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Nonlinear Effects of Eco-Industrial Parks on Sulfur Dioxide and Carbon Dioxide Emissions—Estimation Based on Nonlinear DID

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Abstract: Eco-industrial parks (EIPs) promote the coordination of economic development and environmental protection. This paper uses the nonlinear DID method, with the data of 288 cities spanning from 2003–2019, to study the nonlinear effects of EIPs on SO_2 and CO_2 emissions, aiming to portray the nonlinear and heterogeneous characteristics of EIP's effects. Meanwhile, this paper examines the effects of EIPs more accurately and completely. The main results are as follows: 1. EIPs can significantly reduce CO_2 and SO_2 emissions, but there is significant heterogeneity between the effects. 2. The effect of EIPs on SO_2 and CO_2 emissions is nonlinear. In addition, it shows significant nonlinear characteristics as the change of foreign investment and population density in cities. Therefore, it is important to consider these nonlinear characteristics when establishing and evaluating EIPs. This paper accurately identifies the nonlinear effects of EIPs and provides some suggestions for the future development of EIPs.

Keywords: EIPs; SO_2 emissions; CO_2 emissions; nonlinear DID

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1. Introduction

Since the reform and opening up, China has implemented the policy of development zones to promote rapid regional economic development, which has achieved the "miracle of China's economic growth" by taking advantage of the industrial agglomeration effect. As of 2021, there were 387 national-level development zones and 2299 provincial-level development zones in China. However, the extensive mode of development zones has resulted in "high consumption, high pollution and high emissions" [1], leading to serious resource waste and environmental pollution. Meanwhile, a large number of studies have proven that industrial agglomeration will have a negative impact on environment [2–4]. Behind the rapid economic growth, China's environmental problems are becoming increasingly prominent, with regional environmental quality repeatedly breaking the bottom line [1]. Some regions have even experienced economic regression and severe environmental pollution at the same time. Among them, air pollution and greenhouse gas emissions are two important causes of environmental problems. Many scholars have found that sulfur dioxide emissions have serious impacts on people's health, including impairing the function of immune system [5], damaging the cardiovascular system [6,7], and raising the risk of disease, such as cancer [8]. Greenhouse gas emissions, on the other hand, can cause many climate changes that are harmful to human activities, such as global warming, droughts, floods, and storms. It can also damage people's respiratory systems. Therefore, it is an important issue to properly coordinate between production and ecological balance in economic construction [9,10].

In order to transform the economic growth pattern and achieve high-quality economic development, China's state environmental protection administration (China SEPA) launched the pilot construction of EIP in 2001. The EIP is a new type of industrial park, which is designed according to the requirements of clean production, the concept of circular economy, and the principles of industrial ecology [11]. Unlike the "design-produce-dispose" production mode of traditional development zones, EIPs follow the "recycle-reuse-design-produce" circular economy pattern. It mimics the material cycle in ecosystem, which enables a symbiotic combination of industries sharing resources and exchanging by-products between different enterprises [12]. So, the waste generated in the upstream production process becomes the raw material for the downstream production [13], and the optimal allocation of resources is achieved. The approval of the construction of Guangxi Guigang National Demonstration Eco-industrial (Sugar) Park in August 2001 marked the official start of the construction of China's EIPs. By 2021, a total of 55 EIPs had been established, and 45 EIPs have been approved for construction, as well [14,15].

In addition to China, more countries have started to establish EIPs to achieve a win–win situation for economic development and environmental protection [16–18]. The mechanism of the EIPs in ameliorating environmental pollution has also received much attention from academics. Based on previous studies, this mechanism of action can be divided into three stages: access threshold, regulatory system, and circular economy. EIPs have introduced a large number of preferential and subsidized policies as a way to attract capital and talent clusters and therefore promote technological innovation and industrial upgrading. As a new industrial EIP with the goal of green, low-carbon, and circular development, the EIPs agglomerate mostly high-tech and low-pollution industries, which can reduce the negative impact caused by industrial concentration on environment. Meanwhile, it has strict assessment standards within the park, which makes it necessary for enterprises to take environmental protection into account when developing the economy [19] and continuously improve their own green technology innovation capabilities [20]. Additionally, EIPs build a new type of circular economy system based on the principles of industrial ecology, so their internal industrial systems can operate in a similar way to natural ecosystems. In the EIPs, the rest energy and materials in the production process can be passed on to other processes for use. The whole process forms a collaborative chain network for the efficient transfer and use of energy and materials within or between companies. Consequently, the overall resource and energy use efficiency of the entire production process is improved, and the amount of waste and pollutants generated is reduced [13,21,22].

Previous studies have all focused on the spatial spillover effects of the establishment of EIPs in China on local environmental pollution and surrounding cities [23,24] using differences-in-differences (DID) to assess the effects of building EIPs. However, it is worth noting that many policy effects are revealed progressively in the time dimension, and the effects are heterogeneous across individuals. It was found during the research that the promotion of innovation by high-tech zone policies was more significant for firms located in eastern regions and highly open areas, compared to cities in other regions [23]. Studies have found that the environmental impacts of development zone policies generally begin to emerge three years after their establishment and increase over time. Additionally, the policy effects persist. The well-known environmental Kuznets curve (EKC) also states that public demand for quality of life and environmental awareness will change with increasing income. Environmental quality deteriorates with economic growth at the initial stage, but after reaching a turning point, economic growth leads to an improvement in environmental quality [25,26]. With a vast territory, China has different cultures and customs. China's population distribution is uneven, and the economic development varies greatly, as well. In this situation, there may also be temporal or individual differences in the effects of EIPs in different cities. When such heterogeneity effects are ignored in the model setting, it may result in serious estimation bias [27,28].

