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Voluntary environmental regulations and their impact on marginal abatement costs: empirical results from the national ecological demonstration park

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During China's industrialization, its development zones encountered issues of environmental pollution and resource depletion while fostering economic growth. For this reason, the Chinese government encouraged the establishment of national eco-industrial demonstration parks (NEDP). Based on data from 211 Chinese cities with National Development Zones from 2003 to 2020, this article uses the construction of NEDP as the research entry point to study the role of self-regulated environmental policies on the marginal abatement cost (MAC) of CO_2. The multi-period DID method is used for the analysis. We find that the NEDP policy plays a key role in significantly reducing the MAC of CO_2 in urban areas. The NEDP policy affects cities' MAC of CO_2 through green innovation and carbon intensity effects. Although the latter offsets part of the reduction, the former dominates, resulting in a significant overall decrease in marginal abatement costs. However, the policy's effects exhibit some delay. The impact of the NEDP policy varies across cities, primarily influenced by the policy's intensity and the timing of the parks' establishment. Multiple demonstration parks and parks established at an early stage see greater reductions in abatement costs. On the other hand, single parks or those developed at later stages do not lead to a significant reduction in abatement costs and may, in fact, cause an increase in costs due to the carbon intensity effect. The policy implications suggest that the government should accelerate park transformation and promote multiple demonstration parks to maximize emission reduction benefits. Encouraging resource sharing between parks and advancing green technology innovation can strengthen the validity of voluntary environmental regulation. Additionally, the government should refine park construction strategies, adopting differentiated policies, especially for late-stage parks, and support green technology innovation to avoid rising emission reduction costs due to technological constraints.

KEYWORDS

national eco-industrial demonstration park, marginal abatement costs, multi-period DID method, voluntary environmental regulation, carbon emission reduction

1 Introduction

Carbon dioxide (CO_2) in the atmosphere is the most significant anthropogenic greenhouse gas, primarily responsible for climate change. Its increased concentration, mainly from human activities, leads to global warming and environmental disruptions (Pörtner et al., 2022). The substantial increase in CO_2 over the past decade can be attributed to historically high emissions from fossil fuels during the 2010s and 2020s. This is despite the fact that the growth of fossil fuel carbon emissions has slowed down over the past decade compared to the 2000s, emissions remain at elevated levels. As a result, the period from 2014 to 2023 shows the highest average decadal growth rate of atmospheric carbon dioxide on record.

In response to the serious environmental problem of global warming, carbon reduction has become a global consensus. China ranks as the top emitter of carbon globally, therefore, it shoulders a major mission to slow down the warming problem and reduce greenhouse gas emissions (Dong et al., 2023). To this end, China has set a dual carbon target for this purpose. This requires that all regions in China, during the process of promoting low-carbon transformation, need to not only reduce carbon emission intensity through regulatory measures, but also bear certain economic costs for controlling and reducing carbon dioxide emissions (Yu et al., 2023a). Given its significant contribution to total energy use, the industrial sector plays a key role in emission reduction. Improving energy efficiency and adopting cleaner technologies are essential for meeting China's climate goals (Bao et al., 2008).

China is a country with rapid industrialization. Therefore, contemporary social development should focus more on fostering the harmonious development of economic growth and environmental sustainability, as both are essential for sustainable development and long-term prosperity in the face of growing environmental concerns. Against this background, China has carried out circular economy pilots in areas including national economic and technological development regions, as well as high-tech industrial parks to build national eco-industrial demonstration parks (NEDP). In the form of a government-led voluntary environmental regulation, the establishment of NEDP is a key initiative for promoting the circular economy in regions with a high concentration of industrial enterprises. The primary goal of China's development zones was originally to stimulate economic growth and promote local economic development and restructuring of the industrial system through the introduction of foreign and domestic investment and the promotion of rapid industrialization (Zhou et al., 2018). The formation of state-level development zones has undoubtedly led to the agglomeration of enterprises and the formation of many industrial clusters, which has strengthened the development capacity of enterprises through the agglomeration effect. It has a good contribution to the development of regional economic construction (Zheng et al., 2008). From a theoretical perspective, the positive environmental externalities of industrial agglomeration should far outweigh its negative externalities. However, from a realistic point of view, as economic development enters a new stage, the traditional mode of development zones is gradually exposed to environmental pollution, waste of resources and other problems, and urgently needs to be transformed and upgraded (Wang and Nie, 2016).

In this process, eco-industrial demonstration parks came into being and became an important exploration of a new regional economic development model. In 2003, the "Regulations on the Declaration, Naming and Management of National Eco-Industrial Demonstration Parks (for Trial Implementation)" was formally issued, which marked that the construction of NEDP entered into a preliminary exploration stage. In 2007, the relevant Chinese governmental departments further promulgated "the Circular on the Development of National Eco-Industrial Demonstration Parks". The approval and construction of the NEDP then entered a fast lane. Unlike command-and-control or market-based environmental regulations, NEDPs are a government-led, voluntary form of environmental regulation. After voluntary applications for construction are submitted by development zone management committees or local governments, the Ministry of Environmental Protection is tasked with approving, reviewing, naming, conducting regular evaluations, and overseeing the parks. This strict approval system sets high entry requirements for applicants. Parks with stronger economic foundations and existing ecological industry infrastructure are more likely to succeed in the application process. As a result, only national or provincial development zones with a certain foundation will apply for a NEDP and receive government approval for construction. The development of the NEDP is illustrated in Figure 1. By the end of 2020, 93 parks in China have completed or were in the process of building NEDPs, with policies radiating to 49 cities in China. The construction of new economic development zones is not just a continuation and expansion of the traditional development zone model, but also a significant shift towards more efficient, green, and sustainable development. The goal is to foster an industrial system that recycles waste and reduces energy consumption through the strategic development of circular economy value chains and the development of eco-friendly industrial systems. This approach can effectively change the model of economic development in a more intensive and cleaner direction. In addition, it can effectively alleviate the pressure of resource scarcity and environmental protection on regional development and creates a model of an industrial park that conforms to the ecologically sustainable development. It has been shown that the NEDPs work well in facilitating economic performance of the host region (Tian et al., 2014; Yu et al., 2015) and foreign direct investment (Hua and Tan, 2022). In addition, some academics have studied the environmental benefits of these environmental regulations, and this impact has included analysis of the release of greenhouse gases

