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Performance Evaluation of Economic Relocation Effect for Environmental Non-Governmental Organizations: Evidence from China

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Abstract: In this paper, an economic natural experiment in China is analyzed and the performance evaluation of economic relocation effect of informal environmental regulations imposed through the channel of environmental nongovernmental organizations (ENGOs) are suggested. ENGOs are found to have a significantly negative impact on the overall economic location quotient of six major polluting industries. The economic relocation effect from ENGOs exhibits industrial and regional heterogeneity, as the effect is stronger among easy-to-relocate industries and in market-oriented areas. The underlying mechanism is the ENGOs, as informal environmental regulations could motivate firms to enhance their investment in environmental governance, ultimately crowding out these economically polluting industries.
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1. Introduction

The pollution haven hypothesis, first proposed by Walter and Ugelow (1979), has been used by environmental economists to refer to the phenomenon of polluting industries tending to relocate to countries with looser environmental regulations. Subsequently, the literature on the pollution haven hypothesis has been mostly based on the extended Heckscher-Ohlin (H-O) model, to which some studies have applied pollution emission data (Hoffmann et al., 2005; Levinson & Taylor, 2008; Dean et al., 2009; Kheder & Zugravu, 2012; Marconi, 2012) or FDI data (Eskeland & Harrison, 2003; Leiter et al., 2011) to analyze the relationship between environmental regulations and industrial relocation. With the expanding application of environmental economics over the past few years, not only do foreign investors need to choose a location, but polluting enterprises and polluting industries also need to choose a location given the environmental regulations (Millimet & Roy, 2016; Dechezleprêtre & Sato, 2017). There is stronger evidence for the existence of pollution havens in pollution-intensive industries and enterprises (Ruan & Zhang, 2014; Yin et al., 2015; Zhou et al.,2015; Wu et al., 2016). There is a U-shaped relationship between environmental regulation and the transfer of pollution-intensive industries (Zhang & Guo, 2015).

Pollution havens are mainly caused by the implementation of weak environmental regulations (Féres & Reynaud, 2012; Zheng et al. 2017; Zhang et al. 2017; Ruan & Zhang, 2014). It has been found that polluting industries have a tendency to relocate to regions with looser formal environmental regulations. Stronger formal regulations in adjacent regions may push polluting companies to relocate to regions with weak environmental regulations, turning the latter into pollution havens (Wu et al., 2016; Zheng et al. 2017). This shows that regional differences in environmental regulations and policies play a dominant role in the location choice of polluting industries (Li et al., 2021; Zhang et al., 2020). However, due to the endogeneity of local environmental governance and regulations, it is worthwhile to extend existing studies and incorporate more policy instruments and identification methods with microlevel data.

An academic gap still remains in that so far, most empirical studies on the pollution haven and relocation effects have focused on the impact of formal environmental regulations caused by governmental intervention. However, the impact of informal environmental regulations imposed by other social sectors in the pollution haven has seldom been empirically examined (Li & Ramanathan, 2018; Orlins & Guan, 2016). The important role of public participation in environmental regulation has always been ignored in empirical studies on the relocation effect (Zheng & Shi, 2017; Hasan et al., 2018). In addition to formal environmental regulations, informal environmental regulations may also have a significant impact on the transfer of pollution-intensive industries (Wheeler & Pargal, 1999; Li et al., 2018). For example, as an informal environmental regulation mechanism, environmental nongovernmental organizations (ENGOs) may also affect polluting industries and enterprises as well as their operation and survival. However, what kind of underlying roles do ENGOs play in influencing polluting enterprises to purposefully or passively relocate their polluting industries, and what is the mechanism through which this occurs? Does the pollution haven hypothesis stand when such informal environmental regulations are effective? There are still no clear answers.

This paper contributes to the existing literature as follows: First, the growth of ENGOs are taken as an informal environmental regulation, and that growth is regarded as a quasi-natural experiment in order to overcome endogeneity and to investigate the performance evaluation of economic relocation effect for ENGOs. This paper could enrich the literature on the economic relocation effects of informal environmental regulation on pollution-intensive industries. Second, the mechanism analysis finds that the growth of ENGOs could, on the one hand, increase environmental supervision, information disclosure, environmental education and environmental litigation. On the other hand, ENGOs motivate governments to strengthen formal environmental regulations and force companies to enhance their investments in environmental governance, ultimately crowding out polluting industries.

The rest of this paper is organized as follows: the second part is the theoretical analysis, the third part is the methodology, the fourth part is the empirical results, the fifth part is the mechanism analysis, and the final part is the conclusion.

2. Theoretical Analysis

The rise of ENGOs is putting political pressure on local government officials with respect to environmental issues. Over the past 20 years, scholars have extensively studied the role of ENGOs on environmental laws and policies. Globally, the effects of pollution on human health can result in a strong public demand for environmental and energy policies in order to accelerate governmental action and improve accountability (Grano, 2012). ENGOs have many means, such as medias, to influence the environmental governance and policies, highlight the need for implementation of laws, and represent the interests of vulnerable population.

Despite these facts, ENGOs in China are among the least likely to have influence on policymakers (Lu, 2007; Sun & Zhao, 2008). Indeed, ENGOs are perceived as social movements that focus on individual interests and act on behalf of mankind (Wang & Liu, 2009). ENGOs are more likely to influence green policies when these do not oppose stakeholder interests (Betsill & Corell, 2008). Therefore, the lower the political stakes, the higher the ENGO influence. In particular, ENGOs usually have a better chance of playing an important role in negotiation process during the early stages of environmental policy making rather than the later stages of development actions (Betsill & Corell, 2008). However, it is worth noting that these organizations are able to address and reflect the needs of local residents and community groups through grassroots communication, by creating trust and reducing distrust in bureaucratic encounters.

Due to the authoritarian constraints to which ENGOs in China are subjected, some of them are able to push their agendas to the attention of authorities without openly criticize the local government, as opposed to other ENGOs around the world (Radkau, 2008). However, the non-political and non-antagonistic nature of Chinese ENGOs can still have wide-ranging civic and political implications, as they learn the subtlety of domestic politics by cautiously pushing the boundaries of advocacy (Young, 2001).

Given the inherently superior ability of ENGOs, some successes have been achieved via: (i) legal suits that generate pressure on the authorities; (ii) the involvement of key actors, such as the media, which contribute to make the issue more well-known, and (iii) the conventional method of utilizing bureaucratic political channels and conflicts between politicians and businesses. The long-term battle is not only to defeat a single corrupt official or relocate polluting factories, but also to build a more transparent and open system in which citizens are actively involved.

Moreover, ENGOs can also exert positive influences on the firms' environmental regulations (Doh & Guay, 2006; Heyes et al., 2018), environmental inspections and enforcement actions, including issuing new guidance and initiating social movements (Li et al., 2018). In this regard, cognitive theory has emphasized the importance of attitudes, beliefs, ideology and personal values in driving a corporate behavior. Specially, when the firms are situated in a community that advocates for a sustainable environment, they may tend to implement similar measures to strengthen the social cohesion and remove the barriers among themselves (Sun et al., 2019).

