between environmental expenditures and firm efficiency. Also, the negative coefficients of time and its square term show the positive effect of time on firm efficiency during the sample period, which is consistent with our main findings.

7 Heterogeneous analysis

7.1 Heterogeneous effects (by industry)

We further compare the location effect of firms in pollution-heavy industries and non-pollution-heavy industries. As presented in Fig. 4, we can observe the similar inverted U pattern in both industries, but the threshold in non-pollution-heavy industries appears earlier than in pollution-heavy industries. This finding suggests that firms in non-pollution-heavy industries may be affected less than their counterparts in pollution-heavy industries, given that the EID program mainly covers listed firms in pollution-heavy industries and the program requires these firms to devote a large amount of capital to pollution control and environmental protection. We observe the positive effect of time on efficiency in both industry types, as shown in the marginal effect over time.

Figure 5 presents the estimated scale effect in both the pollution-heavy and non-pollution-heavy industries. We observe a clear inverted-U relation for pollution-heavy industries, indicating that low levels of environmental

[18] The computation is completed via the function dea.env.robust in rDEA package in R.

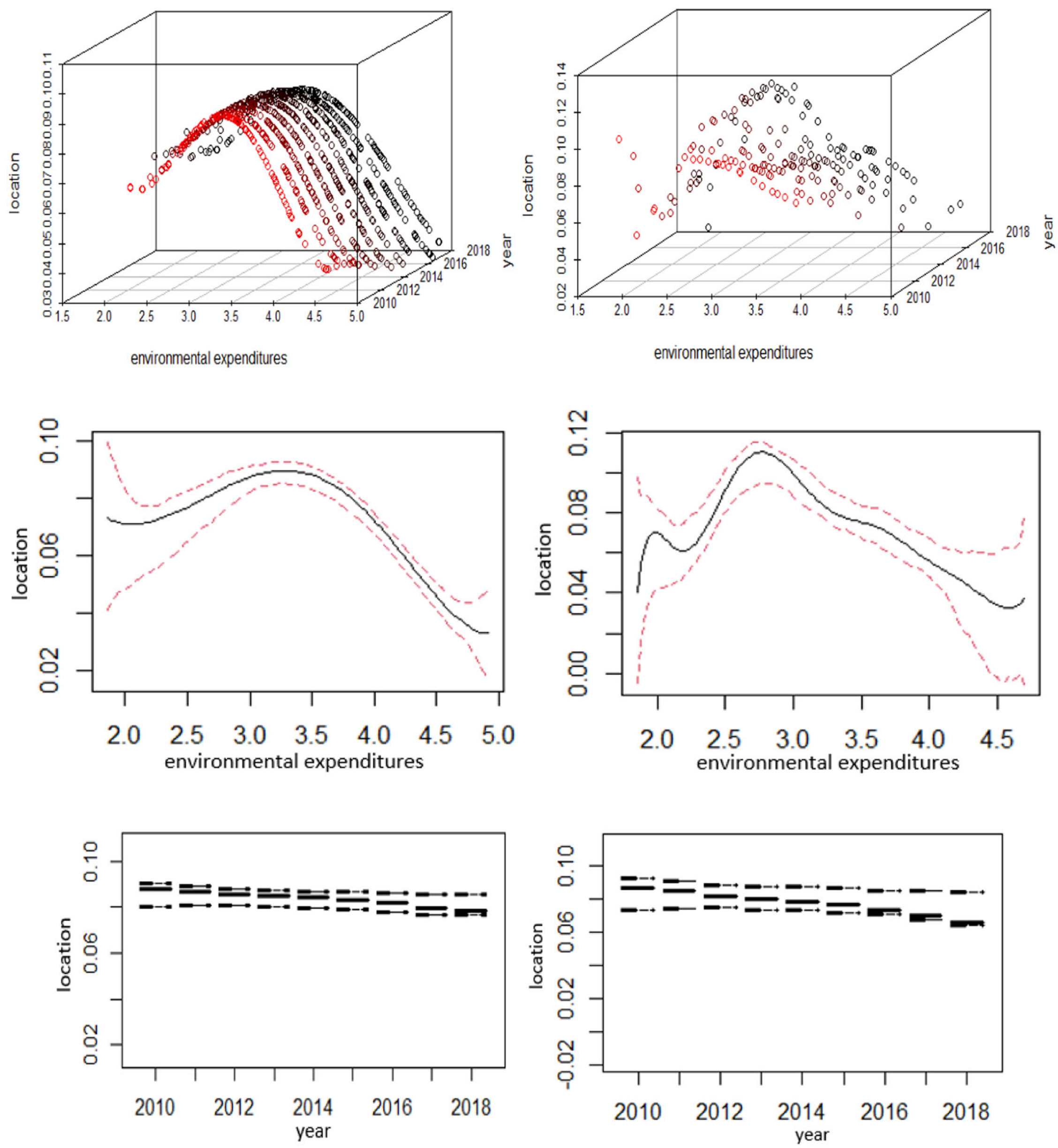


Fig. 4 Estimated location effects for firms in pollution-heavy industries (left panel) and in non-pollution-heavy industries (right panel). Log $\lambda(x, y)$ is used as the dependent variable, and the vertical axis represents the estimated location $\widehat{\mu}(z_{i,t}, t)$, i.e., the conditional mean of unconditional efficiency, $\mathbb{E}[\lambda(X, Y)|Z = z, T = t]$, capturing the average effects of environmental expenditures and time on efficiency; 95% bootstrapped confidence bands are also shown in the two marginal views