To solve the above problem, Terasvirta and Andorson (1992) [29] proposed the smooth transition autoregression (STAR), which allows for a continuous smoothed transition in the transfer process and effectively portrays the dynamic nonlinear effects against the time series. In addition, to address the possible structural mutations in economic variables, Hansen (1999) [30] proposed the panel threshold regression (PTR), which was later widely used in academia [31–33]. Based on the STAR and PTR models, González et al. (2004) [34] created the panel smooth transition model (PSTR) with wider applicability. In this nonlinear model, the effect of the explanatory variables on the explained variables is related to another exogenous factor. Therefore, it can effectively identify the characteristics of different individual heterogeneity and is suitable for portraying the nonlinear causal relationship between variables. Aidoo et al. (2022) [35] demonstrated that the capabilities of nonlinear smooth transition autoregressive (STAR) model for improved forecasting of COVID-19 incidence in the African sub-region were investigated. Godil et al. (2020) [36] used the quantile autoregressive distributed lag (QARDL) model to research the dynamic nonlinear effect of ICT, financial development, and institutional quality on CO_2 emission in Pakistan. Dada et al. (2021) [37] employed the STAR model to investigate the nonlinearity in exchange rate process in Nigeria. Babangida and Jamilu (2021) [38] examined the nonlinear effect of monetary policy decisions on the performance of the Nigerian stock exchange market by employing the STAR model. The traditional DID approach does not reveal the variability of the impact of EIPs in different cities and the differences over time. Drawing on the idea of setting up a panel smoothing transition model, this paper expands the traditional DID model into a more generalized and applicable nonlinear DID model, in order to characterize the nonlinear process and individual heterogeneity of the impact of EIPs establishment on environmental pollution in China.

The innovations of this paper are: 1. Distinguishing from the traditional time-varying DID model, i.e., a new model (nonlinear DID model) is used to evaluate the effects of EIPs' establishment on sulfur dioxide and carbon dioxide emissions, capturing the incrementality and regional heterogeneity of EIP's effectiveness. 2. It confirms the non-linear effects of EIPs on CO_2 and SO_2 emissions at different FDI and population densities andshows the differences in EIPs' effects over time and under different FDI and population densities. 3. It provides a piece of evidence for establishment and evaluation of EIPs. Setting up EIPs in cities with high levels of both FDI and POD, rather than relatively backward cities, will make it more effective. In the assessment process of EIPs, the establishment time and development status should be taken into consideration. Cities with higher economic levels and longer established EIPs require more rigorous standards. The remainder of the paper is organized into five sections: Section 2 introduces the policy background and theoretical analysis. Section 3 introduces the empirical strategy of DID and nonlinear DID. Section 4 discusses the basic empirical analysis results of how EIPs affect the emissions of CO_2 and SO_2. Section 5 is the conclusion.

2. Theoretical Analysis

2.1. Policy Background and Heterogeneity Analysis

EIP is the third generation of industrial parks in China, after the economic and technological development zone and high-tech development zone. The biggest difference from the previous two parks is that the EIP is designed according to the theory of circular economy and the principle of industrial ecology, with the goal of improving the economic efficiency of enterprises, while minimizing their environmental impact. Guided by the ecological industrial theory, it focuses on the construction of ecological chains and networks in the park. Meanwhile, it can maximize the utilization of resources, minimize the pollutant emissions from the industrial source, and realize regional clean production.

Western countries have started the construction of EIP at the end of 20th century, while China's EIPs started later. The establishment of Guangxi Guigang's National Demonstration Eco-industrial (Sugar) Park in 2001 marked the preliminary exploration of China's EIPs development. In 2003, the *National Eco-Industrial Demonstration Zone Declaration*, *Naming and Management Regulations*, and the *Eco-Industrial Demonstration Zone Planning Guide* were released, marking the beginning of the standardization of eco-industrial parks in China. In 2007, the *National Eco-Industrial Park Management Measures* was released, and it marked that China's eco-industrial parks had entered a relatively stable development stage. An application for demonstration zones must be created by the construction companies to the provincial environmental protection department. After its review, the application will be reported to the SEPA. With approval by SEPA, the construction companies of demonstration zones can organize their planning. After the construction pilot period, the construction companies can submit an application for the naming of demonstration zones to the provincial environmental protection department, which will be reported to SEPA. The SEPA will review the materials submitted and report to the general administration for approval. Qualified applicants will be approved as demonstration areas and granted unified specifications of the sign. Construction companies of demonstration areas shall report quarterly to SEPA on the construction, development, and problems of the demonstration areas. They shall also report the annual summary at the end of the year. In the process of construction and approval, SEPA publishes the latest information about the development of national circular economy demonstration zones on the *Circular Economy and Eco-Industry Newsletter*. In 2008, China's first national EIP was officially established. As of 2021, a total of 55 national EIPs have been completed, a very rare number. This is inextricably linked to the strict assessment criteria for EIPs. There is a standard and regulated evaluation system in the EIPs, which takes the environmental and economic benefits of enterprises into account. Moreover, it assigns special functional departments to collect and count the data involved in the evaluation indexes. According to the *National Eco-Industrial Park Management Measures*, the assessment is based on the following indicators: 1. Economic development indicators, such as indicators of economic development level and indicators of economic development potential. 2. Eco-industrial characteristic indicators, such as the presence of mature eco-industrial chains, reuse indicators, flexible characteristic indicators, infrastructure construction indicators. 3. Eco-environmental protection indicators, such as environmental protection indicators, environmental performance indicators, ecological construction indicators, and ecological environment improvement potential. 4. Green management indicators, such as policy and regulation system indicators and management and awareness indicators. It can be seen that, while economic development is considered, the national approval of eco-demonstration zones is more focused on environmental indicators. The requirements for development zones to become national industrial eco-demonstration zones are very strict. Parks that cannot reach the assessment indexes will not be upgraded to EIPs, while those that successfully transform into EIPs will gain more advantages, especially in terms of national policy support. EIPs enjoy not only the original preferential policies, but can also obtain special funds that are set up by the local finances. Local finances provide targeted financial subsidies for national EIPs and focus on increasing subsidies, subsidized loans, or tax breaks for policy research and key projects in national EIPs [39].