The ability of ENGOs can bring pressure to bear on the firms for the implementation of environmental standards and indicators (McCarthy & Zen, 2010). If a company refuses to comply with the pollution criteria, ENGOs begin to affect state policy in response to the threat of negative actions, including consumers' boycotts (Gunningham, Kagan, & Thornton, 2004). In this sense, the involvement of ENGOs' in green decision making and enforcement remains crucial.

The partnership between ENGOs and advocacy campaigns plays important roles in raising public awareness, increasing consumer satisfaction, and developing new environmental regulations (Hopkins et al., 2011). To a certain extent, the accelerated development of ENGOs reflects a need of more responsible environmental management, and the increasing demand for corporate leaders towards green value creation (Dauvergne & Lister, 2012). Through their demonstrating commitment, companies have gained legitimacy and influenced by ENGOs with respect to corporate production and environmental governance. Besides, climate changes and global environmental issues also create conducive conditions for policy decision making.

There may be some intriguing possibilities for ENGOs to leverage company initiatives, reach into corporate networks and accelerate economic reforms, at unprecedented speed and scale. The lever for ENGOs to drive corporate environmental improvements, is much greater now that companies have tied their products so openly to far-reaching sustainability commitments. The costs resulting from failing to meet the goal of company reputation are considerably high, and even higher if competitors have made good progress towards corporate sustainability (Dauvergne & Lister, 2012).

It is insightful to reveal the importance of ENGOs' in shaping the context of private environmental governance mechanisms, such as eco-certification (Gulbrandsen, 2010; Lister, 2011). Previous research has shown that ENGOs can start a partnership with industry frames, and play a critical role in the face of conflict over corporate legitimacy, thus creating new forms (state-led and market-led) of environmental governance (Dauvergne & Lister, 2012).

The environmental issues (such as climate change and air pollution) may be even worse, as the state capacity or willingness to address the causes is low, leaving the government failure to do much about it. Thus, ENGOs should explore creative ways to leverage the scale, speed and innovative ideas of corporate governance to increase regulatory efforts. ENGOs also needs to focus the roles of companies in protecting the environment at different stages of the product life cycle, ranging from material sourcing to manufacturing, retailing, and consumer use. Most companies are forced to decrease the intensity of environmental impact per unit of output, mainly through energy-efficient appliances and energy-conserving practices encouraged by ENGOs (Dauvergne & Lister, 2012).

ENGO-corporate partnerships are anticipated to become more important, along with the acceleration of sustainable development. This may either raise a warning flag or initiate positive developments (MacDonald, 2008; Rogers, 2010). Hence, we believe that the growths of ENGOs could on one hand directly lift environmental supervision, information disclosure, environmental education and environmental litigation. On the other hand, they indirectly motivate governments to strengthen formal environmental regulations. These could further force enterprises to enhance investment in environmental governance and finally crowd out polluting industries (see Fig. 1).

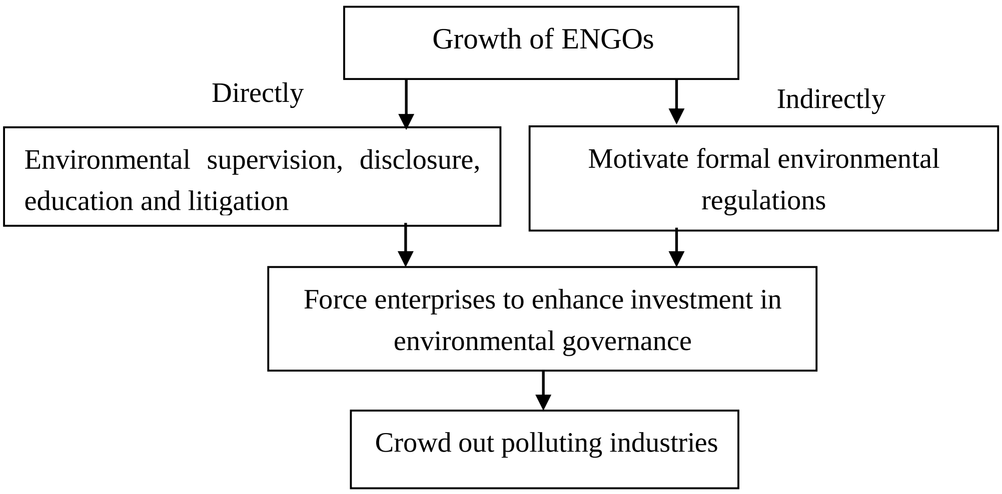


Fig. 1. Mechanism of ENGOs' crowding-out effect on polluting industries

3. Methodology

3.1. Model

We take the emergence of ENGOs in a region as a quasi-natural experiment, in which the dependent variable is the development level of the polluting industry under the influence of ENGOs, and the core variables are *engodata* and *engopop*: the number of ENGOs and their employees in the region, respectively. The specific econometric model is as follows:

$$poll\_loc_{it} = \alpha_0 + \beta \mathrm{engodata}_{it} + \mathrm{Z}\gamma + \mu_i + \upsilon_t + \xi_{it} \quad (1)$$

$$poll\_loc_{it} = \alpha_0 + \beta \mathrm{engopop}_{it} + \mathrm{Z}\gamma + \mu_i + \upsilon_t + \xi_{it} \quad (2)$$

where the subscripts i and t denote different cities and years, respectively; *poll_loc* is the overall development level of the polluting industry, which is represented by its location quotient; and Z represents other control variables that affect the location quotient of the polluting industry. γ is the corresponding coefficient matrix for the control variables; ξ is the random disturbance term; and μ and υ are regional fixed effects and time fixed effects, respectively, to control for factors that change over time and across regions.

It has been acknowledged in the literature that the relationship between ENGOs and the location quotient of polluting industries is indirect. Based on previous research, we know that ENGOs have an impact on two major environmental governance investments: government investments and business investments made at the request of the government. Moreover, ENGOs have a direct influence on pollution industry governance investments. Therefore, to investigate whether ENGOs play a role in the relocation of polluting industries through environmental governance investments, interactions between the ENGO variables and environmental governance investments are introduced into the econometric equation. Specifically, the econometric model is as follows:

$$\begin{aligned} poll\_loc_{it} = {} & \alpha_0 + \beta \mathrm{engodata}_{it} + \varphi Env\_I_{it} + \mathrm{Z}\gamma \\ & + \phi \mathrm{engodata}_{it} * Env\_I_{it} + \mu_i + \upsilon_t + \xi_{it} \end{aligned} \quad (3)$$

$$\begin{aligned} poll\_loc_{it} = {} & \alpha_0 + \beta \mathrm{engopop}_{it} + \varphi Env\_I_{it} + \mathrm{Z}\gamma \\ & + \phi \mathrm{engopop}_{it} * Env\_I_{it} + \mu_i + \upsilon_t + \xi_{it} \end{aligned} \quad (4)$$

In the above two models, the coefficient of interest is ϕ. When ϕ is significantly negative, it indicates that ENGOs have indeed reduced the location quotient of polluting industries in the area through environmental governance investments, which also indirectly verifies the economic relocation effects and industrial upgrading effects of ENGOs. It is worth noting that environmental governance investments in this paper are still measured by indices such as aggregate investment in environmental pollution treatments, investment in urban environmental infrastructure, investment in industrial pollution controls, three simultaneous environmental investments into construction items, and aggregate investments in environmental pollution treatments as a share of GDP.