expenditure initially increase the variance of unconditional efficiency, thus showing that dispersion of the firms' performance is increasing; however, after a flat plateau, higher levels of expenditure make such dispersion decrease suddenly. While the pattern shown in non-pollution-heavy industries has many sharp peaks, the variance of efficiencies becomes large for a relatively low level of environmental expenditure. Moreover, the marginal effect over time perspective shows that the dispersion of the performance of listed firms in pollution-heavy industries is stable over time while the pattern in non-pollution-heavy industries shows that time has a slight inverted-U effect on efficiency distribution.

Overall, we can observe the existence of a turning point for the location-environmental expenditures relationship and for the scale-environmental expenditures relationship. This indicates that firms have to achieve a certain level of environmental expenditure to cover the regulatory costs before they can benefit from the Porter-type positive effects. A small amount of investment in pollution abatement and environmental protection can do harm to a firm's efficiency and increase the dispersion of efficiency.

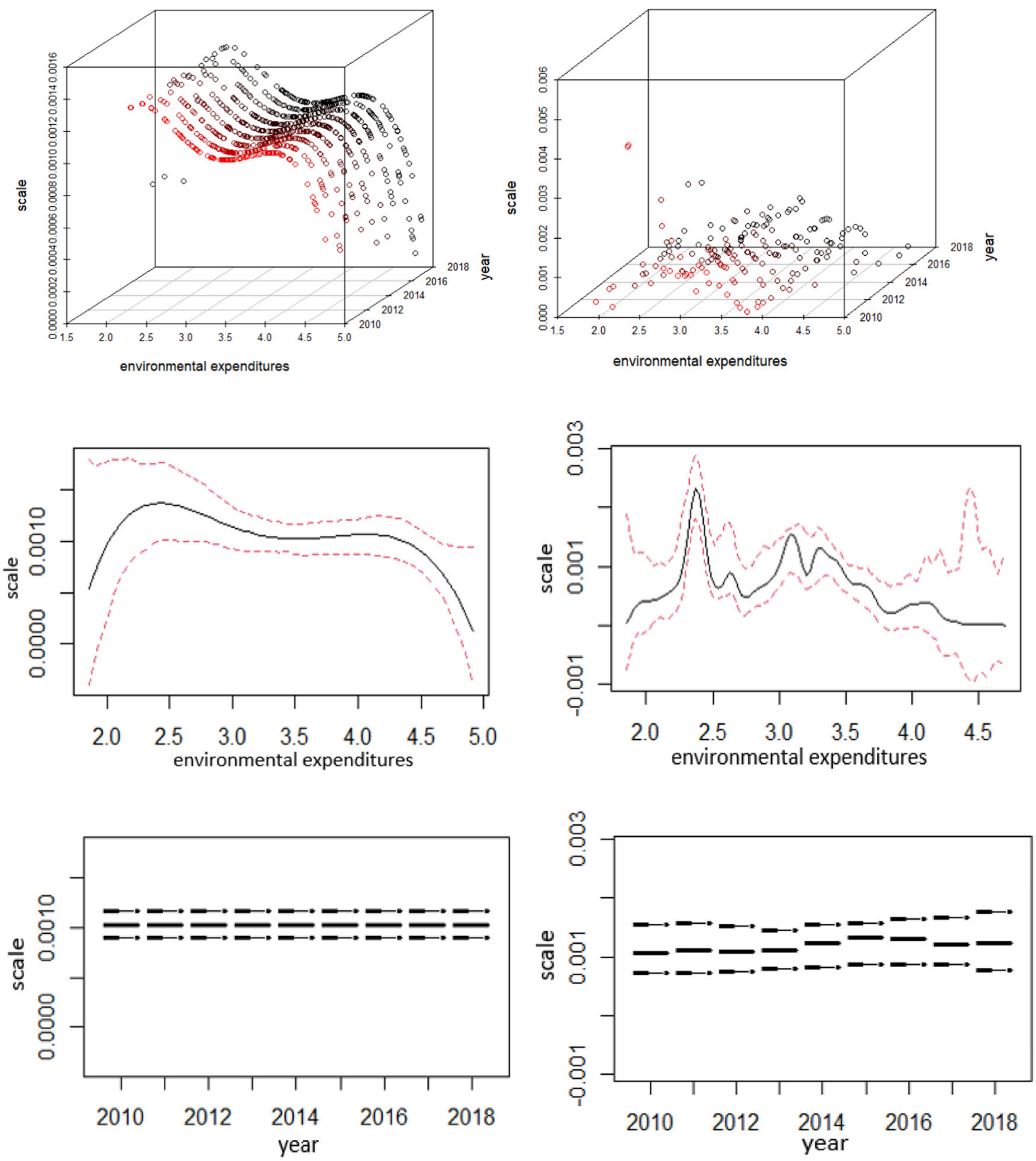


Fig. 5 Estimated scale effect for firms in pollution-heavy industries (left panel) and in non-pollution-heavy industries (right panel). Log $\lambda(x, y)$ is used as the dependent variable, and the vertical axis represents the estimated scale $\widehat{\sigma}(z_{i,t}, t)$, i.e., the conditional variance of unconditional efficiency, $\sigma^2(z, t) = \mathbb{V}[\lambda(X, Y)|Z = z, T = t]$, capturing the impact of environmental expenditures and time on the dispersion of efficiency distribution; 95% bootstrapped confidence bands are also shown in the two marginal views

7.2 Heterogeneous effects between firms with and without government subsidy

We also compare the location effect of firms with and without government subsidy in the pollution-heavy industry. In Fig. 6 3D plot and marginal views, we can observe the different patterns presented in these two groups. The turning point is around 1000 thousand yuan for firms with a government subsidy whereas the threshold lies at a higher level of environmental expenditure, about 3162~10,000 thousand yuan, for firms without a government subsidy. This finding indicates that government subsidies related to pollution reduction and environmental protection lowers the threshold and thus help firms pass the threshold easily. Government assistance reduces the financial burden on firms and requires less effort by firms (e.g., employing additional employees and buying new facilities), further leading to a less negative effect of pollution reduction requirements on their production. In addition, we observe a positive effect of time on efficiency in the group with a