FIGURE 1
Total quantity change trend.
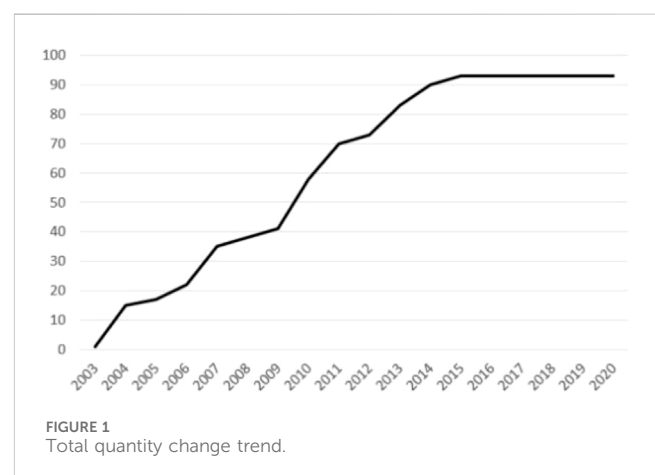
(Qian et al., 2022; Cao et al., 2022; Chen et al., 2023) and sulfur compounds (Cao et al., 2022; Chen et al., 2023). Moreover, the role of environmental regulations in increasing green total factor productivity in cities (Liu et al., 2022), total factor energy efficiency (Zhang et al., 2023), and eco-efficiency (Liu et al., 2015) has been explored by some researchers from the perspective of efficiency. Although existing studies on voluntary environmental regulation have examined its effects on both firms' financial performance and environmental behavior (Alnafrah et al., 2024; Piekkola and Rahko, 2024; Bokor, 2024), research focusing specifically on environmental behavior remains limited, with insufficient attention paid to developing countries. Furthermore, considering that scholars, when studying the carbon reduction effect of environmental regulations, mostly focus on carbon emission intensity and carbon emission efficiency, while neglecting to analyze its impact from the perspective of cost-benefit (David and Sinclair-Desgagné, 2005; Yu et al., 2023b), the relationship between the magnitude of marginal emission reduction cost and carbon price determines the willingness of enterprises to reduce emissions (Baumol and Oates, 1988). Therefore, there is an urgent need to examine whether self-imposed environmental regulation has an influence on MAC in the city-level dimension. Based on this, we explore the impact of voluntary environmental regulatory policies on the regional MAC represented by the NEDP, which is the main objective of this paper. This paper seeks to address the following questions: First, in the setting of China, can the NEDP pilot projects encourage enterprises to focus on emission reduction, thereby lowering the regional MAC? Second, by what means does NEDP implementation impact regional MAC? Finally, what are the factors that influence the effectiveness of a city's MAC? Exploring these questions will contribute to improving research on voluntary environmental regulation, encouraging businesses to better adapt to such policies, and ultimately achieving both sustainable development and environmental protection goals.

On this basis, this paper utilizes data from 211 Chinese cities with national development zones from 2003 to 2020 and the multi-period DID method to analyze how NEDP construction affects the city's MAC, aiming to enrich the related research on voluntary environmental regulation. The following are some possible contributions of this paper: First, existing studies on marginal abatement costs have mainly focused on their measurement and estimation, while relatively few have examined the factors that influence them. Moreover, empirical evidence on how environmental regulation affects urban marginal abatement costs remains limited. This study examines the impact of the NEDP policy from the perspective of voluntary environmental regulation, thereby enriching the empirical evidence on the determinants of cities' marginal abatement costs. Second, unlike other forms of voluntary environmental regulation, the NEDP policy represents a government-led, systematic, and cluster-oriented approach. Analyzing this policy helps to provide a more comprehensive understanding of the mechanisms and practical effects of voluntary environmental regulation in promoting urban green development. Third, this study explores the pathways through which voluntary environmental regulation affects urban marginal abatement costs and identifies the distinct effects of two mechanisms. The findings offer useful insights for governments to design and coordinate different types of environmental regulation more precisely, to promote green innovation, avoid cost increases caused by the carbon intensity effect, and enhance the overall efficiency and synergy of policy implementation.

Next up in this article are these: first the paper will conduct a literature review and formulate hypotheses based on it in Section 2.

In Section 3, the paper will construct the multi-period DID model, describe the selection of variables and explains the sources of data. In the next Section, a data-driven analysis is conducted on the impact of the NEDP pilot policy on regional MAC, accompanied by robustness checks to validate the findings. In Section 5, the mechanism of the impact is examined. Also, we will further explore the heterogeneous effect of this policy on regional MAC in Section 6. In Section 7, we present the key conclusions derived from the study and provide an in-depth discussion of the policy implications informed by the empirical results and their broader significance.

2 Literature review and hypothesis development

Prior to analyzing the influence of NEDP on marginal abatement costs, it is essential to first calculate these costs. The marginal abatement cost (MAC) of CO_2 resents the cost per unit of CO_2 emission reduction, considering the current production technology (Cheng et al., 2022). In recent years, numerous scholars have undertaken its measurement and analyzed the MAC of CO_2 using various modeling methods. Using the CGE model, Gernot Klepper et al. developed the MAC curve and discovered that the prices of fossil fuels influence the shape of the marginal abatement cost curve (Klepper and Peterson, 2006). Färe et al. proposed the use of the Shephard Distance Function and applying the duality theory to measure the shadow price of undesired output (Färe et al., 1993). This method allows researchers to calculate the incremental cost of unintended outputs despite the lack of cost information. Given that CO_2 can be considered as a non-expected output, this paper further improves on the study by Färe et al. We use the DDF-SFA (Directional Distance Function and Stochastic Frontier Analysis) method to further measure the marginal MAC of CO_2. This method combines the advantages of Dynamic Distance Function (DDF) and Stochastic Frontier Analysis (SFA), and is able to provide a more accurate estimate of abatement costs while taking into account time series data and technology heterogeneity.

Moreover, it has been shown that the MAC curve of carbon dioxide has a U-shaped curve (Cheng et al., 2022; Du et al., 2015). Due to the economies of scale, in the early phase of emissions mitigation, the MAC will decrease as the carbon intensity decreases. Nevertheless, as the emission reduction process gradually reaches a bottleneck, it is becoming increasingly difficult to reduce carbon emissions per unit, and the cost required becomes larger, therefore, as the carbon intensity decreases, the MAC will gradually increase (Xu et al., 2022). The research on NEDP shows that promoting the construction of NEDP can be effective in minimizing CO_2 emissions (Hua and Ye, 2023) and carbon intensity (Nie et al., 2022) in the pilot area, and improve CO_2 emissions, in terms of efficiency (Ji et al., 2024). Existing studies indicate that voluntary environmental regulation can, to some extent, compensate for the limitations of formal government supervision, demonstrating considerable flexibility and regulatory effectiveness (Arimura et al., 2019). Moreover, such regulatory mechanisms contribute to enhancing firms' environmental management capabilities and internal governance, thereby improving their overall performance (Lajmi et al., 2025). On this basis, research hypotheses 1 and hypotheses 2 are formulated in this paper.

Hypothesis 1: The NEDP policy will affect the regional MAC.

Hypothesis 2: The NEDP policy will affect the MAC by affecting regional carbon intensity.