3.2. Polluting industries

Most studies on the relocation of polluting industries mainly draw from industry-related data, while determining the definition of a polluting industry is the first step in this study. Following different standards, there are three main classification methods for dirty industries in international academic circles.

The first method is environmental cost classification. Although it is difficult to calculate the pollution abatement costs of every industry, it is possible to calculate their pollution-control costs. By calculating the ratio of pollution-control costs to total value added, we can determine whether an industry is a polluting industry. It is easier to measure the ratio of pollution-control costs to total sales and relied on that ratio to define polluting industries. Through this method, it could be classified into five industries, including the papermaking, mining, nonferrous metals, steel and chemical industries, as polluting industries. Specifically, he calculated each industry's ratio of pollution-control costs to total production costs, and then through an empirical study, he determined the cutoff for this ratio to be 1.85%, meaning an industry is regarded as a polluting industry when its ratio is larger than 1.85%; otherwise, it is not. This method may be applicable to an entire country but not to a region, as its industrial structure is not necessarily complete.

The second method is pollution damage classification, which takes damage to the natural ecology and to public health as its criteria. If an industry causes greater damage to these two features, it is classified as a polluting industry; otherwise, it is not. Through this method, McGuire (1982) ultimately classified 17 industries as polluting industries, such as mining, food manufacturing, tobacco and beverage manufacturing, textiles (including clothing, footwear, and hat manufacturing), fur and leather products, and papermaking.

The third method is pollution intensity classification using the Industrial Pollution Projection System (IPPS), which was proposed by the World Bank in 1994 and has mainly been used to evaluate the extent of industrial pollution. It is currently the most mature and widely used classification standard for polluting industries in the world. Referring to the International Standard Industrial Classification (ISIC2.0) level, the method calculates each firm's pollution intensity by 4-digit Standard Industrial Classification (SIC) code, and pollution intensity is used as a criterion for defining polluting industries. If an industry's emission intensity exceeds the critical value, that industry is considered a polluting industry; otherwise, it is not. Then, Mani & Wheeler (1998) classified American industries at the three-digit International Standard Industrial Classification (ISIC) level following this criterion and defined five sectors as leading candidates for dirty industry status: iron and steel, nonferrous metals, industrial chemicals, pulp and paper, and nonmetallic mineral products.

As China's industrial categorization differs from other countries to some extent, some scholars have proposed their own classification criteria. Otsuki et al. (2004) divided 20 two-digit manufacturing industries from the National Economical Industry Classification (GB/4754-2011) into three categories on the basis of their average pollutant concentration: severely polluting, moderately polluting and lightly polluting industries.

In terms of national policymaking, the Chinese State Council divided pollution sources into industrial pollution sources, agricultural nonpoint source pollution sources, domestic pollution sources and centralized pollution sources in the *First National Pollution Source Survey Program* issued in 2006. Of these sources, industrial pollution sources include all secondary industries except for the construction industry and can be further divided into major and general pollution sources.

Based on international standards and existing studies in China, this paper chose six polluting industries, i.e., mining, papermaking, chemical fiber manufacturing, nonmetallic mineral products, the smelting and processing of ferrous metals, and the production and supply of electric power. Additionally, since this paper studies ENGOs' role in environmental governance, we need to consider whether pollution behavior is easy to observe and therefore neglect industry-level pollution costs, damages and intensity. The reasons we chose these six industries are as follows. For the mining industry, its major pollutant is the waste residue generated during the mining process that is piled up haphazardly and causes environmental problems, which are particularly easy for ENGOs to observe. It should be pointed out that the mining industry here includes all of its subsectors. As the most traditional dirty industries, papermaking and chemical fiber manufacturing have always been a focus of ENGOs because they usually produce a huge amount of sewage and odor. Nonmetallic mineral products and the smelting and processing of ferrous metals have also been representative of heavy industries, resulting in severe air, water and soil pollution, another major cause of concern for ENGOs. The production and supply of electric power (mainly referring to thermal power plants and heating companies) are mainly fueled by coal, which also draws ENGOs' attention.

3.3. Industrial relocation

Existing studies have found strong evidence for the existence of pollution havens in China. In particular, research integrating environmental regulations on polluting industries has found strong evidence in favor of the fact that polluting industries tend to relocate to regions with looser environmental regulations as well as to midwest China. Once environmental regulations in adjacent regions are strengthened, polluting companies in those places may relocate to local areas, turning these areas into pollution havens. However, the economic relocation effect of ENGOs has not yet received much attention in academia. By contrast, this paper aims to fill this research gap through an empirical examination. After defining the polluting industries of concern to ENGOs as above, we then focus on the relocation index for polluting industries. Previous studies have adopted the location quotient of polluting industries or the share of the output value of a region's polluting industries in the output of the country as a measure of polluting industries (Zhang & Zhou, 2017). These indicators partly reflect the development level of certain polluting industries in a region. As we aim to determine whether the relocation of polluting industries is influenced by the development of ENGOs, industrial and growth indicators fail to reflect whether these industries have relocated or not. Ultimately, we chose the employment location quotient, denoting the study area as a region (*j*) within a nation (*n*) and using employment (*worker*) as the measure of economic activity. Then, the location quotient for industry *i* may be expressed as:

$$poll\_loc_{ij} = \frac{worker_{ij}}{worker_j} / \frac{worker_{in}}{worker_n} \ (i=1\ ,2,...,6) \tag{5}$$

where $worker_{ij}$ represents employment in industry *i* and region *j*; $worker_{in}$ represents employment in industry *i* throughout the whole nation. It should be noted that industry refers to the six polluting industries and region refers to the 31 Chinese provinces in this paper. Formula (5) compares the relative concentrations of employment in industry *i* in two economies (i.e., the industry's share of employment in each economy). If the location quotient for an industry is greater than 1, it is assumed that the industry occupies an important position in this province. If it is equal to or less than 1 for an industry, it is assumed that this industry is not dominant compared with the average national level.

Since this paper focuses on six polluting industries, we add up the six industries' employment in the province to obtain total employment. For a country with *j* regions and *i* industries, let $worker_{ij}$ denote the employment in industry i in region j so that $\sum_{i=1}^{6} worker_{ij}$ is the total employment within the six industries in region *j*. Let $worker_{in}$ denote national employment in industry i, so that $\sum_{i=1}^{6} worker_{in}$ is the national employment within the six industries. The location quotient index for region *j*, $poll\_Loc_j$, is defined as in Formula (6).

$$poll\_Loc_j = \frac{\sum_{i=1}^{6} worker_{ij}}{worker_j} / \frac{\sum_{i=1}^{6} worker_{in}}{worker_n} \tag{6}$$

It should be noted that the total location quotient does not add up to the sum of the location quotients for the six polluting industries. Rather, it is measured by comparing the share of employment in the six polluting industries at the province level with the share of employment in the polluting industries' throughout the country.