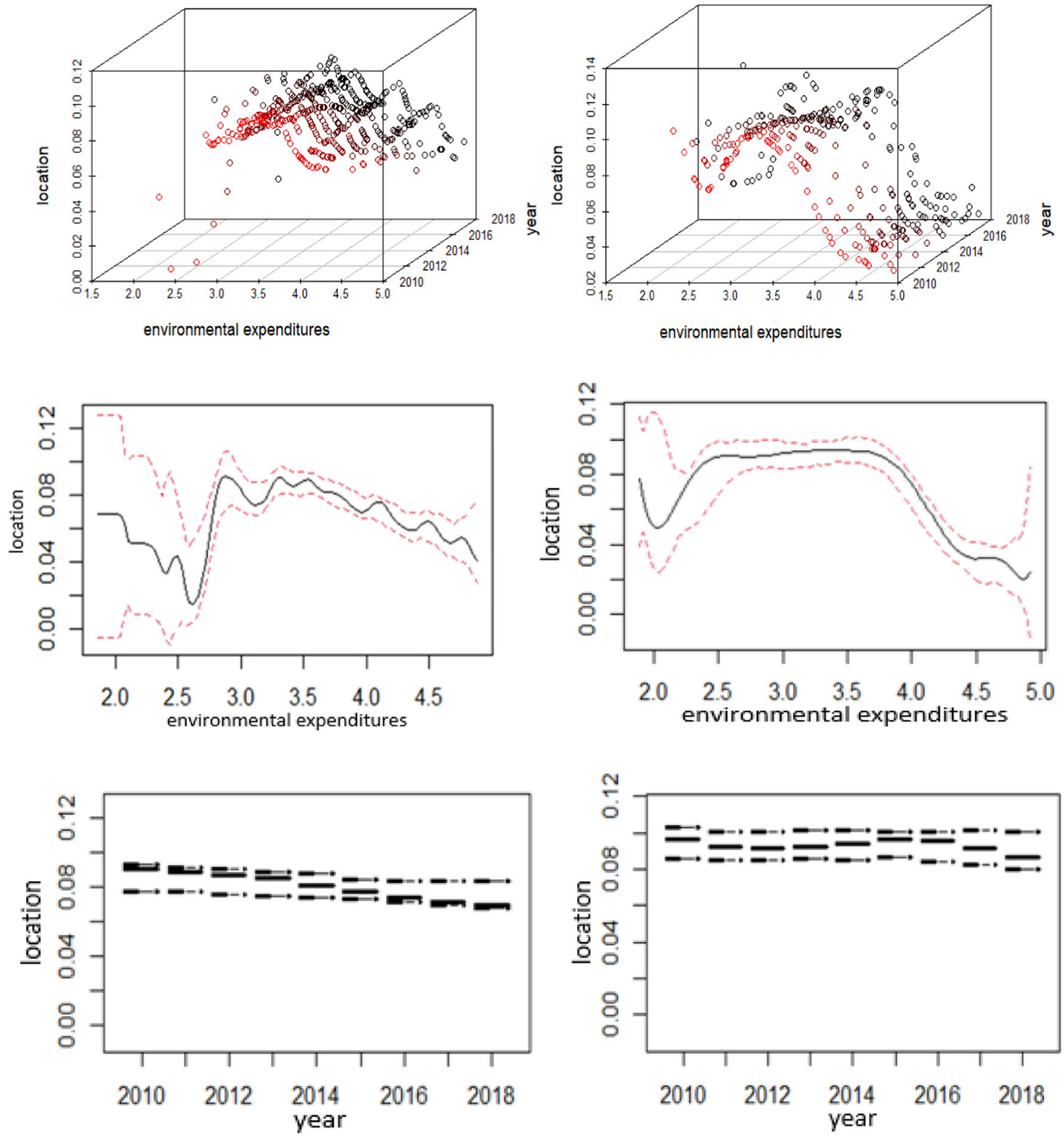


Fig. 6 Estimated location effects for firms with a government subsidy (left panel) and firms without a government subsidy (right panel). Log $\lambda(x, y)$ is used as the dependent variable, and the vertical axis represents the estimated location $\widehat{\mu}(z_{i,t}, t)$, i.e., the conditional mean of unconditional efficiency, $\mathbb{E}[\lambda(X, Y)|Z = z, T = t]$, capturing the average effects of environmental expenditures and time on efficiency; 95% bootstrapped confidence bands are also reported in the two marginal views

government subsidy and a slightly inverted-U effect of time on efficiency in the other group.

Figure 7 plots the results of the estimated scale effect for firms with and without a government subsidy. In the 3D plots and marginal views, we can clearly observe the inverted-U effect of environmental expenditures for both groups, which suggests that low levels of expenditure slowly increase the variance of performance efficiency. However, after the threshold level of around 3162 thousand yuan, such dispersion decreases with higher expenditures. The time effects are quite different between these two groups: the dispersion remains relatively stable over time in the group with a government subsidy, whereas an inverted-U effect of time on the dispersion of performance is observed in the other group.

8 Conclusion and policy implications

In this study, we examined the impact of environmental expenditures in the environmental information disclosure program on the production of listed enterprises in the manufacturing industries for the period 2010–2018. We used conditional efficiency analysis and nonparametric location-scale regression to analyze the average effect of environmental