The updating of technology directly affects the MAC curve of CO_2. Technological innovation or learning effect can reduce the cost of certain abatement technologies, which shifts the MAC curve to the left (Rekker et al., 2023). As carbon intensity decreases, so does the MAC in the role of technological creativity. In the construction of the NEDP, government departments also focus on the importance of the park to enable the widespread use of low-carbon technologies and the translation of innovations. Also, government points out that they should make full use of the think tank of the demonstration park to carry out energy substitution technology, process carbon reduction, and other technologies, and promote the industrialization of low-carbon technology. In the Guiding Opinions on Strengthening the Construction of National Eco-Industrial Demonstration Parks issued in 2011, it was explicitly stipulated that national eco-industrial demonstration parks characterized by circular or end-of-pipe industries should prioritize the improvement of waste recycling and detoxification technologies, as well as the innovation of pollution control technologies. These policy directives have compelled enterprises within the parks to engage in targeted technological innovation, thereby promoting regional transitions toward low-carbon and cleaner production technologies, thus changing the MAC curve of carbon dioxide. Therefore, this paper sets forth the third hypothesis of this study.

Hypothesis 3: The NEDP policy will affect the MAC by influencing green technology innovation.

3 Research methodology and data origins

3.1 Baseline regression model

Since the parks were approved for construction at different times, a multi-period DID model is employed to evaluate the effect of NEDPs on the MAC in urban regions. The multi-period DID method is a widely utilized approach for assessing policy impacts and measuring their effectiveness. This model assumes that the policy only affects areas where the policy is implemented, then trends between implemented and non-implemented areas are expected to diverge after the policy is implemented, while staying consistent prior to the policy implementation. The multi-period DID approach quantifies the causal effects of a policy by assessing the variations in effects between treatment and control groups pre- and post-policy is implemented at different points in time. Specifically, we compare the change in MAC between cities that have undertaken a demonstration park and those that have not before and after policy implementation. By analyzing this difference, we assess the impact of NEDP construction as a form of voluntary environmental regulation. The baseline model applied in this evaluation is presented below:

$$MAC_{it} = \beta_0 + \beta_1 Park_{it} + \theta X_{it} + \varphi_i + \mu_t + \varepsilon_{it} \qquad (1)$$

Where, MAC_{it} denotes the MAC of city i in year t; $Park_{it}$ is a binary indicator that assumes a value of 1 if city i is authorized to

implement a NEDP in year t, and 0 if not. Cities with an approved NEDP are the treatment group, and cities without an approved NEDP are the control group. Variable β_1 represents the change in MAC metrics in the treatment group relative to the control group after NEDP approval for construction. X_{it} indicates a range of city-level control variables potentially impacting MAC, including: population density, GDP per capita, FDI and urbanization rate; φ_i means city-level fixed effects; μ_t is time fixed effects; and ε_{it} is error terms.

3.2 Construction of variables

3.2.1 Explained variable

We adopt the DDF-SFA methodology to measure the MAC of urban CO2. In the production process, the production entity wants to obtain more target output y and less unintended output b under an certain input x. This suggests the need to incorporate the direction vector in the construction of the directional distance function (DDF). Drawing on the research methodology of Chung et al. (1997), the DDF is as shown in Equation 2.

$$\vec{D}_0(x, y, b; g) = sup\{\beta: (y + \beta g_y, b - \beta g_b) \in P(x)\} \qquad (2)$$

where $P(x)$ is the set of production possibilities satisfying weak disposability and zero-binding. Direction vector is denoted by $g = (g_y, -g_b)$, and meets the condition that $g_y > 0, g_b > 0$. Building on the research approach of Zhang et al. (2022), the expression for the shadow price of undesired output (i.e., MAC) is as follows:

$$Mac_i = -p_i\left(\frac{\partial \vec{D}_i(x, y, b; g)/\partial b_i}{\partial \vec{D}_i(x, y, b; g)/\partial y_i}\right) \qquad (3)$$

where Mac_i denotes the marginal cost of unwanted output and p_i denotes the price of intended output.

Equation 3 shows that the estimation of DDF process needs to satisfy the differentiability condition. The nonparametric estimation method does not satisfy the differentiability, so this paper chooses the parametric method for estimation. Because the estimation process, need to use the DDF convertibility and differentiability, this paper chooses the quadratic function for estimation, the function form is given by the Equation 4:

$$\vec{D}(x, y, b; g) = \alpha_0 + \sum_{n=1}^{m} \alpha_n x_n + \beta_1 y_i + \gamma_1 b_i + \frac{1}{2}\sum_{n=1}^{m}\sum_{n=1}^{m} \alpha_{n,n} x_n x_{n'}$$
$$+ \frac{1}{2}\beta_{11} y_i^2 + \frac{1}{2}\gamma_{11} b_i^2 + \sum_{n=1}^{m} \delta_{n1} x_n y_i + \sum_{n=1}^{m} \eta_{n1} x_n b_i$$
$$+ \theta_{11} y_i b_i \qquad (4)$$

The translatability of the DDF is expressed as Equation 5.

$$\vec{D}(x, y, b; g) - \alpha = \vec{D}(x, y + \alpha, b - \alpha; g) \qquad (5)$$

Adding a random error term to a quadratic DDF v, and let $\vec{D}(x, y, b; g) = \mu$. The orientation vector is $g = (1, -1)$. Combined with DDF convertibility, this yields the following Equation 6.

$$-\alpha = \vec{D}(x, y + \alpha, b - \alpha; 1, -1) + v - \mu \qquad (6)$$

FIGURE 2
Time trend of MAC between the experimental group and the control group.

This equation is the basic expression for SFA estimation. By making $\alpha = b_i$, and take into account both year fixed effects and city fixed effects, the following equation can be obtained:

$$-b_i = \alpha_0 + \sum_{n=1}^{m} \alpha_n x_n + \beta_1 y_i + \gamma_1 b_i + \frac{1}{2} \sum_{n=1}^{m} \sum_{n=1}^{m} \alpha_{n,n} x_n x_{n'} + \frac{1}{2} \beta_{11} y_i^2$$

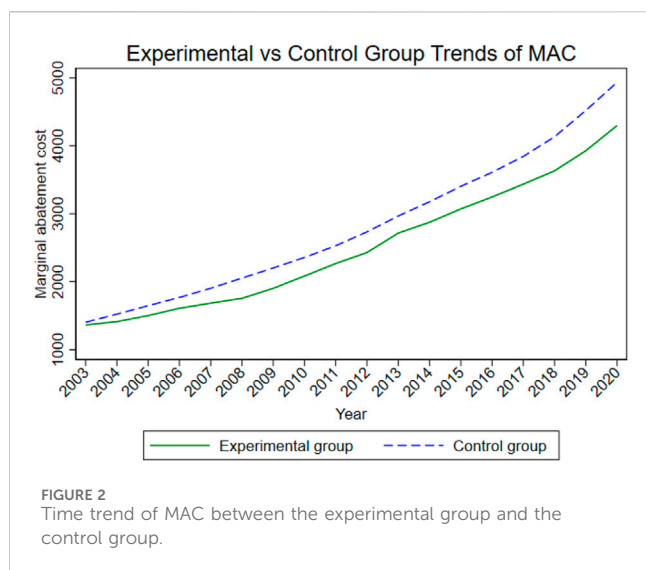$$+ \frac{1}{2} \gamma_{11} b_i^2 + \sum_{n=1}^{m} \delta_{n1} x_n y_i + \sum_{n=1}^{m} \eta_{n1} x_n b_i + \theta_{11} y_i b_i + \nu - \mu + \sum_{n=2}^{h} \tau_n D_n$$