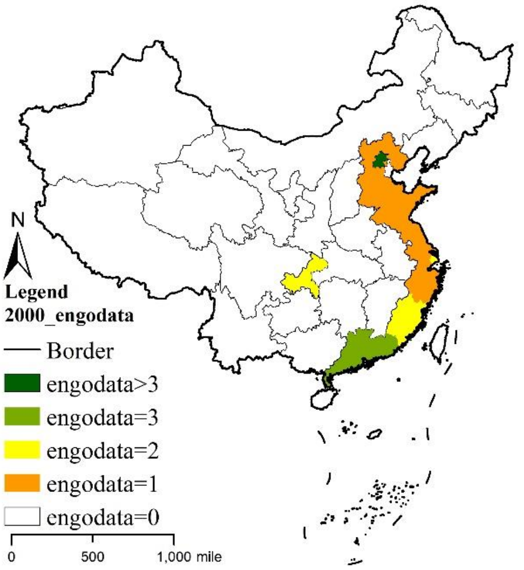
In recent years, the utilization of the location quotient for estimating regional economic or industrial development levels has been widely used and has attracted an increasing number of scholars from various fields. Liu (2009) regarded the location quotient as a criterion for selecting regional pillar industries. In this paper, the location quotient is used to measure the competitive advantage of a certain polluting industry in a province relative to in the country as a whole, justifying its pillar position. Specifically, a decreasing location quotient indicates that this industry is losing its pillar position in the region, meaning it is relocating to other regions. In addition, instead of the output location quotient, this paper adopts the employment location quotient index to measure the geographic concentration of the polluting industries across regions. If the employment location quotient declines, it is an indicator that this industry's employment is less advantaged. This may be caused either by the industry relocating or by the industry introducing advanced production technology, leading to labor declines or transfers to other industries. Generally, most polluting industries are labor intensive; hence, using the employment share to calculate the location quotient index can serve as an indirect indicator of the employment effect and the economic relocation effect.

3.4. Explanatory variables

In this paper, we choose *engopop* and *engodata* as the core explanatory variables (see Eq. (1) and Eq. (2)). However, ENGO data are not carefully calculated in China. The data used in our study are mainly from the *China Development Brief*, a Chinese-English bilingual network platform founded in 1996 with a directory of NGOs. It provides professional observations, research, network platform support and services to charity organizations, and the relevant information on most NGOs can be found through this platform (website: http://www.chinadevelopmentbrief.org.cn).

We define nongovernmental organizations engaged in the environmental protection business as ENGOs. The platform includes each ENGO's information, such as its name, date of establishment, organization size (number of personnel), and business field, and identifies the ENGO's registration place at the province-prefecture-county level. With these data, we can manually collect the relevant information on each ENGO and then pool those data to the province-prefecture level and obtain two-administrative level ENGO data. It should be noted that the data currently available are relatively comprehensive, although they are not perfectly so. the data include whether there are any ENGOs (*engo*), the number of ENGOs (*engodata*) and the number of ENGO employees (*engopop*).

In this paper, we use provincial-level data on the number of ENGOs (*engodata*) and the number of ENGO employees (*engopop*) as core explanatory variables. Then, we chose two years, 2000 and 2010, to analyze the trends in these two indicators. Figs. 2 and 3 reveal the spatial distribution of the number of ENGOs in all provinces in 2000 and 2010, respectively. By comparing the two figures, ENGOs can be seen to have only existed in the coastal areas and in Chongqing in 2000, where there were a larger number of ENGOs in the province-level municipalities of Beijing and Shanghai, and in Guangdong Province. However, ENGOs expanded into more provinces by 2010, although they were mainly still concentrated in coastal provinces and did not yet exist in every province. They began to appear in the southwestern region and Heilongjiang and Ningxia provinces. The central part of the country also saw the appearance of ENGOs. However, in Shanxi, Inner Mongolia, and Shaanxi, where environmental pollution is heavy, ENGO development lagged behind.



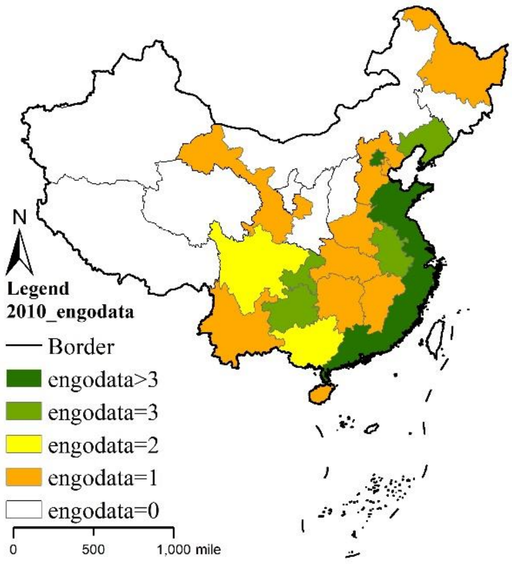
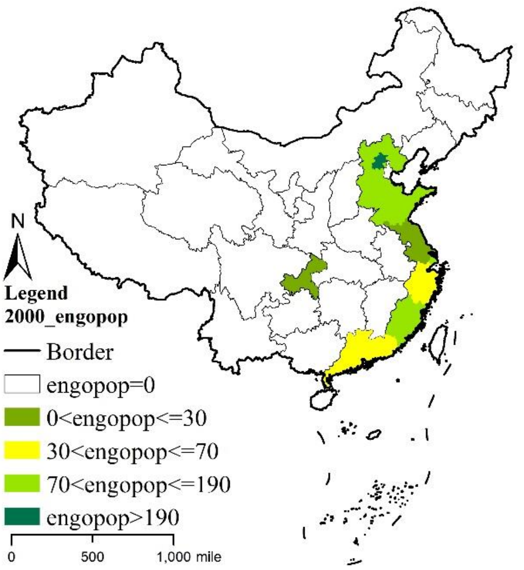


Fig. 2. Spatial distribution of the ENGOs' number of all provinces in 2000

Fig. 3. Spatial distribution of the ENGOs' number of all provinces in 2010

Figs. 4 and 5 reveal the spatial distribution of ENGO employees in all provinces in 2000 and 2010, respectively. By comparing the distribution maps for 2010 and 2000, the regions with the largest number of ENGO employees can be seen to have spread from Beijing to Shandong, including Shanghai and Jiangsu and Fujian Provinces. In addition, Hebei, Henan, Sichuan, Hubei, Zhejiang, Guangdong and Guangxi provinces had the most ENGO employees. However, in 2010, Chongqing, Guizhou, and Heilongjiang provinces had relatively fewer employees. In Ningxia, Liaoning, Yunnan, Henan, and Jiangxi provinces, where there was only one ENGO each, the number of ENGO employees was small.