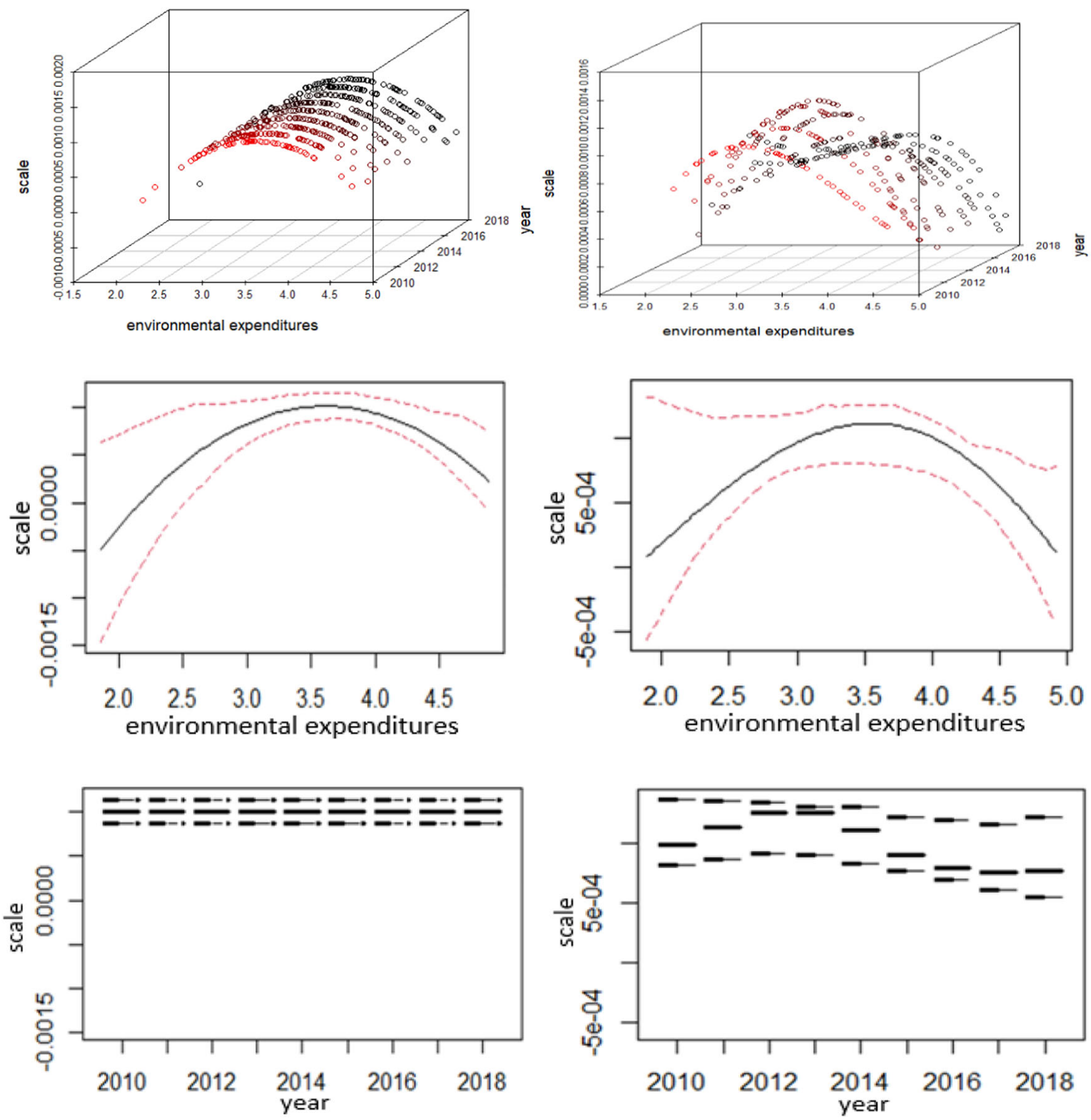


Fig. 7 Estimated scale effects for firms with a government subsidy (left panel) and firms without a government subsidy (right panel). Log $\lambda(x, y)$ is used as the dependent variable in the regression, and the vertical axis represents the estimated scale $\widehat{\sigma}(z_{i,t}, t)$, i.e, the conditional variance of unconditional efficiency, $\sigma^2(z, t) = \mathbb{V}[\lambda(X, Y)|Z = z, T = t]$, capturing the impact of environmental expenditures and time on the dispersion of efficiency distribution; 95% bootstrapped confidence bands are also reported in the two marginal views

expenditures and the variability of the effect across enterprises and over time. Specifically, we firstly computed conditional and unconditional efficiency for an exploratory analysis. We then regressed unconditional efficiency on environmental expenditures and time using the location-scale regression approach introduced by Hall and Racine (2015).

The traditional view believes environmental regulation is not beneficial to firms' competitiveness, while the Porter hypothesis holds the opposite view. Our results show that both may coexist in an inverted U-shaped relationship. The first part of the relationship before the threshold is in line with traditional wisdom, and the second part of the relationship, which occurs after reaching a certain threshold, supports the Porter hypothesis. We also find a nonlinear relation between dispersion of firms' efficiency and environmental expenditures. Although we did not identify the precise turning points, these findings reflect that firms' efforts in pollution reduction and environmental protection do not always change their performance in the same way, as pointed out by Huiban et al. (2018). One possible explanation for these results is that knowledge spillovers may need a certain level of investment to cover the existence of fixed regulatory costs, and firms need to make enough effort to obtain positive spillover effects. Understanding this mechanism requires further research.

Second, the results also show that the listed manufacturing firms in pollution-heavy industries may be more influenced than firms in non-pollution-heavy industries by environmental expenditures. This is because in the initial stages, the EID program mainly covered firms in the pollution-heavy industries and urged these firms to meet the standards. As the EID program gradually covers all listed companies, it is expected that the performance of firms in non-pollution-heavy industries will also be strongly affected. Moreover, firms receiving a government subsidy reach the threshold earlier than firms without a subsidy, suggesting that by providing financial support, government or financial institutions can assist firms to minimize the negative effects of the EID program.

To sum up, for listed companies in China, to obtain the positive effects of environmental expenditures on firms' efficiency and reduce the dispersion of firms' efficiency distribution, a certain level of expenditure is necessary, otherwise firms' efforts to reduce pollution may be detrimental to their economic performance. Meanwhile, to help firms reach the threshold and the transition, the government can set up a fund that can mainly be used to provide subsidies to those firms covered by the EID program to support their expenditure on pollution abatement and environmental protection. Regulators should also be responsible for the implementation of the EID program to ensure authentic and reliable environmental information is disclosed by the listed firms. However, how to set up the optimal level of subsidy for firms remains an issue when taking both efficiency and equity into consideration. A precise estimation of the threshold is of importance to provide policy guidance for the government to determine the appropriate level of subsidy. We leave this for future research.

Data availability

The datasets generated during and/or analysed during the current study are available from the author on reasonable request.

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Compliance with ethical standards

Conflict of interest The authors declare no competing interests.