$$(7)$$

In Equation 7, there are m types of input factors, D_n is a dummy variable for cities, and there are h cities. Bringing Equation 7 into Equation 3, the city's MAC can then be determined. The input factors here are labor and capital. Of these, labor is expressed as the number of employees per unit at the end of the year in the city. As for capital, other estimation methods have to be used since official data at the city level are not available. Here, we follow Ke and Xiang's method and use the perpetual inventory method to estimate the capital stock of the city (Ke and Xiang, 2012), with the base year being 2003. The expected output is the GDP of the city, and the unexpected output is the carbon dioxide emissions of the city. After measurement, the MAC is logarithmized.

Using the aforementioned methodology, we calculate the marginal abatement cost of CO_2 for 211 cities in China. Furthermore, we divide the sample into a control group and an experimental group, calculate their annual average values respectively, and the results are presented in Figure 2. Our preliminary findings indicate that the marginal abatement cost of the experimental group is lower compared to that of the control group. This also indirectly suggests that the NEDP policy may be capable of reducing the marginal abatement cost of enterprises, and the specific results and mechanism of action require further investigation on our part.

3.2.2 Policy variable

The binary indicator is employed to represent whether the policy is performed in the model. Taking the existence of parks approved to carry out construction in a city as a criterion, if there is a park approved for construction in city i in year t, then $Park_{it} = 1$; conversely, $Park_{it} = 0$.

3.2.3 Control variables

Control variables that might affect the city's MAC are also included in the analysis. The following specific variables are included in the model: (1) population density (density): used the logarithm of the number of people per square kilometer as population density; (2) *per capita* Gross Domestic Product (pgdp): measured as the natural logarithm of the actual *per capita* GDP for each city; (3) foreign direct investment (fdi): expressed as the natural logarithm of the actual foreign direct investment utilized within the city; (4) urbanization rate (urban): calculated the ratio of the resident urban population to the total resident population of the area as the urbanization rate.

3.3 Data

The research sample in this paper spans from 2003 to 2020, covering 211 cities with national development zones. This represents 72% of all cities in China. In the time span studied, a total of 49 cities were approved to establish NEDPs, which serve as the treatment group in the study. The remaining 162 municipalities do not have approved NEDPs and therefore constitute the control group for this study. This study focuses only on prefecture-level cities with national-level development zones, some of which are excluded from the analysis to keep the treatment and control groups as consistent as possible at the initial stage, thus reducing potential bias due to sample selection. We find the sample cities selected for this paper from the "Catalog of China's Development Zones Audit Bulletin (2018 Edition)". The information on NEDPs is gathered from the 2017 government document "List of National Eco-Industrial Demonstration Parks" and other relevant audit documents.

Among them, we extract CO_2 data in the Emissions Database for Global Atmospheric Research (EDGAR), and the values for other variables are gathered from the China Urban Statistical Yearbook, with some gaps in the data are filled in through the corresponding data in the statistical yearbooks published by each city. Table 1 displays the symbolic representations and detailed meanings of the other variables. Meanwhile, Table 2 outlines the summary statistics for the variables studied.

4 Regression results

4.1 Benchmark regression analysis

Table 3 illustrates the results from the benchmark regression. In particular, columns (1) and (2) illustrate the effect of NEDP on the MAC of CO_2, excluding the inclusion of city and time fixed effects. Going a step further, column (3) builds on the analysis in column (1) by fixing the city and year, thus accounting for the potential impact of common shocks on cross-sectional variation. In column (4), additional city-level representation variables are introduced for a more comprehensive examination. The findings across columns (1) through (4) consistently indicate that voluntary environmental

TABLE 1 Overview of the variables.

Variable classifications	Variables labels	Symbolic representation	Units
Explained variable	Marginal abatement cost of CO2	MAC	Yuan/ton
Policy variable	The binary indicator for national eco-industrial demonstration parks	Park	
Control variables	Population density	Density	The number of people/km2
	Per capita GDP	pgdp	Ten thousand yuan
	Foreign direct investment level	fdi	Million dollars
	Urbanization rate	Urban	%

TABLE 2 Summary statistics.

VarName	Obs	Mean	SD	Min	Median	Max
MAC	3,798	7.850	0.388	7.109	7.844	8.739
Park	3,798	0.139	0.346	0.000	0.000	1.000
Pgdp	3,798	10.397	0.805	8.021	10.478	13.056
Fdi	3,798	5.400	1.859	−0.991	5.478	11.241
Urban	3,798	0.521	0.173	0.114	0.506	1.001
Density	3,798	5.875	0.847	2.303	6.011	7.882

TABLE 3 Regression results of NEDP policy on MAC.

	(1)	(2)	(3)	(4)
	MAC	MAC	MAC	MAC
Park	−0.053***	−0.068***	−0.053***	−0.048***
	(0.009)	(0.017)	(0.009)	(0.008)
pgdp		0.450***		0.071***
		(0.010)		(0.011)
fdi		−0.062***		0.005***
		(0.004)		(0.001)
Density		−0.001		0.031
		(0.008)		(0.028)
Urban		−0.497***		−0.014
		(0.049)		(0.022)
_cons	7.857***	3.778***	7.857***	6.919***
	(0.002)	(0.089)	(0.002)	(0.200)
City FEs	No	No	Yes	Yes
Year FEs	No	No	Yes	Yes
N	3,798	3,798	3,798	3,798
R^2	0.965	0.420	0.965	0.966

*, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively; the values in parentheses represent t-statistics.

**FIGURE 3**
Parallel trend test.

FIGURE 4
Placebo test.
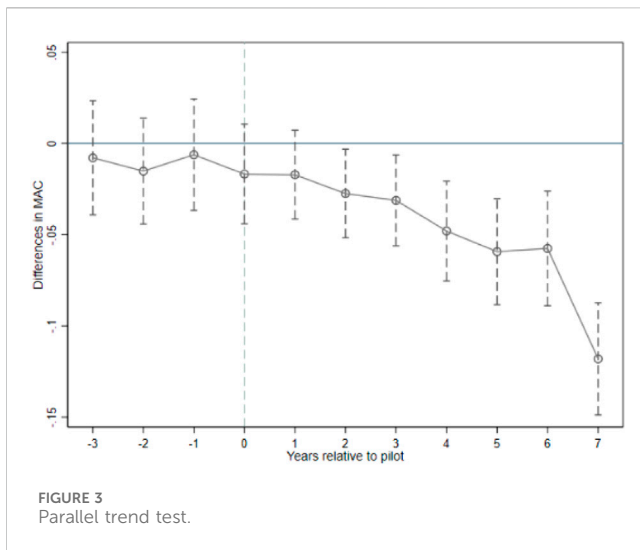
regulations, such as the NEDP, contribute significantly to the reduction of the MAC of CO2 emissions. In particular, the regression coefficient in column (4) is −0.048, implying that NEDP approval lowers the MAC by 4.8%. This finding supports Hypothesis 1, demonstrating that the policy effectively amplifies the impact of green technology advancements, surpassing the effect of carbon intensity. A deeper exploration of this mechanism will be presented in the subsequent section.