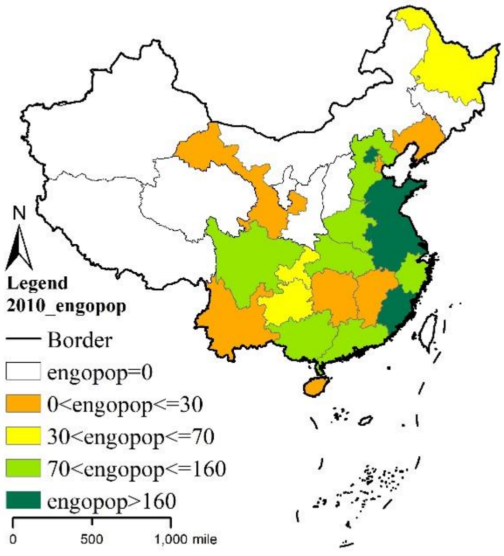


Fig. 4. Spatial distribution of the ENGOs' employee of all provinces in 2000

Fig. 5. Spatial distribution of the ENGOs' employee of all provinces in 2010

3.5. Summary & Data

We structure the variables as follows:

Dependent variables: the employment location quotient for the six polluting industries in a region ($poll\_loc_{ij}$) and the total employment location quotient ($poll\_Loc_j$).

Key explanatory variables: the number of ENGOs (*engodata*) and the number of ENGO employees (*engopop*) in a region. Our main estimation strategy follows the same logic as a standard difference-in-differences (DD) strategy. Since not every region has ENGOs at all times, we use a continuous measure for intensity and thereby capture more variation in the data. It should be especially noted that ENGO development varies considerably across the different parts of China, so we add 1 to each data point and take its logarithm.

In line with the former research, the following variables are used as the main control variables: the natural logarithm of per capita GDP (*lnpgdp*) and the natural logarithm of per capita GDP squared (*lnpgdp2*), which indicate the level of economic development; the industrial structure (*ind*), which is measured by the proportion of the secondary industry; the capital labor ratio (*lncap_lab*), which is the ratio of fixed assets to the labor force; foreign direct investment (FDI), which is the ratio of FDI to GDP and is multiplied by 100%; population density (*lnden*), which is measured by the natural logarithm of the number of people per unit of area; and energy efficiency (*en*), which is the natural logarithm of electricity consumption per unit of GDP.

In addition, the variables we selected for detecting the underlying mechanisms are as follows: aggregate investment in environmental pollution treatments, investment in urban environmental infrastructure, investment in industrial pollution controls, three simultaneous environmental investments in construction items, and aggregate investment in environmental pollution treatments as a share of GDP. The data for these variables come from the *China Environmental Statistical Yearbook* (2003-2016). The employment data come from the *China Labor Statistical Yearbook* (2000-2016). Other control variables are derived from the *China Statistical Yearbook* and *China Regional Economic Statistical Yearbook*. Some missing data are estimated by interpolation, while those areas with large amounts of missing data are indicated with a missing value in this paper. Since employment data for each manufacturing sector are at the provincial level only, our final data set includes the 31 provinces in mainland China from 2000 to 2016 and from 2003 to 2016. The descriptive statistics of the main variables are shown in Table 1.

Table 1. Descriptive statistics of variables.

Variable	Obs.	Mean	Std. dev.	Min	Max
Dependent variable					
poll_loc	527	1.067	0.544	0.003	3.128
poll_loc1	527	1.078	0.961	0.002	7.709
poll_loc2	510	0.928	0.740	0.005	5.439
poll_loc3	493	0.840	0.887	0.000	3.831
poll_loc4	527	0.967	0.342	0.043	2.619
poll_loc5	510	1.060	0.756	0.012	6.985
poll_loc6	527	1.172	0.747	0.185	10.348
Key explanatory variable					
engodata	527	3.154	6.564	0	61
engopop	527	2.977	2.496	0	8.226
lnengopop	527	2.977	2.496	0	8.226

lnengodata	527	0.897	0.911	0	3.127
Control variable					
lnpgdp	527	8.815	1.218	3.769	11.300
lnpgdp2	527	79.193	20.673	22.743	127.699
ind	527	45.310	8.193	19.262	60.133
lncap_lab	527	0.806	0.454	0.254	3.351
fdi	527	2.301	2.356	0.001	13.652
lnden	527	5.269	1.464	0.723	8.245
en	527	0.128	0.081	0.037	0.521

Notes: *poll_loc* represent total location quotient of polluting industry, *poll_loc1-poll_loc6* respectively represent location quotient of Mining Industry; Papermaking; Chemical Fiber Manufacturing; Nonmetal Mineral Products; Smelting & Processing of Ferrous Metal; Production & Supply of Electric Power.

4. Results

4.1. Benchmark regression

Table 2 reports the benchmark regression results based on Eq. (1) and Eq. (2). All four models are estimated by controlling for time fixed effects, and the models' F-test values are greater than 3, indicating that the models have reached a significance level of 1% or better. In column (1), we estimate the single impact of *engodata* on the total polluting industrial location quotient ($poll\_loc$), while in column (2), we add in other control variables. The estimation results show that when controlling for time fixed effects and region fixed effects, regardless of other factors, the coefficients on the core explanatory variable (*lnengodata*) are -0.014 and -0.012, respectively, which are significantly negative, indicating that when *engodata* increases by a percentage point, *poll_loc* drops by approximately 0.012～0.014. This change of 0.012 is incredibly large considering that the location quotient index is either above or below 1, an indication that ENGOs do have an effect on reducing the importance of polluting industries. Columns (3) and (4) investigate the impact of the number of ENGO employees (*engopop)* on the importance of polluting industries. The estimation results show that when controlling for time fixed effects and region fixed effects, regardless of other factors, the coefficients on the core explanatory variable (*lnengodata*) are significantly negative and basically remain the same at -0.028, indicating that increasing *engodata* significantly reduces the importance of polluting industries. These four models verify the pollution haven hypothesis. That is, polluting industries prefer to relocate to regions with laxer environmental regulations. In this paper, we find that polluting industries gather in areas where NGOs are weaker, while in areas where ENGOs are relatively mature, the importance of the polluting industry is significantly reduced.

The estimation results for the control variables show that when the location quotient of the polluting industries is used as the explained variable, the impact of the overall economic development level exhibits an inverted U-curve similar to an environmental Kuznets curve. As the economy grows in a region, the location quotient of the polluting industries in that region increases first before it decreases, indicating that the share of polluting industries increases because there is no marked preference for the industry at the beginning of the economic development, which leads to environmental deterioration. However, when the region strengthens its environmental regulations and requirements with the development of its economy, its polluting industries decline. In addition, the increase in the proportion of the secondary industry greatly reduces the location quotient of the polluting industries because such an increase is mainly due to nonpolluting industries, an indication that the industrial structure has upgraded in the region, which leads to a decline in the proportion of polluting industries. The capital-labor ratio represents the type of industries, and its increase shows that industry has become more capital intensive, with workers being replaced by machines, and so more energy is required and more pollution is generated. The increase in the proportion of foreign investment significantly reduces the location quotient of polluting industries because regions tend to allow cleaner foreign investment, which reduces the importance of polluting industries. Industrial electricity consumption dramatically reduces the proportion of polluting industries because the consumption of electricity indicates that machines are replacing labor and there is a shift to more advanced industries, which causes the importance of polluting industries to decline. There is no significant relationship between population density and the location quotient of polluting industries.