9 Appendix

Figures 8–12, Tables 4–6

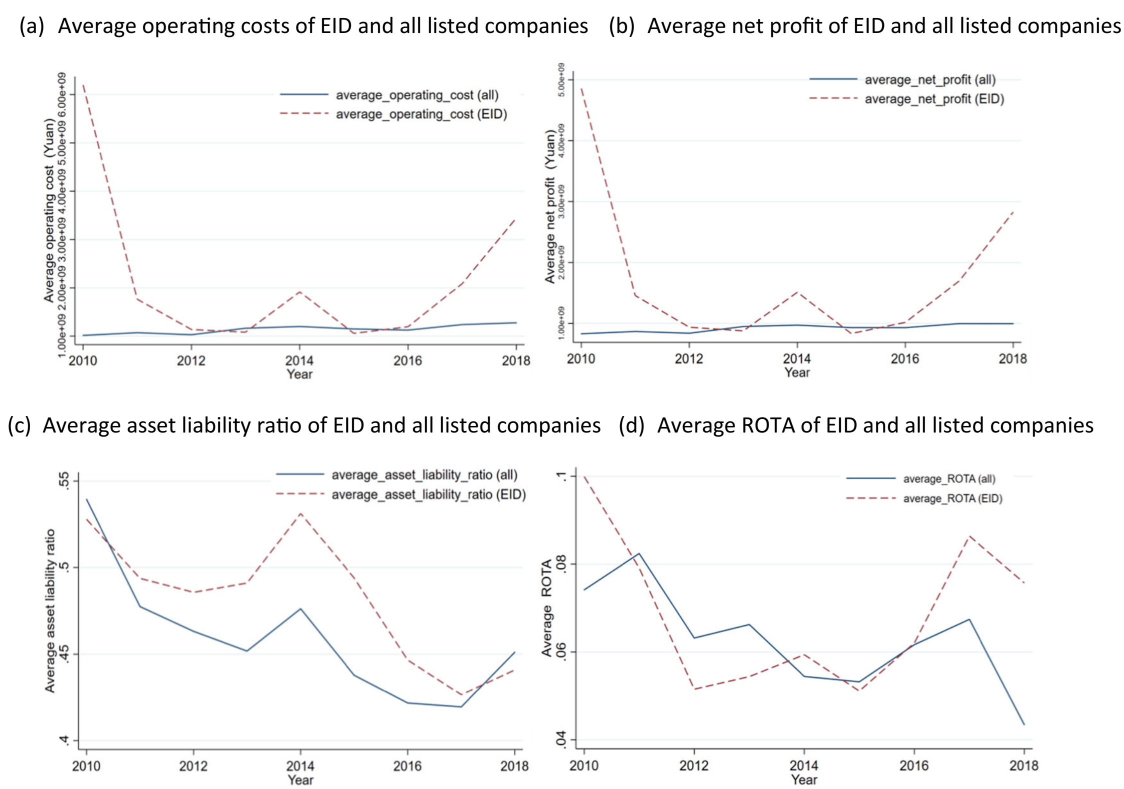


Fig. 8 Economic situation of EID listed companies and all listed companies. This figure describes the annual mean values of four indicators (operating cost, profit, asset liability ratio and ROTA (return on total assets)) for EID listed companies and all listed companies. Authors' calculation based on CSMAR database