China's SEPA has proposed that the design and operation of EIPs should be closely focused on local natural conditions, industry advantages, and location advantages. Therefore, each EIP has its own characteristics at the beginning of construction, which can be mainly divided into two aspects: industry characteristics and regional characteristics. The representative EIP with industry characteristics is Guangxi Guigang National Demonstration Eco-industrial (Sugar) Park, which is the first circular economy pilot park in China, with electronic information, sugar and paper recycling, textile, and garment as the leading industries and the logistics industry as the subsidiary industries. The park locates in downtown Guigang and enjoys a good geographical location. It is an important channel for Western China to expand its opening-up and enter the international market, as well as an important entry point for enterprises from coastal developed areas to enter the western region. However, compared with other eastern EIPs, the regional competitiveness of Guangxi Zhuang Autonomous Region is lower. Its foundation of economic development is weak, and its talents and technology are less compeititve. Therefore, the development of EIP in Guigang relies more on land, raw materials, and capital, and there is still a considerable gap in technical development with EIP in the Pearl River Delta and other places. The EIP with regional characteristics mainly refers to the EIPs that are transformed from the existing economic and technological development zones and high-tech development zones. These EIPs themselves are characterized with good infrastructure and high green innovation capacity. The priority of future construction is to introduce the concept of eco-industry and circular economy in these parks and adopt the view of life cycle and ecological design methods to minimize resource consumption and waste generation. The production shall be easy to disassemble and recycle. Thus, the product structure can be optimized and the product chain can be improved, thereby improving resource efficiency, reducing environmental emissions, finding new growth points for the parks, and promoting the sustainable development of the parks.

It can be seen that each EIP has its own characteristics from the very beginning of its establishment. Some of them were transformed from the original national economic development zones and high-tech zones, with a solid economic foundation and sound infrastructure. So, the focus of their construction was on establishing a circular economy system and improving resource utilization, while others are not yet mature in scale and have a weak foundation. However, they still take important national support industries, such as energy conservation and environmental protection, as their leading industries. They locate at important nodes of China's economic belt, mainly taking on the function of responding to national policies and supporting regional development.

2.2. Foreign Direct Investment and Environmental Pollution

Since the reform and opening up, economic globalization has further accelerated, and China has been the developing country attracting the most foreign investment for many years. FDI has not only bridged the capital gap in China's economic development [40], but it has also brought new management experience and technology through spillover effects [41], which accelerated the regional industrial restructuring and marketization process. However, with the expansion of foreign investment, China's environmental quality is also deteriorating dramatically, with a series of environmental problems, such as air pollution and acid rain, becoming increasingly serious [42]. Coordinating FDI with regional environmental issues has become a serious and realistic problem faced by local governments. A prevalent view in the existing literature on the impact of FDI on environmental pollution is the "pollution in paradise" hypothesis. It emphasizes that loose environmental policies in developing countries are an important factor in attracting foreign investment. Since firms in developed countries often face higher pollution costs and harsher environmental regulations than developing countries, multinational firms in developed countries will reduce their pollution treatment costs and production costs by relocating their pollution-intensive firms to developing countries with less stringent environmental regulations. Strict environmental regulations will reduce FDI [43,44]. At the same time, in order to attract foreign investment, developing countries compete to lower their environmental standards, which inevitably leads to a decline in local environmental quality in the host country. A number of scholars have provided strong evidence for the "pollution in paradise", pointing out that FDI deteriorates regional environmental quality [45,46]. However, some other scholars point out that FDI does not deteriorate the environmental quality of the host country, but contributes to improving regional pollution [41,47]. First, both the production activities, and pollution treatment activities of FDI are characterized with incremental economies of scale, which can improve regional environmental quality by increasing income levels and optimizing industrial structure. Second, the international environmental standards implemented by foreign firms can promote the development of environmental technology in the host country and create a pollution halo effect [48]. Finally, FDI provides opportunities for developing countries to adopt new technologies that lead to clean or green production [49] and improve the environmental welfare of the host country by introducing environmentally friendly technologies and products.

The above studies all start from linearity to explore the impact of FDI on environmental pollution, and there is no unified conclusion yet. Based on this, this paper considers that there may be a non-linear correlation between FDI and environmental pollution, i.e., different degrees of FDI have different impacts on local environment. Due to the different levels of EIPs, each of them may have different impacts on environmental pollution.

2.3. Population Agglomeration and Environmental Pollution

In the process of urbanization in China, large-scale population agglomeration has contributed to the rapid development of the regional economy in the short term. However, while population agglomeration has a scale economy effect on local areas [50], it has also brought about serious environmental pollution [51]. Studies have shown that rapid population growth has put enormous pressure on the ecological environment. The environmental pollution caused by population problems has caused widespread concern in society.

Similar to the impact of FDI on environmental pollution above, there are studies on the impact of population agglomeration on environmental pollution with different conclusions. The majority of studies show that an increase in population density intensifies environmental pollution. Excessive spatial agglomeration of population will produce large amounts of domestic and production waste. It will increase environmental pollution when the amount of waste produced exceeds the self-purifying capacity of the ecological environment. For example, the increase in urban population density increases transportation demand, which adds harmful emissions in central areas and exacerbates air pollution [52], and the effect of increased population density on PM2.5 is higher than other socio-economic factors [53]. However, some scholars argue that the population agglomeration in cities is beneficial to reduce the average cost of natural monopolies, such as electricity, gas, natural gas, and public transportation, thus increasing residents' consumption of clean energy and common transportation services. In this way, the pollutant gas emissions can be reduced, and the efficiency of resource utilization and air quality can be improved. Chen et al. (2020) [54] validated this conclusion using China as a sample area, namely increasing population density is beneficial for reducing greenhouse gas emissions.

In consideration of the different effects of increasing population density on environmental pollution, it is reasonable to assume that the EIPs in areas with different population densities will have different effects on environmental pollution. Therefore, the coordinating variable of population density should be included in the study of the impact of EIP construction on environmental pollution.