Table 2. Benchmark regression results for the entire sample

EV	DV:*poll_loc*			
	(1)	(2)	(3)	(4)
lnengodata	-0.014***	-0.012***		
	(0.004)	(0.004)		
lnengopop			-0.028***	-0.028***
			(0.008)	(0.008)
lnpgdp		0.613**		0.644***
		(0.242)		(0.237)
lnpgdp2		-0.039***		-0.039***
		(0.009)		(0.009)
indstr		-0.008*		-0.009**
		(0.004)		(0.004)
lncap_lab		0.090*		0.102**
		(0.052)		(0.052)
fdi		-0.021***		-0.021***
		(0.008)		(0.008)
lnden		0.172		0.194
		(0.211)		(0.211)
en		-2.498***		-2.504***
		(0.588)		(0.584)
Constant	0.992***	-1.636	0.997***	-1.903
	(0.048)	(1.784)	(0.048)	(1.761)
N	527	527	527	527
Region fixed effect	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y
F test	3.571	5.286	3.665	5.527
(p-value)	[0.000]	[0.000]	[0.000]	[0.000]
R-squared	0.112	0.212	0.115	0.219

Notes: The numbers in parenthesis are robust standard errors; P value are in square bracket; *, **, and *** represent 10%, 5%, and 1% significant level, respectively. DV stands for dependent variable; EV stands for explanatory variable.

4.2. Region-based discussion

The vast territory and the unbalanced marketization of China (eastern China has a higher marketization level than midwestern China) result in remarkable regional differences (Chen, Xie, & Siquan, 2000), while the development of ENGOs varies significantly among regions (Bebbington, 2004). Therefore, ENGOs have heterogeneous influences on the location quotient of regional polluting industries. We chose 31 provincial-level administrative districts (according to China's existing administrative system) in the mainland as geographic units and further divided them into two regions: East China, including Liaoning, Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong and Hainan Provinces, and midwestern China, including the remaining 20 provinces. Table 3 reports the estimation results for the above two regions. Columns (1) and (2) show the impact of ENGOs on East China. The results show that both coefficients are significantly positive, indicating that ENGOs have a crowding-out effect on polluting industries in the eastern region, which leads to a decline in the location quotient of total polluting industries in the region. Columns (3) and (4) show the impact of ENGOs on polluting industries in midwestern China. The estimation results show that the coefficients from the two models are neither significant nor different from the previous two, indicating that ENGOs do not significantly reduce the location quotient of polluting industries in these areas. This is caused by the fact that ENGOs in East China are relatively mature and have pushed the polluting industries into midwestern China. In East China, the relationship between the level of economic development and the location quotient of polluting industries follows a significant inverted U-shaped curve, whereas such a curve also exists in midwestern China, it is not significant. Some other control variables are not significant, but the signs on the coefficients are basically consistent with those from the benchmark regression.

Table 3. Regression results for eastern and Midwestern China

EV	DV: poll_loc			
	Eastern		Midwestern	
	(1)	(2)	(3)	(4)
lnengodata	-0.008**		0.010	
	(0.003)		(0.016)	
lnengopop		-0.016**		-0.031
		(0.006)		(0.033)
lnpgdp	1.089***	1.187***	0.402	0.246
	(0.295)	(0.287)	(0.355)	(0.356)
lnpgdp2	-0.048***	-0.051***	-0.021	-0.013
	(0.013)	(0.013)	(0.014)	(0.013)
indstr	0.003	0.001	-0.016***	-0.016***
	(0.006)	(0.006)	(0.006)	(0.006)
lncap_lab	0.047	0.063	0.151	0.118
	(0.048)	(0.049)	(0.098)	(0.101)
fdi	-0.004	-0.005	-0.019	-0.022*
	(0.011)	(0.011)	(0.013)	(0.012)
lnden	-0.061	-0.069	0.924**	0.941**
	(0.181)	(0.180)	(0.464)	(0.464)
en	0.947	0.682	-2.753***	-3.016***
	(1.669)	(1.678)	(0.731)	(0.742)

Constant	-3.703**	-5.113**	-3.029	-3.320
	(2.162)	(2.126)	(2.821)	(2.790)
N	187	187	340	340
Region fixed effect	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y
F test	3.415	3.459	3.660	3.686
(p-value)	[0.000]	[0.000]	[0.000]	[0.000]
R-squared	0.350	0.353	0.274	0.275

4.3. Robustness check

The fact that some areas suffer from substantial missing data at the provincial level and the number of employees in the polluting industries in those regions is relatively low may lead to inaccuracy in our estimation. Therefore, robustness tests are conducted in this section, in which observations from four regions, i.e., Tibet, Qinghai, Xinjiang and Inner Mongolia Provinces were deleted for re-estimation. Table 4 reports the estimation results from the full samples and the subsamples. The first three columns present the impact of *engodata* on the polluting industries' location quotient (*poll_loc*). The coefficients for the whole sample and for the eastern region are significantly negative and lower than those from the baseline regression, indicating that the estimation results are affected by the sample composition. For the midwestern China subsample, the estimated coefficient is positive but not significant. Once again, the results verify that in the full and eastern region samples, ENGOs have a crowding-out effect on polluting industries, an effect which does not exist in midwestern China, indicating that the midwest has become a pollution haven.

The last three columns present the impact of *engopop* on the polluting industrial location quotient (*poll_loc*). The results show that in the full sample and the eastern sample, the coefficients on the core explanatory variables are highly and significantly negative, but they are not significant in the midwestern sample. The six models all verify that ENGOs have a significant crowding-out effect on polluting industries in the full sample and the eastern region, while midwestern China has received some of the polluting industries from the eastern region and has become a refuge for polluting industries. The estimation results for the other control variables are in line with the estimation results from the benchmark regression and the previous regional regression, so they are not repeated here.

Table 4. Results of robustness check.

EV	DV: *poll_loc*					
	Entire sample	Eastern	Midwestern	Entire sample	Eastern	Midwestern
	(1)	(2)	(3)	(4)	(5)	(6)
lnengodata	-0.009**	-0.008**	0.040			
	(0.004)	(0.003)	(0.035)			
lnengopop				-0.016**	-0.021***	0.028
				(0.006)	(0.007)	(0.032)
lnpgdp	0.773***	1.089***	0.489	1.187***	0.815***	0.317
	(0.279)	(0.295)	(0.467)	(0.287)	(0.273)	(0.469)
lnpgdp2	-0.057***	-0.048***	-0.042**	-0.051***	-0.058***	-0.028
	(0.011)	(0.013)	(0.021)	(0.013)	(0.011)	(0.021)

indstr	-0.003	0.003	-0.009	0.001	-0.004	-0.011
	(0.004)	(0.006)	(0.007)	(0.006)	(0.004)	(0.007)
lncap_lab	0.075	0.047	0.116	0.063	0.085*	0.108
	(0.048)	(0.048)	(0.093)	(0.049)	(0.048)	(0.098)
fdi	-0.016**	-0.004	0.003	-0.005	-0.016**	-0.004
	(0.007)	(0.011)	(0.012)	(0.011)	(0.007)	(0.012)
lnden	0.108	-0.061	1.010**	-0.069	0.128	0.863*
	(0.196)	(0.181)	(0.464)	(0.180)	(0.195)	(0.470)
en	-1.466*	0.947	-2.062*	0.682	-1.399*	-2.280**
	(0.748)	(1.669)	(1.068)	(1.678)	(0.744)	(1.080)
Constant	-1.832	-3.703**	-3.892	-5.113**	-2.167	-3.530
	(1.998)	(2.162)	(3.573)	(2.126)	(1.974)	(3.592)
N	459	187	272	187	459	272
Region fixed effect	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y
F test	3.135	3.415	3.047	3.459	3.324	3.687
(p-value)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R-squared	0.196	0.350	0.295	0.353	0.203	0.276