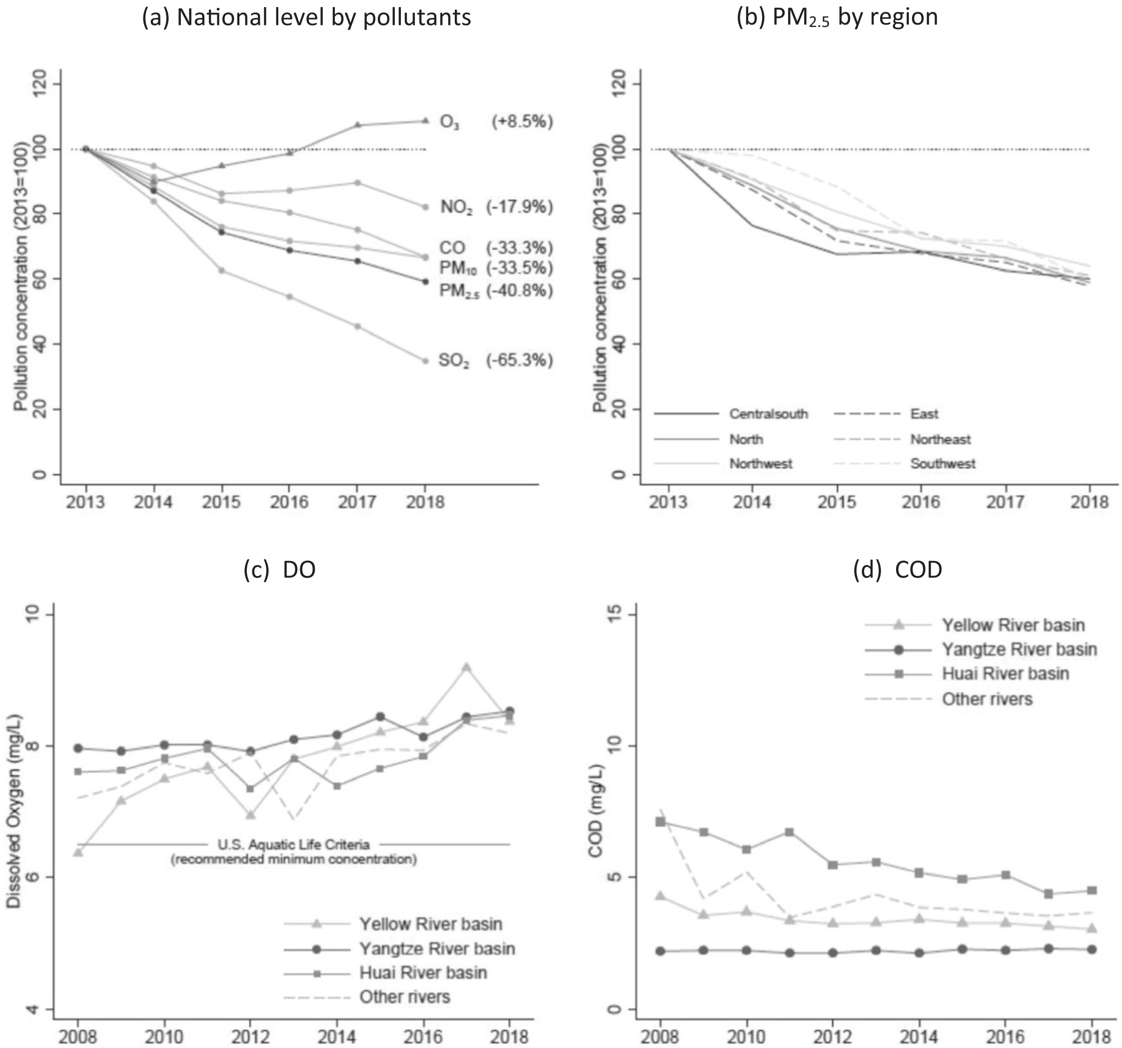


Fig. 9 Trends in air pollution and surface water quality. Panel (**a**) shows the annual concentrations of six pollutants. The estimates are obtained from separate OLS regressions of city-daily pollution concentration on calendar year indicators (2013 is omitted) and city fixed effects for each pollutant. Values are normalized to 100 in 2013. Panel (**b**) shows annual $PM_{2.5}$ concentration by region. The estimates are obtained from 6 separate OLS regressions (one for each region) of city-day $PM_{2.5}$ concentration on calendar year indicators (2013 is omitted) and city