3. Empirical Strategy

In this paper, the impact of EIP policies on SO_2 and CO_2 emissions are first estimated by using the traditional time-varying DID method. We set the dummy variable did for EIPs, where the variable did for cities with established EIPs is equal to 1; the variable did for cities without established EIPs takes the value of 0. The corresponding econometric model is:

$$Pollution_{it} = \beta_0 + \beta_1 did_{it} + \alpha X_{it} + u_i + \nu_t + \varepsilon_{it}$$

$$\beta = \Delta Y_{treatment} - \Delta Y_{control} = (Y_{treatment,t1} - Y_{treatment,t0}) - (Y_{control,t1} - Y_{control,t0})$$

The explained variable pollution is expressed by using the SO_2 and CO_2 emissions intensity of city i at year t. The logarithm of the ratio of SO_2 and CO_2 emissions to gross product of each city is taken as a measurement index here. The control variables X mainly include: the foreign investment variable FDI, measured by the ratio of total foreign direct investment (converted to CNY using the annual average real effective exchange rate) to GDP; the industrial structure variable INS, measured by the proportion of total value added of secondary and tertiary industries in GDP; the population density variable POD, measured by the number of people per unit of land area; the financial development level variable FID, measured by the ratio of year-end financial institutions' various remaining loan balance to GDP; and the city size variable CIZ, measured by the logarithm of total city population. U_i denotes the city's fixed effects, and V_t denotes the year's fixed effects.

The SO_2 emission data used in this paper are obtained from the prefecture-level cities in the China City Statistical Yearbook. The SO_2 emission data in this yearbook have only been disclosed since 2003, and the latest data are up to 2019. Therefore, the data used in this paper span from 2003 to 2019 and include 288 cities at the prefectural level and above. The CO_2 emission data are obtained from the *Center for Global Environmental Research*, which provides global carbon dioxide emission data from January 2003 to December 2019. The raster data within China are extracted, categorized, and aggregated according to cities in this paper. The panel data of CO_2 emission for Chinese cities from 2003 to 2019 are obtained. The statistical analysis of the main variables is shown in Table 1:

Table 1. Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
LnSD	4680	10.309	1.214	0.693	13.434
LnCD	5770	−12.932	0.656	−15.674	−9.36
did	7831	0.026	0.16	0	1
POD	7333	0.43	0.335	0	3.606
FDI	6551	0.026	0.042	0	0.627
INS	6714	0.837	0.104	0.387	1.046
FID	4823	0.871	0.556	0.075	9.623
CIZ	7338	5.76	0.804	−3.219	8.136

However, the premise is that two assumptions must be satisfied before using a time-varying DID approach: the parallel trends assumption and the assumption that the effects of the treatment groups are constant both between groups and across periods. The individual or period homogeneity hypothesis of the latter assumption is usually not satisfied, i.e., policy heterogeneity effects are very common in reality. Ignoring the setting of heterogeneity effects in the model is likely to cause serious estimation bias [28,55].

On the one hand, there may be differences in the policy treatment effects over time, and it is not reasonable to compare the treatment groups affected by the policy earlier with those affected by it later. β-estimated coefficients of time-varying DID should be decomposed into weighted averages of DID estimates for several groups [55]. In addition, Callaway et al. (2021) [56] suggested that there is a selection bias in the estimates of the time-varying DID approach, which arises from heterogeneous effects across treatment groups. Establishing a relationship between dose and response helps explain the causal relationships in more detail and identify potential mechanisms.

The existing literature mainly deals with the problem of the individual heterogeneity effect by distinguishing regional characteristics, such as geographical location and economic development. They model separately and compare the significance and magnitude of the DID estimates. However, the direct comparison of coefficients between different groups may lose significance, due to the difference in samples. For example, Jia et al. (2021) [57] divided Chinese cities into groups and used DID to estimate the impact of HSR opening on urban CO_2 emissions, noting that the effect of HSR opening on CO_2 emission reduction was more pronounced in East China, large cities, and resource cities. Meanwhile, the opening of HSR in these cities was detrimental to CO_2 emission reduction in their neighboring cities. Their study of the impact of HSR opening on urban land expansion in China divided cities into three groups: east, central, and west. It was found that mid-western cities were more vulnerable to the effects of HSR, compared to eastern cities. The net effect of HSR on urban land expansion in central and western cities was 10.9% higher than that in eastern cities.

In fact, there is not only individual heterogeneity in the effects of policies, but also temporal asymptotics. Neglecting the time-incremental characteristics of policy effects can lead to biased estimates of policy effects. The smooth transition autoregression (STAR) proposed by Terasvirta and Anderson (1992) [29] allows for continuous smoothed transitions in the transfer process, and it can effectively portray the dynamic nonlinear effects against the time series. Moreover, to address the possible structural mutations in economic variables, Hansen (1999) [30] proposed panel threshold regression (PTR). Based on the STAR and PTR models, González et al. (2004) [34] created the panel smooth transition model (PSTR) with wider applicability to address the problem of possible structural mutations in economic variables. It highlights that the transformation of regression coefficients is slow and gradual.

In order to more accurately identify EIPs' effects and characterize the asymptotic process and individual heterogeneity of EIPs' effects, this paper expands the time-varying DID model to a more generalized and applicable nonlinear DID model by referring to the panel smooth transition model. The interaction term that multiplies the policy variable with the smooth transition function is introduced into the traditional two-way time-varying DID model. It retains the original linear form of the covariates and two-way fixed effects, so the estimated coefficients of the policy variable include a constant term and a smooth transition function with different individual and time effects. This approach can not only portray the asymptotic process of EIPs' effects, but can also effectively estimate the differential effects of EIPs on different individuals, which makes the evaluation results more accurate. As an extension of the traditional time-varying DID model, the nonlinear DID model can degenerate into the traditional DID model when certain conditions are satisfied. In addition, this paper can choose the setting of a nonlinear DID model or traditional time-varying DID model by linearity test and nonlinearity test [34].

This paper uses a nonlinear DID approach to investigate whether there is significant heterogeneity in the impact of EIPs on regional SO_2 and CO_2 emissions. The evaluation of this nonlinear effect answered an important question: whether the impact of EIPs on pollutant emissions is sustainable and consistent with the requirements of regional coordination and high-quality development in China. As a pilot demonstration area, to coordinate environmental and economic development in the new development stage of China's economy, EIPs are an active exploration and a major initiative to achieve industrial transformation and upgrading, as well as high-quality economic development in China. In contrast to most previous studies, this paper considers that EIPs, as a location-oriented policy, may have significantly different impacts on CO_2 and SO_2 in different cities at different times. Therefore, a nonlinear DID method is used to estimate the nonlinear characteristics and heterogeneous effects of EIPs' establishment on urban CO_2 and SO_2 emissions.