4.4. Industry-based discussion

While the first three sections of this chapter mainly examine the total effects of polluting industries, this section considers the effect of each polluting industry individually. The variables *poll_loc1*-*poll_loc6* represent the location quotient for mining, papermaking, chemical fiber manufacturing, nonmetallic mineral products, the smelting and processing of ferrous metals, and the production and supply of electric power, respectively. Table 5 reports the estimation results for the six polluting industries. The results show that *engodata* has a negative influence on the six polluting industries, while only in columns (2), (3) and (5) are the coefficients significantly negative, indicating that *engodata* has a negative impact on the location quotients of the following three industries: papermaking, chemical fiber manufacturing, and the smelting and processing of ferrous metals.

Table 5. Regression results for six polluting industries (*engodata*).

EV \ DV	*poll_loc1*	*poll_loc2*	*poll_loc3*	*poll_loc4*	*poll_loc5*	*poll_loc6*
	(1)	(2)	(3)	(4)	(5)	(6)
lnengodata	-0.010	-0.013*	-0.020**	-0.005	-0.038***	-0.009
	(0.008)	(0.007)	(0.010)	(0.004)	(0.008)	(0.010)
lnpgdp	0.823*	-0.246	0.281	-0.065	-1.118**	1.796***
	(0.461)	(0.411)	(0.612)	(0.226)	(0.471)	(0.548)
lnpgdp2	-0.064***	0.030*	-0.003	0.015*	0.035*	-0.089***
	(0.017)	(0.017)	(0.027)	(0.008)	(0.019)	(0.020)
indstr	-0.011	-0.002	-0.002	-0.002	-0.002	-0.011
	(0.008)	(0.007)	(0.010)	(0.004)	(0.008)	(0.010)
lncap_lab	-0.103	-0.214**	0.227*	0.038	0.213**	0.058
	(0.099)	(0.085)	(0.120)	(0.048)	(0.097)	(0.117)
fdi	-0.018	-0.010	-0.030	-0.011	-0.025*	0.008
	(0.015)	(0.013)	(0.018)	(0.007)	(0.015)	(0.018)

lnden	0.294	-0.546	-0.834*	0.321	-0.068	-0.015
	(0.402)	(0.346)	(0.497)	(0.197)	(0.396)	(0.478)
en	-3.987***	6.750***	2.539*	1.624***	1.829	-3.587***
	(1.118)	(0.984)	(1.416)	(0.547)	(1.128)	(1.330)
Constant	-1.888	3.120	2.938	-1.310	7.574**	-6.296
	(3.394)	(3.015)	(3.411)	(1.660)	(3.458)	(3.036)
N	527	510	493	527	510	527
Region fixed effect	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y
F test	2.931	3.051	1.080	1.264	2.138	3.817
(p-value)	[0.000]	[0.000]	[0.311]	[0.212]	[0.045]	[0.000]
R-squared	0.130	0.176	0.056	0.060	0.101	0.163

The impact of ENGOs on the other three industries, i.e., mining, nonmetallic mineral products and the production and supply of electric power, is not significant. This may be because ENGOs have not closely monitored these three industries. First, compared with the other industries, the mining industry is not located in the center of a region, while ENGOs mainly serve urban areas or key cities. Then, the nonmetallic mineral products industry is dominated by cement production and includes glass, ceramics, gypsum and other manufacturing industries, which are critical polluting enterprises that are often relatively evasive and difficult to supervise. Last, the supply of electric power mainly refers to thermal power plants and heating companies, which are industries that face rigid demand due to regional economic development and are mostly state-owned enterprises. In conclusion, ENGOs have relatively weak supervisory power over these companies, but their negative impact remains.

Table 6 reveals the impact of *engopop* on each polluting industry. The results show that *engopop* has a negative impact on every polluting industry, but its negative impact is significant on papermaking, chemical fiber manufacturing, and the smelting and processing of ferrous metals. Although the other coefficients fail to reach a significance level of 10%, the *t* values in columns (1) and (4) are both above 1.5; that is, the two models are significant within the 20% level. This indicates that *engopop* reduces the location quotients of the six polluting industries, causing a crowding-out effect that makes these industries relocate to regions with laxer environmental regulations.

Table 6. Regression results for six polluting industries (*engopop*).

DV / EV	*poll_loc1*	*poll_loc2*	*poll_loc3*	*poll_loc4*	*poll_loc5*	*poll_loc6*
	(1)	(2)	(3)	(4)	(5)	(6)
lnengopop	-0.023	-0.009***	-0.016**	-0.012	-0.072***	-0.016
	(0.015)	(0.03)	(0.08)	(0.008)	(0.015)	(0.018)
lnpgdp	0.854*	-0.388	0.057	-0.054	-0.935**	1.844***
	(0.452)	(0.405)	(0.602)	(0.221)	(0.462)	(0.538)
lnpgdp2	-0.064***	0.035**	0.005	0.014*	0.029	-0.091***
	(0.016)	(0.017)	(0.026)	(0.008)	(0.019)	(0.020)
indstr	-0.012	-0.003	-0.003	-0.002	-0.004	-0.012
	(0.008)	(0.007)	(0.010)	(0.004)	(0.008)	(0.010)
lncap_lab	-0.093	-0.216**	0.223*	0.043	0.243**	0.065
	(0.099)	(0.085)	(0.121)	(0.048)	(0.097)	(0.118)
fdi	-0.018	-0.012	-0.033*	-0.011	-0.023	0.009

	(0.015)	(0.013)	(0.018)	(0.007)	(0.015)	(0.018)
lnden	0.311	-0.511	-0.782	0.331*	-0.047	-0.012
	(0.402)	(0.347)	(0.499)	(0.197)	(0.396)	(0.479)
en	-3.987***	6.633***	2.352*	1.620***	1.898*	-3.565***
	(1.116)	(0.986)	(1.419)	(0.546)	(1.126)	(1.328)
Constant	-2.132	3.767	3.963	-1.413	6.448*	-6.577
	(3.364)	(3.000)	(3.389)	(1.645)	(3.427)	(3.004)
N	527	510	493	527	510	527
Region fixed effect	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y
F test	2.965	3.913	0.940	1.309	2.182	3.814
(p-value)	[0.000]	[0.000]	[0.343]	[0.1320]	[0.041]	[0.000]
R-squared	0.131	0.171	0.049	0.062	0.103	0.162