4.2 Parallel trend test

For causal inferences based on the multi-period DID approach to be valid, the parallel trend assumption must be met. That is, there should not be a significant difference in MAC between the treatment and control groups prior to the implementation of the NEDP. To test this assumption, a parallel trends test was conducted using the event study approach proposed by Jacobson et al. (Jacobson et al., 1993). The analytical framework for this method is outlined as Equation 8.

$$MAC_{it} = \beta_0 + \sum_{k=-3}^{k=7} \alpha_k Park_{i,t_{0+k}} + \delta X_{it} + \varphi_i + \varphi_i + \varepsilon_{it} \quad (8)$$

Where t_0 denotes the ongoing phase of NEDP development and $Park_{i,t_{0+k}}$ is a set of binary indicators, represents the k th year of NEDP construction in city i. The remaining variables are defined in the same way as the variables in Equation 1. Coefficient α_k is central to this study. It captures the variation in MAC between cities with and without NEDP construction during the specified period t_{0+k}. This paper organizes the data into two periods: the 4 years before the policy implementation are categorized as period −4. Data after the eighth year of park's construction were grouped into period 7, and we selected period - 4 as the starting period of the study to represent the time before the NEDP policy was introduced. Figure 3 presents the outcome of the parallel trend test conducted, which shows that none of the estimated coefficients on the impact of NEDP on MAC before its implementation are statistically significant. This suggests that the difference in MAC between cities with and without NEDP
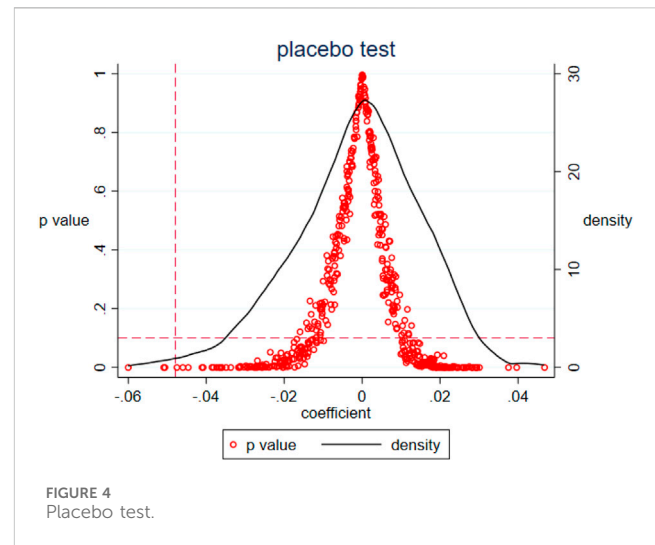
was not significant before the policy was introduced, thus confirming that the sample complies with the parallel trends assumption. In addition, the coefficients are not statistically significant until 2 years after the policy implementation, suggesting that the establishment of the NEDP has a delayed effect on the MAC of CO_2.

4.3 Robustness tests

4.3.1 Placebo test

To address potential confounding due to omitted variables in the regression results, a placebo test was conducted. This test helps eliminate the possibility of unobserved factors influencing the findings and ensures that the shocks in the demonstration areas were not randomly assigned (Li et al., 2016). We repeat the test 500 times and obtained placebo test results as shown in Figure 4. The results clearly show that the distribution is essentially normal. The coefficients are mainly concentrated around 0, which is significantly different from the baseline value of −0.048, suggesting that the impact of NEDP on MAC remains unaffected by other unmeasured variables, confirming the stability of the results.

4.3.2 Winsorize treatment

Potential outliers may have unintended effects on study results, so we use the quartile substitution method by replacing the lowest and highest 1% (or 5%) of the data points in the MAC to prevent extreme values from having an undue influence on the model's estimation. Columns (1) and (2) of Table 4 detail the coefficients and significance of the regressions. The results show that replacing the data with the values of the 1% and 5% quartiles does not significantly change the magnitude or sign of the coefficients. This implies that the primary findings hold up under scrutiny.

4.3.3 PSM-DID

When using the multi-period DID model for analysis, we could not guarantee that the cities in the control and experimental groups have exactly the same characteristics. In addition, estimation bias may be attributed by systematic differences between pilot cities and

TABLE 4 Results of two robustness tests.

	Winsorize treatment		PSM-DID		
	(1)	(2)	(3)	(4)	(5)
	1%	5%	Nearest-neighbor matching	Kernel matching	Radius matching
Park	−0.048***	−0.048***	−0.026**	−0.026**	−0.026**
	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)
pgdp	0.071***	0.071***	0.059***	0.059***	0.059***
	(0.011)	(0.011)	(0.015)	(0.015)	(0.015)
fdi	0.005***	0.005***	0.005	0.005	0.005*
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Density	0.031	0.031	0.054	0.035	0.038
	(0.028)	(0.028)	(0.035)	(0.034)	(0.034)
Urban	−0.014	−0.014	0.035	0.054	0.029
	(0.022)	(0.022)	(0.034)	(0.035)	(0.033)
_cons	6.919***	6.919***	7.028***	7.028***	7.076***
	(0.200)	(0.200)	(0.262)	(0.262)	(0.258)
City FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
N	3,798	3,798	2,969	2,969	2,959
R2	0.966	0.966	0.957	0.957	0.958

*, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively; the values in parentheses represent t-statistics.

other cities. We introduced the PSM-DID methodology to address this issue in order to eliminate potential bias. Considering differences between cities, we introduce city control variables and apply the PSM method to match control group cities that closely resemble those in the treatment group (i.e., cities with NEDP implementation). Table 4 demonstrates the regression results of the PSM-DID method, with columns (3), (4), and (5) representing the outcomes of the 1:1 nearest neighbor matching, kernel matching, and radius matching techniques, respectively. The regression coefficients for all methods pass the test at the 5% significance level, reinforcing the robustness of the findings. Therefore, the implementation of NEDP indeed decreases the MAC of cities.