By introducing a smooth transition function in the framework of the traditional DID model, this paper constructs a nonlinear DID model to describe the asymptotic process and heterogeneity of policy effectiveness. The model setting form is based on the linearity test and nonlinearity test, attempting to mechanistically characterize the asymptotic process and heterogeneity of policy effectiveness. Unlike the traditional time-varying DID model, the nonlinear DID model introduces an interaction term that multiplies the policy variables with the smooth transition function, and the model is defined as follows: choose the target language, different from the traditional multi-period double difference model, and the nonlinear double difference model introduces the interaction term of multiplying the policy variables with the smoothing transformation function. The model is defined as follows:

$$Pollution_{it} = \beta_0 + \beta_1 did_{it} + \beta_2 G(z_{it};\gamma,c) did_{it} + \alpha X_{it} + u_i + \nu_t + \varepsilon_{it}$$

$Pollution_{it}$ is a dependent variable, u_i denotes individual fixed effects, ν_t denotes time fixed effects, X_{it} is the control variable, ε_{it} represents the random errors, and did_{it} is the dummy variable for the EIPs, the core variable for assessing EIPs' effects. These above settings are consistent with the traditional time-varying DID model. Additionally, a new interaction term $G(z_{it};\gamma,c)did_{it}$ is constructed in this paper. This function is a continuous function determined by the exogenous transition variables, where c is an m-dimensional vector of location parameters, and the slope parameter γ determines the slope of the smooth transition function. In this paper, the smooth transition function is multiplied by the policy variables to characterize the dose (dose) of the EIPs between 0 and 1. Since the implementation of the EIPs, the effects on different individuals are not the same. The intensity of the EIPs itself and the effects brought by the EIPs may change significantly as time progresses.

Hurn (2016) [58] argueds that the exponential smooth transition function (ESTR) captures the asymptotic process of EIPs, as follows:

$$ESTR : G(z_{it}; \gamma, c) = 1 - exp\left\{-\gamma(z_{it} - c)^2\right\}$$

The characteristic of nonlinear DID model is that the interaction term is multiplied by a smooth transition function, which is a continuous and bounded function on the exogenous variables a_{it}. It allows for smooth transitions of the DID estimates over time and across individuals from β_1 to $\beta_1 + \beta_2$. The different value of γ determines the nature of the model as follows:

(1) When $\gamma = 0$, the nonlinear DID model becomes the traditional DID model:

$$ESTR : Pollution_{it} = \beta_0 + \beta_1 did_{it} + \alpha X_{it} + u_i + \nu_t + \varepsilon_{it}$$

(2) When $\gamma \to +\infty$, the nonlinear DID model is transformed into a transient nonlinear DID model:

$$ESTR : Pollution_{it} = \beta_0 + (\beta_1 + \beta_2) did_{it} + \alpha X_{it} + u_i + \nu_t + \varepsilon_{it}$$

(3) When $0 < \gamma < +\infty$, with the change of a_{it}, the EIPs' effect smoothly transfered from β_1 to $\beta_1 + \beta_2$ over time. The individual impact is significantly different from the implementation of the EIPs.

In order to test the heterogeneity in the effects of EIPs, it is necessary to have a linearity test first for the nonlinear DID model. In economic terms, the linearity test provides an explanation for the economic theory and explains that EIPs' effects are heterogeneous across individuals and time, instead of homogeneous. From the view of statistics, it is difficult to identify a nonlinear DID model whether the modeling results are linear. The linearity test [34] is a test of the validity of the original hypothesis. In order to avoid identification problems due to a large number of unknown parameters, an auxiliary regression model is constructed, with $G(z_{it}; \gamma, c)$ as a Taylor expansion of order m around $\gamma = 0$, with respect to the linearity of the parameters:

$$Pollution_{it} = \beta_0^* + \beta_1^* did_{it} z_{it} + \ldots + \beta_m^* did_{it} z_{it}^m + \alpha X_{it} + u_i + \nu_t + \varepsilon_{it}^*$$

where the parameter vector $\beta_1^*, \ldots, \beta_m^*$ is the m-th continued product of γ, $\varepsilon_{it}^* = \varepsilon_{it} + R_m \beta_1 did_{it}$, and R_m is the remainder term of the Taylor expansion, so testing H0: $\gamma = 0$ is equivalent to testing H0: $\beta_1^* = \ldots = \beta_m^* = 0$. We estimate the linear fixed model and its auxiliary regression separately to obtain the residual sum of squares SSR_0 and SSR_1. Based on the F-test, the statistic is the linear original hypothesis tested:

$$F = \frac{(SSR_0 - SSR_1)/mk}{SSR_0/(TN - N - mk)} \sim F(mk, TN - N - mk)$$

where TN is the total sample size, k is the number of explanatory variables, and the F statistic follows the $F(mk, TN - N - mk)$ distribution. M represents the number of location parameters, usually taken as $m = 1$.

4. Empirical Results

4.1. Traditional Time-Varying DID Model

The premise of using a traditional time-varying DID model for policy evaluation is that the experimental and control groups must have parallel trends. So, this paper first conducts a parallel trend test, referring to Howell (2017) [59], and constructs the model as follows:

$$Pollution_{it} = \beta_0 + \sum_{j=-6}^{6} \beta_j set_{it}^{j} + \alpha X_{it} + u_i + \lambda_t + \varepsilon_{it}$$

where set_{it}^{j} represents the time of policy enactment dummy variable. We suppose the EIPs started to be established in the year s_i, if $t - s_i$< = (−6), then set_{it}^{-6} = 1, otherwise = 0; If $t - s_i$ > = 6, then set_{it}^{6} = 1, otherwise=0; If $t - s_i = j$, then set_{it}^{j} = 1, otherwise = 0, $j = (-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5)$. When $j < 0$, it reflects the difference between the experimental and the control group j year before the policy implementation, when $j > 0$, it describes the dynamic impact of the policy after its implementation.