fixed effects. Annual values are then obtained by adding the regression constant to the coefficients on the year indicators. Panel (**c**) shows annual average dissolved oxygen concentration (higher is better). The "U.S. Aquatic Life Criteria" (6.5 mg/L) refers to the U.S. EPA Quality Criteria for Water (1986) recommended 30-day minimum dissolved oxygen concentration criteria for cold water, non-early life stages aquatic lives. Panel (**d**) shows annual average chemical oxygen demand (lower is better) of Greenstone et al. (2021)

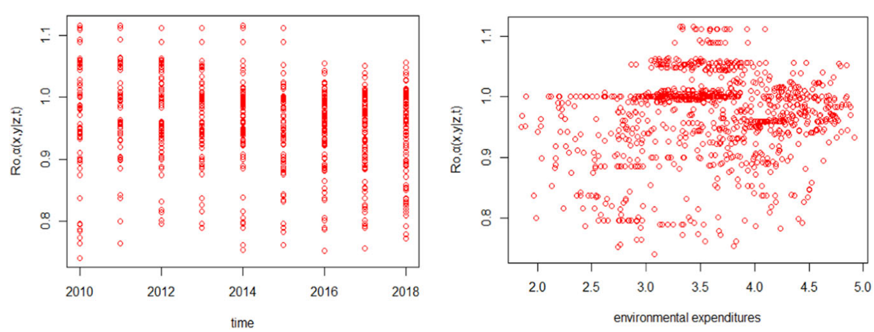
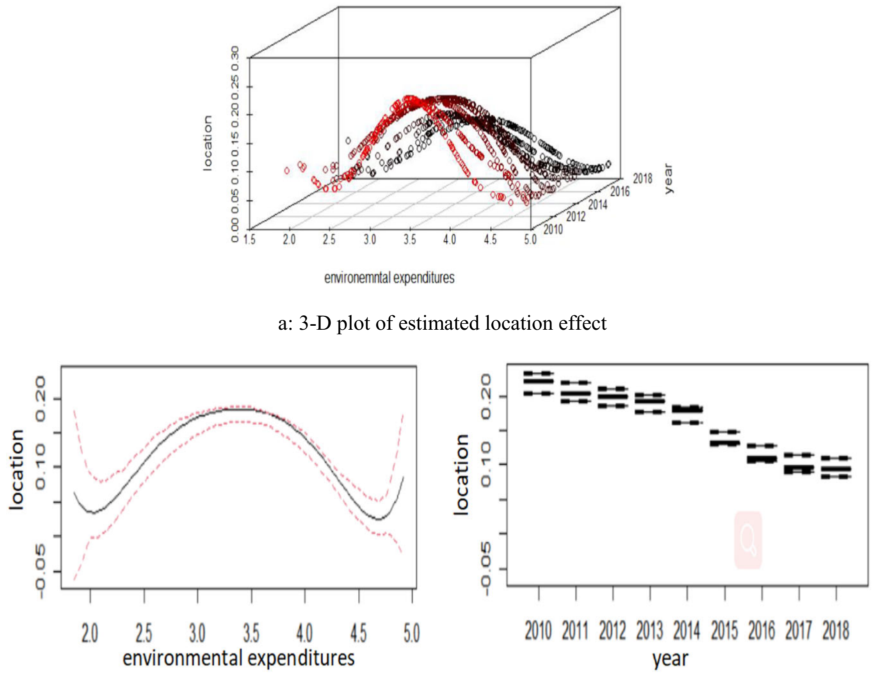