5 Mechanism analysis

Based on Hypotheses 2 and Hypotheses 3, the following Equation 9 is developed for detailed analysis determined by the effect of NEDP on the extent of green innovation and regional carbon intensity:

$$Y_{it} = \beta_0 + \beta_1 Park_{it} + \theta X_{it} + \varphi_i + \varphi_i + \varepsilon_{it} \quad (9)$$

Where Y_{it} is the mechanism variable, referring to the extent of green innovation (innovation) and carbon intensity (intensity). In this case, the degree of green innovation is used as the logarithm of the number of patents for green inventions among the patents that

the city is approved to receive each year (Danish and Ulucak, 2021). In addition, the carbon emission intensity uses the carbon dioxide emissions-to-GDP ratio, and the logarithm of this value is taken, which is also suggested by previous studies (Lee and Wang, 2022). Table 5 presents the regression results, which show that NEDP can significantly boost the extent of green technology innovation. This effect is consistently irrespective of the inclusion of control variables. Compared with cities that have not established National Eco-Industrial Demonstration Parks (NEDPs), those with NEDPs tend to set up low-carbon technology incubators at the park level to promote the industrialization of low-carbon technologies. This industrial agglomeration effect not only enhances the efficiency of technological exchange and cooperation among firms but also reduces the research, development, and application costs of low-carbon technologies through economies of scale. Given that the marginal abatement cost (MAC) curve of carbon dioxide generally exhibits a U-shaped pattern and that China is situated on the left-hand side of this curve (Xu et al., 2022), green innovation can shift the MAC curve downward and to the left, thereby reducing cities' marginal abatement costs of carbon dioxide. At the same time, the NEDP policy also helps to lower the carbon intensity of cities, which causes the points on the marginal emission reduction cost curve to move upward. Comparing these two mechanisms, the effect of green innovation dominates; thus, on balance, the NEDP policy exerts an overall mitigating impact on the marginal abatement cost of carbon dioxide in cities.

TABLE 5 Mechanism analysis.

	(1)	(2)	(3)	(4)
	Innovation	Innovation	Intensity	Intensity
Park	0.149***	0.171***	−0.096***	−0.135***
	(0.030)	(0.029)	(0.016)	(0.014)
pgdp		0.391***		−0.618***
		(0.054)		(0.034)
fdi		0.015		−0.015**
		(0.010)		(0.005)
Density		0.509**		−0.402***
		(0.159)		(0.092)
Urban		0.861***		−0.079
		(0.143)		(0.093)
_cons	4.167***	−3.425**	9.805***	18.714***
	(0.008)	(1.135)	(0.004)	(0.570)
City FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
N	3,798	3,798	3,798	3,798
R2	0.948	0.950	0.935	0.953

*, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively; the values in parentheses represent t-statistics.

6 Heterogeneity analysis

6.1 Policy intensity

In our study sample, there are some cities with multiple ongoing or completed NEDPs. In general, the difference in the number of demonstration parks a city has reflects the difference in policy intensity and construction goals. In the case of multi-park cities, the local government seeks to strengthen environmental regulations and build a clean city through the construction of multiple demonstration parks. For single-park cities, the motives for setting up the parks are more diverse, which may be to meet environmental requirements, to highlight the performance of officials, to follow the example of neighboring cities, and so on. Based on this, this paper further breaks down the research sample. Referring to the study by Kong et al., we categorized the cities into those with a single demonstration park, cities with two demonstration parks, and cities with three or more demonstration parks, and regressed them one by one (Kong and Chai, 2021). The regression estimates, displayed in first three columns of Table 6, reveal that NEDP construction has an impact on the City's MAC with a coefficient of 0.061. It indicates that cities with one demonstration park are more difficult to break through the carbon intensity effect, which will make the city's MAC increase rather than decrease. This indicates that cities with only a single NEDP exhibit insufficient innovation effects and still rely primarily on reducing carbon intensity to achieve emission reduction. Although this approach contributes to lowering carbon emissions, it entails relatively high marginal abatement

costs. The impact coefficient of cities with three or more parks on MAC is −0.063, indicating that as the number of demonstration parks in a city increases, the marginal abatement cost of CO_2 is more strongly suppressed. This result supports the conclusions of Qian et al. that cities with multiple demonstration parks benefit more from this policy compared to cities with a single demonstration park (Qian et al., 2022). Therefore, cities should vigorously promote the transformation of national development zones into NEDPs.

6.2 Time of establishment of the park

The impact of the construction of NEDPs on MAC may vary with the timing of the establishment of the park. Compared to parks built first, those built later will face stronger pressure to reduce emissions, and their related technological bottlenecks will be more difficult to break through. Consequently, this paper categorizes the study sample into two different phases based on when the parks were established: the first stage spanning 2003 to 2009, and the second covering 2010 to 2020, for a more detailed analysis. The choice of 2009 as the time point is based on the following considerations: first, as shown in Figure 1, the number of NEDPs increased dramatically around 2009; second, in 2009, the Ministry of Environmental Protection (MEP) issued "The Notice on Strengthening the Development of Low-Carbon Economy in National Eco-Industrial Demonstration Parks". In this notification, the government introduced the concept of aligning NEDP construction with low-carbon objectives for the first time. This shift likely resulted in notable variations in the carbon reduction motivations and behaviors across different groups of parks. Regressing the samples of the two

TABLE 6 Heterogeneity analysis.

	Policy intensity			Time of establishment of the park	
	(1)	(2)	(3)	(4)	(5)
	Single park	Two parks	Three or more parks	2003–2009	2009–2020
Park	0.061***	−0.032	−0.063*	−0.144***	0.057***
	(0.014)	(0.018)	(0.030)	(0.023)	(0.012)
pgdp	0.498***	0.497***	0.498***	0.495***	0.499***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
fdi	−0.021***	−0.022***	−0.021***	−0.022***	−0.022***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Density	0.362***	0.378***	0.393***	0.370***	0.377***
	(0.051)	(0.058)	(0.059)	(0.058)	(0.051)
Urban	0.539***	0.540***	0.561***	0.590***	0.494***
	(0.039)	(0.039)	(0.041)	(0.040)	(0.037)
_cons	0.446	0.404	0.287	0.417	0.359
	(0.284)	(0.316)	(0.323)	(0.320)	(0.279)
City FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
N	3,402	3,186	3,042	3,168	3,546
R2	0.877	0.881	0.880	0.879	0.878

*, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively; the values in parentheses represent t-statistics.

batches, the study's findings are presented in the final two columns of Table 6. Although the construction of both batches of parks had an impact on MAC, the effects were completely opposite. This may be because the earlier-established parks have undergone longer periods of development and have already accumulated more mature green innovation technologies. In such cases, the green innovation effect outweighs the carbon intensity effect, leading to a significant reduction in marginal abatement costs. In contrast, parks established in more recent years are more strongly influenced by the carbon intensity effect, whereby park construction tends to increase marginal abatement costs. This suggests that the implementation and reinforcement of the policy require sufficient time to yield substantial effects.