The first year before the policy implementation was selected as the base period, i.e., the dummy variables, set_{it}^{-1} were removed from the regression. The results are shown in Table 2, and it can be seen that none of the coefficients are significant before the policy implementation, satisfying the parallel trend. While the reduction of SO_2 and CO_2 emissions starts in the third year after the implementation of the EIPs, and the reduction effect has been sustained thereafter.

Table 2. Parallel trend test.

	LnSD	**LnCD**
pre_6	0.191	0.0413
	(0.107)	(0.0262)
pre_5	0.0788	0.0487
	(0.135)	(0.0332)
pre_4	0.036	0.0511
	(0.135)	(0.0332)
pre_3	0.0143	0.0255
	(0.136)	(0.0331)
pre_2	0.00734	0.0241
	(0.136)	(0.0332)
current	−0.173	−0.0217
	(0.135)	(0.0332)
post_1	−0.0497	−0.044
	(0.142)	(0.0331)
post_2	−0.0651	−0.0262
	(0.141)	(0.0359)
post_3	−0.151	−0.0622 *
	(0.143)	(0.037)
post_4	−0.363 **	−0.0689 *
	(0.153)	(0.0417)
post_5	−0.314 **	−0.0866 *

Table 2. *Cont.*

	LnSD	LnCD
	(0.153)	(0.0456)
post_6	−0.565 ***	−0.106 ***
	(0.132)	(0.0377)
Constant	1.636 *	−10.14 ***
	(0.888)	(0.235)
Observations	4423	4250
R-squared	0.774	0.873

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, similarly hereinafter.

In this paper, we empirically analyzed the effects of EIP's establishment on SO_2 and CO_2 emissions using the traditional time-varying DID model, and the results are shown in Table 3: Columns (1)–(2) show the effects of EIP policies on SO_2 emission, and columns (3)–(4) show the effects of development zone policies on CO_2 emission. The regression results showed, based on what the variable did, that with or without the inclusion of the control variable, EIP will significantly reduce the intensity of SO_2 and CO_2 emissions in the city. Guo et al. (2018) pointed out that EIPs will totally contribute 94% and 98% in direct and indirect CO_2 emissions reductions [60]. Song and Zhou (2021) indicated that the establishment of EIPs reduced SO_2 emissions by 25.2% in the area [10]. Tulchynska et al. (2021) also found that EIPs can significantly reduce industrial SO_2 emissions. The findings of this paper are consistent with their results. It indicates that, through recycling and agglomeration, China's EIP can bring about an increase in resource allocation efficiency, as well as reducing energy use. It can upgrade the industrial structure, which promotes economic development, while reducing SO_2 and CO_2 emissions. The main reason for this is that the EIP focuses on the environment, while promoting industrial agglomeration. The EIP follows the principle of sustainable development in the application and approval process, incorporates environmental indicators, and imposes environmental regulations on the region. This allows industries to consider the interaction between enterprises and industries in the agglomeration process, resulting in a "reduce, reuse and recycle" economic model that greatly improves resource efficiency.

Table 3. Effect of EIPs.

	LnSD	LnSD	LnCD	LnCD
did	−0.298 ***	−0.278 ***	−0.0626 ***	−0.0919 ***
	(0.054)	(0.0534)	(0.0209)	(0.0134)
FID		0.142 ***		0.125 ***
		(0.0329)		(0.00795)
INS		−0.572 *		−0.960 ***
		(0.308)		(0.0752)
CIZ		−0.563 ***		−0.420 ***
		(0.165)		(0.0407)
FDI		−0.326		−0.412 ***
		(0.539)		(0.128)
POD		−1.288 ***		0.0507
		(0.236)		(0.0568)

Table 3. *Cont.*

	LnSD	LnSD	LnCD	LnCD
Constant	−4.575 ***	−0.442	−12.16 ***	−9.512 ***
	(0.0315)	(0.966)	(0.0127)	(0.239)
City effects	YES	YES	YES	YES
Time effects	YES	YES	YES	YES
Observations	4680	4423	5770	4120
R-squared	0.0420	0.1370	0.0366	0.1207

Notes: Standard errors in parentheses *** $p < 0.01$, * $p < 0.1$, similarly hereinafter.

4.2. Nonlinear DID Model

A linear test is first required before using a nonlinear DID model for estimation [61]. Tables 4 and 5 provide the results of the linearity test and J-test for the nonlinear DID model, with FDI and POD as coordinating variables. In the linearity tests, the *p*-values of the tests are less than 0.01, which indicates that it is necessary and reasonable to use the nonlinear DID model to study the heterogeneous effects of EIP establishment on SO_2 and CO_2. In this paper, we refer to Davidson and Mackinnon (1981) [62] and use the J-test to test the transition function. The results are shown in Table 4: the *p*-values are less than 0.01, implying that the use of exponential smooth function is necessary and reasonable.

Table 4. Linearity test and J test (FDI).

LnSD				
H_0	F	df1	df2	prob
b2 = 0	7.434	2	3791	0.001
b2 = b3 = 0	5.652	4	3789	0
b2 = b3 = b4 = 0	5.818	6	3787	0
b2 = b3 = b4 = b5 = 0	4.371	8	3785	0
Escribano-Jorda linearity test (based on 4th Taylor expansion):				
ESTR	4.061	4	3785	0.003
LnCD				
H_0	F	df1	df2	prob
b2 = 0	33.377	2	3767	0
b2 = b3 = 0	16.836	4	3765	0
b2 = b3 = b4 = 0	13.165	6	3763	0
b2 = b3 = b4 = b5 = 0	11.675	8	3761	0
Escribano-Jorda linearity test (based on 4th Taylor expansion):				
ESTR	6.522	4	3761	0

Table 5. Linearity test and J test (POD).