Fig. 10 The two panels represent the ratios $\widehat{R}_{o,\alpha}(x, y|z, t)$ for $\alpha = 0.99$ as a marginal function of environmental expenditures and time

Fig. 11 Estimated location of conditional efficiency and the corresponding two marginal views. Log λ_t $(x, y|z)$ is used as the dependent variable, and the vertical axis represents the estimated location $\widehat{\mu}(z_{i,t}, t)$, i.e. the conditional mean of conditional efficiency, $\mathbb{E}[\lambda_t(x, y|z)|Z = z, T = t]$, which captures the average effects of environmental expenditures and time on efficiency; 95% bootstrapped confidence bands are also shown in the two marginal views



a: 3-D plot of estimated location effect

b: Marginal effect of environmental expenditure (in logs)

c: Marginal effect over time

Fig. 12 Histogram of idiosyncratic efficiencies and their scatter plot against environmental expenditures and time

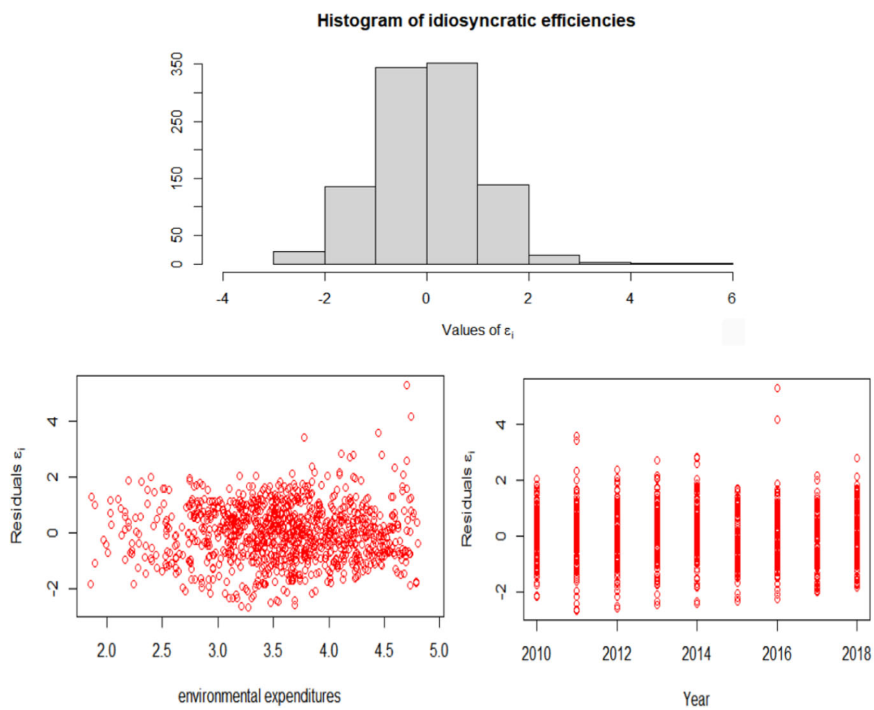


Table 4 Statistical values for results of alternative bootstrap approach

	Mean	SD	Mann-Whitney test	Kolmogorov-Smirnov test
λ_t $(x, y\|z)_{\text{bootstrap}}$	1.121	0.102		
Null hypothesis: λ_t $(x, y\|z) = \lambda_t$ $(x, y\|z)_{\text{bootstrap}}$			−1.553 (0.121)	0.035 (0.546)

p values are reported in parentheses

Table 5 Correlations between residuals ε and environmental expenditures and time

	corr (ε, time)	corr (ε, environmental expenditures)
Pearson correlations	−0.028	0.004
Spearman rank correlations	−0.033	−0.040
Kendall correlations	−0.022	−0.027

Table 6 Regression results using Algorithm #2

	coefficients	95% confidence interval
Observations = 1026		
Environmental expenditures	0.144	[0.049, 0.229]
Time	−0.013	[−0.031, 0.004]
Environmental expenditures#time	0.005	[0.001, 0.008]
Environmental expenditures_2	−0.037	[−0.049, −0.024]
Time_2	−0.001	[−0.002, 0.000]
Constant	1.238	[1.077, 1.412]
$\widehat{\sigma}_{\varepsilon}$	0.096	[0.092, 0.102]

Environmental expenditures#time is the interaction term for environmental expenditures and time. Environmental expenditures_2 and time_2 are the squares of environmental expenditures and time, respectively

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