7 Conclusion and discussion

7.1 Conclusions

The implications of environmental regulations have been widely discussed in academic literature, particularly with regard to how such policies influence various sectors and their overall effectiveness. This paper focuses on voluntary environmental regulations, using the National Eco-Industrial Demonstration Park (NEDP) as an illustrative case. In order to identify the impact of NEDP on the marginal abatement cost (MAC) of urban CO_2 emissions, we utilized a dataset of 211 cities with national development zones from 2003 to 2020. Before conducting the benchmark regression in

this paper, we first calculate the MAC of urban CO_2 emissions using the DDF-SFA method, and then analyze the impacts of NEDP policies on MAC at different stages by using a multi-period DID model. Meanwhile, to guarantee that the result is reliable, we conducted robustness tests and further explored the underlying mechanisms contributing to these effects. Finally, the paper evaluates the heterogeneous impacts of NEDPs on municipal MAC under varying policy intensities and park establishment timelines. The key findings of this study are presented below:

To begin with, carbon emissions' MAC in urban areas is reduced by NEDP construction. As a voluntary form of environmental regulation, NEDPs encourage firms to prioritize cost-effective emission reductions. Nevertheless, it is crucial to recognize that the impact of NEDPs does not manifest instantly. There is a certain lag before the parks begin to show measurable impacts, as it takes time for parks to meet completion standards and for their influence on MAC to become more pronounced.

Second, the NEDP policy influences cities' marginal abatement costs primarily through two channels: enhancing urban green innovation and reducing carbon intensity. However, these two channels operate in opposite directions. Overall, the reduction effect of green innovation on marginal abatement costs outweighs the upward effect resulting from the decline in carbon intensity. This also demonstrates the positive role of eco-industrial practices in enhancing the environmental performance of urban areas.

Third, the effectiveness of the NEDP policy in reducing MAC is influenced by both the intensity of the policy and the timing of park

establishment. The policy's inhibitory effect on MAC is most evident in cities with multiple demonstration zones and those with parks that were established early in the process. Conversely, in cities that have only one park or where parks were established at a later time, the NEDP policy not only fails to reduce the MAC, but may even increase it due to the carbon intensity effect.

7.2 Policy suggestions

In light of the results from this research, various recommendations about this policy can be derived to inform the future planning and execution of NEDPs. First, it is essential to accelerate the transformation and construction of parks. Given the increasing global pressure for environmental protection, governments should encourage cities to expedite the conversion of national development zones into NEDPs. This is particularly important in promoting the construction of multiple demonstration parks, as this will enable the realization of emission reduction benefits on a larger scale. By concentrating green technology innovation and facilitating cross-park resource sharing, different parks can support each other, creating synergistic effects that enhance the overall efficiency of emission reduction efforts. At the same time, the NEDP policy should be aligned with other forms of voluntary environmental regulation such as environmental information disclosure, green certification, and corporate social responsibility (CSR) reporting to establish a synergistic policy framework. Through the interaction among these instruments, the policy can further strengthen firms' incentives for green innovation and enhance environmental governance at the park level, thereby improving the overall effectiveness of voluntary environmental regulation. Moreover, the collective impact of multiple parks can amplify the efficiency of voluntary environmental regulation, pushing enterprises within these parks to accelerate their green transformation. As a result, this could bring about a more significant decrease in MAC of carbon emissions.

Second, optimizing the park construction strategy is crucial for ensuring the success of NEDPs. When developing new demonstration parks, the government should implement customized policies that cater to the unique requirements of each park. These policies should account for factors such as the technological maturity of the park, its stage of development, and the regional variations in carbon intensity. Particularly, the government should implement distinct support strategies for early-stage and late-stage parks. For parks established at a later stage, additional support for green technology innovation is necessary to prevent a rise in emission reduction costs due to technological bottlenecks and the high carbon intensity effect. By offering targeted support, the government can help late-stage parks overcome these challenges and continue to contribute to emission reduction goals.

Finally, it is crucial to strengthen the incentive mechanisms for green innovation. Green technology development is a motivating factor for MAC reduction, and fostering this innovation is key to achieving long-term carbon reduction objectives. To promote corporate investment in green technology development, the government ought to adopt diverse support strategies, such as financial subsidies, tax incentives, and technical assistance. By

creating a favorable environment for innovation, the government can stimulate the technological advancements necessary to lower MAC, thereby contributing to China's broader low-carbon goals. Within this framework, advancing the technological upgrading of parks will be key to China's successful steps towards a low-carbon economy.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

JG: Conceptualization, Data curation, Supervision, Writing – original draft, Writing – review and editing. KW: Formal Analysis, Investigation, Resources, Writing – original draft. FH: Investigation, Project administration, Resources, Writing – original draft. HX: Investigation, Resources, Supervision, Writing – original draft. ZQ: Data curation, Project administration, Visualization, Writing – review and editing. YS: Data curation, Formal Analysis, Methodology, Writing – original draft, Writing – review and editing.

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Conflict of interest

Authors JG, FH, and HX was employed by State Grid Dianyi Digital Technology (XiongAn) Co., Ltd. Authors JG, FH, and HX was employed by State Grid Digital Technology Holding Co., Ltd. Author JG, FH, and HX was employed by China State Gri Xiongan Financial Technology Group Co., Ltd. Authors KW, and ZQ was employed by State Grid Electric Power Research Institute /Nari Group Corporation. Authors KW, and ZQ was employed by State Grid Electric Power Research Institute Wuhan Efficiency Evaluation Company Limited.

The remaining author declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Alnafrah, I., Ding, C. J., and Qing, L. (2024). Beyond transparency: unpacking the financial effects of third-party environmental disclosure in China's semiconductor sector. *J. Environ. Manag.* 360, 121237. doi:10.1016/j.jenvman.2024.121237

Arimura, T. H., Kaneko, S., Managi, S., Shinkuma, T., Yamamoto, M., and Yoshida, Y. (2019). Political economy of voluntary approaches: a lesson from environmental policies in Japan. *Econ. Analysis Policy* 64, 41–53. doi:10.1016/j.eap.2019.07.003

Bao, J.-Q., Miao, Y., and Chen, F. (2008). Low-carbon economy: A new transformation of human economic development. *China Ind. Econ.* 04, 153–160. doi:10.19581/j.cnki.ciejournal.2008.04.018

Baumol, W. J., and Oates, W. E. (1988). *The theory of environmental policy*. 2nd ed. Cambridge: Cambridge University Press.