LnSD				
H_0	F	df1	df2	prob
b1 = 0	44.809	2	4128	0
b1 = b2 = 0	30.664	4	4126	0
b1 = b2 = b3 = 0	21.976	6	4124	0
b1 = b2 = b3 = b4 = 0	19.959	8	4122	0
Escribano-Jorda linearity test (based on 4th Taylor expansion):				
ESTR	10.869	4	4122	0

Table 5. *Cont.*

LnCD				
H_0	F	df1	df2	prob
b1 = 0	164.633	2	3961	0
b1 = b2 = 0	199.174	4	3959	0
b1 = b2 = b3 = 0	205.355	6	3957	0
b1 = b2 = b3 = b4 = 0	163.21	8	3955	0
Escribano-Jorda linearity test (based on 4th Taylor expansion):				
ESTR	158.348	4	3955	0

Table 6 represents the results of the nonlinear DID estimation, with FDI as the coordinating variable, the coefficient of the linear part of did in column (2) is −1.415, which passes the 1% significance test. The coefficient of the non-linear part of did is 0.865, which passes the 1% significance test, as well. It shows that the effect of EIP's establishment on SO_2 emissions is non-linear, and the effect is significantly heterogeneous with the change of FDI in each city. Its effect is in the range of −0.55 to −1.415. In general, the EIP can significantly reduce SO_2 emissions, which is consistent with the results of the traditional model. Further, when the FDI is in the range of [0,0.0334], the effect of EIP's establishment on SO_2 emission reduction increases as the FDI increases, reaching a maximum of −1.415 at 0.0334. This is consistent with Zeng's findings, which pointed out that the role of EIPs is, to some extent, realized by FDI, and the higher the FDI, the more significant the role of EIPs [63], while the effect of EIP's establishment on SO_2 emission reduction starts to diminish when the FDI exceeds 0.0334. Meanwhile, the coefficient of the linear part of the did in column (4) is −0.667, which passes the 1% significance test. The coefficient of the non-linear part of did is 0.176, which also passes the 1% significance test. It shows that the effect of establishing EIP on CO_2 emissions is non-linear, and the effect is significantly heterogeneous with the change of FDI in each city. Its effect is in the range of −0.491 to −0.667. In general, the EIP can significantly reduce CO_2 emissions, which is also consistent with the results of the traditional model. When the FDI is in the range of [0,0284], the effect of EIP's establishment on CO_2 emission reduction increases with the increase of FDI and reaches the maximum −0.667 at 0.0284, while the effect of EIP's establishment on CO_2 emission reduction starts to diminish when the FDI exceeds 0.0284.

Table 6. Nonlinear DID estimation results (FDI coordination variables).

Liner Part	**LnSD**	**LnSD**	**LnCD**	**LnCD**
did	−2.213 ***	−1.415 ***	−0.893 ***	−0.667 ***
	(0.1410)	(0.1190)	(0.0977)	(0.0678)
Non liner Part (FDI)				
did	1.155 ***	0.865 ***	0.225 **	0.176 *
	(0.4320)	(0.3150)	(0.1080)	(0.0953)
c	0.0267 ***	0.0334 ***	0.0300 ***	0.0284 ***
	(0.0047)	(0.0044)	(0.0036)	(0.0051)
$\ln\gamma$	6.935 ***	7.012 ***	9.198 ***	8.665 ***
	(0.6670)	(0.6090)	(1.3760)	(1.3370)
Constant	−5.590 ***	29.04 ***	−12.95 ***	30.18 ***
	(0.0162)	(0.5940)	(0.0053)	(0.5970)
Controls	NO	YES	NO	YES
City effects	YES	YES	YES	YES
Time effects	YES	YES	YES	YES
Observations	4266	4,085	5494	4056
R-squared	0.0825	0.4546	0.0516	0.1109

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, similarly hereinafter.

Table 7 represents the results of the nonlinear DID estimation, with POD as the coordinating variable, the coefficient of the linear part of did in column (2) is −0.752, which passes the 1% significance test. The coefficient of the non-linear part of *did* is −1.566, which passes the 1% significance test, as well. It shows that the effect of EIP's establishment on SO_2 emissions is non-linear, and the effect is significantly heterogeneous with the change of POD in each city. This is consistent with Nie's research, who revealed that EIPs help achieve low-carbon development in China. Additionally, the effects of EIPs have regional heterogeneity [64]. Its effect is in the range of −0.752 to −2.318. In general, the EIP can significantly reduce SO_2 emissions, which is consistent with the results of the traditional model. Further, when the POD is in the range of [0,0.431], the effect of EIP's establishment on SO_2 emission reduction decreases as the POD increases, reaching a minimum of −0.752 at 0.431, while the effect of EIP's establishment on SO_2 emission reduction starts to progressively increase when the POD exceeds 0.431. Meanwhile, the coefficient of the linear part of the *did* in column (4) is −0.331, which passes the 1% significance test. The coefficient of the non-linear part of *did* is −0.303, which also passes the 1% significance test. It shows that the effect of establishing EIP on CO_2 emissions is non-linear, and the effect is significantly heterogeneous with the change of POD in each city. Its effect is in the range of −0.331 to −0.634. In general, the EIP can significantly reduce CO_2 emissions, which is also consistent with the results of the traditional model. When the POD is in the range of [0,0.509], the effect of EIP's establishment on CO_2 emission reduction decreases with the increase of POD and reaches the minimum −0.331 at 0.509. While the effect of EIP's establishment on CO_2 emission reduction starts to progressively increase when the POD exceeds 0.509. This model's estimation results effectively verify the regionally and temporally significant heterogeneous effects of the EIP's establishment on regional economic growth.

Table 7. Nonlinear DID estimation results (POD coordination variables).