5. Mechanism Analysis

Based on the above analysis and Eq. (3) and Eq. (4), it is clear that ENGOs have an impact on investments in regional environmental governance. Therefore, based on Eq. (3) and Eq. (4), this section introduces the interaction terms between ENGOs and environmental governance investment to conduct a mechanism analysis, which consists of two parts. The first is a test of the interaction between *engodata* and environmental governance investment. Table 7 reveals the estimation results that show that when the interaction term is added, the original coefficients on *engodata* are no longer significant, while the coefficients of its interactions become significantly negative. Specifically, column (1) reports the interaction effect between *engodata* and environmental investment, with a coefficient of -0.009, which is significant at the 5% level. Column (2) reveals the interaction effect between *engodata* and investment in urban environmental governance, and column (3) reveals the interaction effect between *engodata* and investment in industrial environmental governance: both coefficients are equal to -0.004 at a significance level of 5%. Column (4) reports the interaction effect between three simultaneous environmental investments in construction items and *engodata*, with a coefficient of -0.001 at a significance level of 10%. All four models indicate that *engodata* affects the location quotient of polluting industries through environmental governance investments. Since the four models are all investigated with the full sample, the coefficients on the other control variables are basically consistent with the estimated results from the benchmark regression.

Table 7. Mechanism analysis results (*engodata*).

EV	DV: *poll_loc*			
	(1)	(2)	(3)	(4)
lnengodata	0.057	0.024	0.005	-0.000
	(0.047)	(0.017)	(0.009)	(0.010)
lnei×*lnengodata*	-0.009**			
	(0.004)			
lncityei×*lnengodata*		-0.004**		
		(0.002)		
lnind_ei×*lnengodata*			-0.004**	
			(0.002)	
lnthr_ei×*lnengodata*				-0.001*

				(0.000)
N	372	372	372	372
Control variable	Y	Y	Y	Y
Region fixed effect	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y
F test	3.372	3.283	3.154	3.068
(p-value)	[0.000]	[0.000]	[0.000]	[0.000]
R-squared	0.214	0.211	0.206	0.202

The second part is a test of the interaction between *engopop* and environmental governance investments. Table 8 reveals the following estimation results. The coefficients on *engopop* in the four models are all negative but not significant, while the coefficients on its interactions are all significantly negative. Column (1) reports the interaction effect between *engopop* and total environmental investment, with a coefficient of -0.003 at a significance level of 10%. Column (2) reveals the interaction effect between *engopop* and investment in urban environmental governance, with a coefficient of -0.002 at a significance level of 5%. Column (3) reveals the interaction effect between *engopop* and investment in industrial environmental governance, with a coefficient of -0.007 at a significance level of 5%. Column (4) reveals the interaction effect between *engopop* and three simultaneous environmental investments in construction items, with a coefficient of -0.004 at a significance level of 5%. In addition, the coefficients on the other control variables are in line with the estimated results from the benchmark regression.

Table 8. Mechanism analysis results (*engopop*).

EV	DV: *poll_loc*			
	(1)	(2)	(3)	(4)
lnengopop	-0.028	-0.032	-0.006	-0.016
	(0.051)	(0.040)	(0.014)	(0.017)
lnei×*lnengopop*	-0.003*			
	(0.001)			
lncityei×*lnengopop*		-0.002**		
		(0.000)		
lnind_ei×*lnengopop*			-0.007**	
			(0.003)	
lnthr_ei×*lnengopop*				-0.004**
				(0.002)
N	372	372	372	372
Control variable	Y	Y	Y	Y
Region fixed effect	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y
F test	3.465	3.503	3.583	3.428
(p-value)	[0.000]	[0.000]	[0.000]	[0.000]
R-squared	0.209	0.210	0.213	0.207

The analysis results for the two sets of mechanisms indicate that ENGOs reduce the agglomeration of polluting industries by affecting investment in environmental governance, causing these industries to relocate or upgrade and thereby reducing their employment location quotient. Unfortunately, due to the limitations in the available data, more in-depth mechanisms cannot be explored in this paper. By increasing in number and expanding their scale, ENGOs exert an influence on polluting firms by providing environmental supervision, information disclosure, environmental education, environmental litigation, etc., causing polluting firms to lose credibility and close their plants or relocate to other areas under pressure. Furthermore, through a series of environmental activities, ENGOs enable companies to increase their investment in environmental governance and enable the government to enhance its formal environmental regulations. Therefore, polluting industries reduce their scale of production in the face of pressure from both the government and enterprises and eventually withdraw from the market.

6. Conclusions

This paper focuses on the economic relocation effects of environmental nongovernmental organizations. First, as industrial relocation refers to the spatial-temporal changes in industrial location, it is difficult to identify in the data. We construct a relocation index, i.e., the industrial location quotient, to investigate the extent to which polluting industries relocate. Any decrease in the index indicates that the competitiveness of an industry in the region has fallen compared with the national average, meaning that this industry has relocated to other areas.

Second, by investigating the impact of ENGOs on the location quotients of polluting industries, ENGOs are found to have a significant negative impact on the overall location quotient of the six polluting industries, indicating that an increase in the number of ENGOs or ENGO employees affects the polluting industries through their active environmental governance and their activities in the target region.

Third, through regressions analyzing the different polluting industries, the growth of ENGOs is found to have a negative impact on all polluting industries. However, the relocation effect is only significant in the papermaking, chemical fiber manufacturing, the smelting and processing of ferrous metals, not in Mining, nonmetallic mineral products, the production and supply of electric power industries. This indicates that the economic relocation effect of ENGOs is heterogenous across industries, with more significant effects on industries that pollute more and can relocate more easily. The underlying reasons for this industrial heterogeneity may be that mining cannot be easily relocated, the pollution from nonmetallic mineral products is relatively inconspicuous, and the production and supply of electric power is essential to life; hence, the relocation effect of ENGOs is not clearly observable.

Fourth, the mechanism analysis reveals that ENGOs exert their economic relocation effects by increasing the environmental investments of polluting industries and enterprises. The growth of ENGOs, including in number and in employees, could enhance their supervisory power over polluting enterprises and motivate governments to engage in environmental treatments. Both of these channels could increase production costs for polluting companies and encourage them to relocate their pollution to other areas.

Hence, this paper is consistent with Chen et al. (2018), who found that the relocation of the chemical and rubber industry and the machinery manufacturing industry had a markedly positive role in industrial land use efficiency. However, the relocation effect of ENGOs in the nonmetallic mineral manufacturing industry is not significant due to that industry’s lower pollution intensity.

This paper supports the findings of Li & Wang (2019) that formal environmental regulation does not necessarily lead to the relocation of pollution-intensive industries due to differences in pollutant generation factors and relocation costs. We found that essential considerations of informal regulations, such as those provided by ENGOs, should be included in policy making related to industrial relocation.

We also supplement the findings of Yu & Chen (2018) and Gidron (2014) that the motivational and supervisory effects of ENGOs on governments and enterprises is more significant in more market-oriented areas, as was the case for the relocation effect in our study. Hence, the facilitation of marketization for ENGOs is conducive to their distinctive role in this green redistribution. However, whether such a relocation effect from ENGOs is helpful for increasing total welfare still needs to be further studied in the future.

Statements and Declarations

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