Liner Part	**LnSD**	**LnSD**	**LnCD**	**LnCD**
did	−1.718 ***	−0.752 ***	−0.379 **	−0.331 ***
	(0.2260)	(0.2250)	(0.1660)	(0.0611)
		Non liner Part(POD)		
did	−1.111 **	−1.566 ***	−0.346 **	−0.303 ***
	(0.4720)	(0.4610)	(0.1680)	(0.0805)
c	0.464 **	0.431 **	0.540 ***	0.509 ***
	(0.2310)	(0.1880)	(0.0057)	(0.0713)
$\ln\gamma$	1.2900	1.2220	9.579 ***	3.004 ***
	(1.1190)	(0.9930)	(1.8260)	(0.8250)
Constant	−5.618 ***	30.18 ***	−12.93 ***	−8.829 ***
	(0.0162)	(0.5970)	(0.0051)	(0.0600)
Controls	NO	YES	NO	YES
City effects	YES	YES	YES	YES
Time effects	YES	YES	YES	YES
Observations	4606	4423	5730	5591
R-squared	0.0772	0.4489	0.0580	0.0998

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, similarly hereinafter.

China's Yangtze River Delta region has one of the most dynamic economic developments, the highest degree of openness, and the strongest innovation capacity. Therefore, the city may, itself, have strong environmental regulations that affect the assessment of EIPs in this paper. Therefore, this paper excludes the sample of cities in the Yangtze River Delta region and conducts robustness tests. Tables 8 and 9 represent the results of the robust tests. The results are consistent with the previous results, indicating that the results of this paper are robust.

Table 8. Robust Test (FDI coordination variables).

Liner Part	LnSD	LnSD	LnCD	LnCD
did	−3.457 ***	−2.571 ***	−1.179 ***	−0.312 **
	(0.432)	(0.347)	(0.173)	(0.141)
		Non liner Part (FDI)		
did	2.104 ***	2.073 ***	0.609 ***	0.419 ***
	(0.483)	(0.372)	(0.209)	(0.154)
c	0.0446 ***	0.0476 ***	0.0513 ***	0.0106 ***
	(0.004)	(0.0028)	(0.00544)	(0.00222)
$\ln\gamma$	8.029 ***	7.849 ***	7.253 ***	9.313 ***
	(0.484)	(0.337)	(0.549)	(0.797)
Constant	−5.559 ***	28.10 ***	−12.92 ***	−12.87 ***
	(0.0169)	(0.647)	(0.00564)	(0.0126)
Controls	NO	YES	NO	YES
City effects	YES	YES	YES	YES
Time effects	YES	YES	YES	YES
Observations	3846	3676	4974	3681
R-squared	0.0583	0.4241	0.0471	0.0867

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, similarly hereinafter.

Table 9. Robust Test (POD coordination variables).

Liner Part	LnSD	LnSD	LnCD	LnCD
did	−1.378 ***	−0.369 **	−0.531 ***	−0.428 ***
	(0.246)	(0.181)	(0.113)	(0.101)
		Non liner Part (POD)		
did	−1.742 ***	−1.921 ***	−0.473 ***	−0.344 **
	(0.499)	(0.365)	(0.149)	(0.144)
c	0.528 ***	0.580 ***	0.496 ***	0.491 ***
	(0.058)	(0.0271)	(0.0569)	(0.092)
$\ln\gamma$	2.573 ***	3.202 ***	3.459 ***	3.241 ***
	(0.828)	(0.501)	(0.889)	(1.004)
Constant	−5.592 ***	29.48 ***	−12.90 ***	−12.85 ***
	(0.0169)	(0.648)	(0.00552)	(0.012)
Controls	NO	YES	NO	YES
City effects	YES	YES	YES	YES
Time effects	YES	YES	YES	YES
Observations	4184	4012	5209	3875
R-squared	0.0471	0.4221	0.0406	0.0741

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, similarly hereinafter.

5. Conclusions

This paper uses a nonlinear DID model to estimate the effects of EIP policies on SO_2 and CO_2 emissions, highlighting the nonlinear characteristics and heterogeneity effects of EIP. The results show that the establishment of EIPs significantly reduces the emissions of SO_2 and CO_2, and the effects are significantly heterogeneous. Firstly, as an extension of the traditional DID model, this paper uses a nonlinear DID model, with FDI and POD as the coordinating variables, to effectively estimate the heterogeneous effects of the EIP's establishment on SO_2 and CO_2 emissions. Secondly, this paper reveals that there is a nonlinear effect between the establishment of EIPs and emissions of SO_2 and CO_2. Moreover, it shows a significant nonlinear characteristic with the change of FDI and POD. Thirdly, the nonlinear DID model with a smooth transition function accurately portrays the nonlinear and heterogeneous effects of the EIP.

Overall, the establishment of EIPs can significantly reduce SO_2 and CO_2 emissions. However, the reduction effect of EIPs on SO_2 and CO_2 emissions varies under different FDI and POD. With the increase of FDI, the reduction effect of EIP on SO_2 and CO_2 emissions increases first and then decreases. The reduction effect of EIP on SO_2 is the greatest when FDI reaches 0.0334; the reduction effect of EIP on CO_2 is the greatest when FDI reaches 0.0284. With the increase of POD, the reduction effect of EIP on SO_2 and CO_2 emissions decreases first and then increases. The reduction effect of EIP on SO_2 is the smallest when POD reaches 0.431; the reduction effect of EIP on CO_2 is the smallest when POD reaches 0.509. Thus, it can be seen that the effect of EIP policies on SO_2 and CO_2 emissions has significant nonlinear characteristics.

Based on the research in this paper, the following policy recommendations are proposed: when setting up EIPs, the state should consider the nonlinear characteristics of the effect, while, in implementation, the effects of FDI and POD on the effect should be taken into account. Setting up EIPs in cities with high levels of both FDI and POD, rather than relatively backward cities, will make it more effective. At the same time, the setting of assessment indicators should be changed, according to the time of implementation and the differences in cities. Fixed indexes should not be used to assess cities with different levels of economic development and different times of policy implementation because of the differences between EIPs and the different effects of EIPs over time. The assessment indicators for EIPs in cities with higher levels of FDI and POD should be more stringent, while the assessment indicators in the later stages of EIPs establishment should be more stringent than those in the early stages. The limitation of this study is that the detailed data on firms' SO_2 and CO_2 emissions is currently unavailable to us, and we hope that we can use the detailed data to identify the mechanisms from the establishment of EIPs to SO_2 and CO_2 emissions, in order to make our understanding of EIP policies more complete.

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