Bokor, B. (2024). Corporate engagement in mitigating plastic pollution: examining voluntary initiatives and EU regulations. *Front. Sustain.* 5, 1420041. doi:10.3389/frsus.2024.1420041

Cao, K., Jin, L., Zhu, Y., Nie, Z., and Li, H. (2022). Does china's national demonstration eco-industrial park reduce carbon dioxide and sulfur dioxide—A study based on the upgrading and transformation process. *Int. J. Environ. Res. Public Health* 19 (19), 12957. doi:10.3390/ijerph191912957

Chen, S., Tan, Z., Wang, J., Zhang, L., He, X., and Mu, S. (2023). Spatial and temporal evolution of synergizing the reduction of pollution and carbon emissions and examination on comprehensive pilot effects–evidence from the national eco-industrial demonstration parks in China. *Environ. Impact Assess. Rev.* 101, 107147. doi:10.1016/j.eiar.2023.107147

Cheng, J., Xu, L., Wang, H., Geng, Z., and Wang, Y. (2022). How does the marginal abatement cost of CO2 emissions evolve in Chinese cities? An analysis from the perspective of urban agglomerations. *Sustain. Prod. Consum.* 32, 147–159. doi:10.1016/j.spc.2022.04.013

Chung, Y. H., Färe, R., and Grosskopf, S. (1997). Productivity and undesirable outputs: a directional distance function approach. *J. Environ. Manag.* 51 (3), 229–240. doi:10.1006/jema.1997.0146

Danish, U., and Ulucak, R. (2021). Renewable energy, technological innovation and the environment: a novel dynamic auto-regressive distributive lag simulation. *Renew. Sustain. Energy Rev.* 150, 111433. doi:10.1016/j.rser.2021.111433

David, M., and Sinclair-Desgagné, B. (2005). Environmental regulation and the eco-industry. *J. Regul. Econ.* 28 (2), 141–155. doi:10.1007/s11149-005-3106-8

Dong, J., Cai, B., Zhang, S., Wang, J., Yue, H., Wang, C., et al. (2023). Closing the gap between carbon neutrality targets and action: technology solutions for China's key energy-intensive sectors. *Environ. Sci. Technol.* 57 (11), 4396–4405. doi:10.1021/acs.est.2c08171

Du, L., Hanley, A., and Wei, C. (2015). Estimating the marginal abatement cost curve of CO2 emissions in China: provincial panel data analysis. *Energy Econ.* 48, 217–229. doi:10.1016/j.eneco.2015.01.007

Färe, R., Grosskopf, S., Lovell, C., and Yaisawarng, S. (1993). Derivation of shadow prices for undesirable outputs: a distance function approach. *Rev. Econ. Statistics* 75 (2), 374–380. doi:10.2307/2109448

Hua, Y., and Tan, X.-Q. (2022). Green location-oriented policies and foreign direct investment: evidence from national eco-industrial demonstration parks. *Int. Trade Issues* 01, 130–145. doi:10.13510/j.cnki.jit.2022.01.008

Hua, Y., and Ye, Y. (2023). The carbon reduction effect of green location-oriented policies: evidence from national eco-industrial demonstration parks. *Quantitative Tech. Econ. Res.* 40 (4), 94–112. doi:10.13653/j.cnki.jqte.20230310.003

Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993). Earnings losses of displaced workers. *Am. Econ. Rev.* 83 (4), 685–709. Available online at: https://www.jstor.org/stable/2117574.

Ji, Y., Shao, Z., and Wang, R. (2024). Does industrial symbiosis improve carbon emission efficiency? Evidence from Chinese national demonstration eco-industrial parks. *Sustainability* 16 (2), 828. doi:10.3390/su16020828

Ke, S.-Z., and Xiang, J. (2012). Estimation of urban fixed capital stock in China from 1996 to 2009. *Stat. Res.* 07, 19–24. doi:10.19343/j.cnki.11-1302/c.2012.07.004

Klepper, G., and Peterson, S. (2006). Marginal abatement cost curves in general equilibrium: the influence of world energy prices. *Resour. Energy Econ.* 28 (1), 1–23. doi:10.1016/j.reseneco.2005.04.001

Kong, L., and Chai, Z. (2021). Does upgrading provincial development zones improve urban economic efficiency? — Quasi-experimental evidence from heterogeneous development zones. *Manag. World* 01, 60–75+5. doi:10.19744/j.cnki.11-1235/f.2021.0005

Lajmi, A., Ben Flah, I., and Shiri, D. (2025). Corporate governance as a moderator of the relationship between environmental regulations and financial performance: evidence from European high-polluting firms. *J. Account. Organ. Change*, 1–25. doi:10.1108/jaoc-03-2025-0088

Lee, C.-C., and Wang, F. (2022). How does digital inclusive finance affect carbon intensity? *Econ. Analysis Policy* 75, 174–190. doi:10.1016/j.eap.2022.05.010

Li, P., Lu, Y., and Wang, J. (2016). Does flattening government improve economic performance? Evidence from China. *J. Dev. Econ.* 123, 18–37. doi:10.1016/j.jdeveco.2016.07.002

Liu, W., Tian, J., Chen, L., Lu, W., and Gao, Y. (2015). Environmental performance analysis of eco-industrial parks in China: a data envelopment analysis approach. *J. Industrial Ecol.* 19 (6), 1070–1081. doi:10.1111/jiec.12233

Liu, L., Yang, X., Meng, Y., Ran, Q., and Liu, Z. (2022). Does the construction of national eco-industrial demonstration parks improve green total factor productivity? Evidence from prefecture-level cities in China. *Sustainability* 14 (1), 26. doi:10.3390/su14010026

Nie, X., Wu, J., Wang, H., Li, W., Huang, C., and Li, L. (2022). Contributing to carbon peak: estimating the causal impact of eco-industrial parks on low-carbon development in China. *J. Industrial Ecol.* 26, 1578–1593. doi:10.1111/jiec.13298

Piekkola, H., and Rahko, J. (2024). The effects of environmental innovations on labor productivity: how does it pay to be green. *Econ. Innovation New Technol.* 34, 1122–1143. doi:10.1080/10438599.2024.2422082

Pörtner, H.-O., Roberts, D. C., and Tignor, M. (2022). "Intergovernmental panel on climate change (IPCC). Climate change 2022: impacts, adaptation, and vulnerability," in *Contribution of working group II to the sixth assessment report of the intergovernmental panel on climate change* (Cambridge, UK and New York, USA: Cambridge University Press).

Qian, L., Xu, X., Sun, Y., and Zhou, Y. (2022). Carbon emission reduction effects of eco-industrial park policy in China. *Energy* 261 (Part B), 125315. doi:10.1016/j.energy.2022.125315

Rekker, L., Kesina, M., and Mulder, M. (2023). Carbon abatement in the European chemical industry: assessing the feasibility of abatement technologies by estimating firm-level marginal abatement costs. *Energy Econ.* 126, 106889. doi:10.1016/j.eneco.2023.106889

Tian, J., Liu, W., Lai, B., Li, X., and Chen, L. (2014). Study of the performance of eco-industrial park development in China. *J. Clean. Prod.* 64, 486–494. doi:10.1016/j.jclepro.2013.08.005

Wang, B., and Nie, X. (2016). Industrial agglomeration and environmental governance: help or hindrance? Evidence from a quasi-natural experiment of the establishment of development zones. *China Ind. Econ.* 12, 75–89. doi:10.19581/j.cnki.ciejournal.2016.12.006

Xu, L., Yang, J., Cheng, J., and Dong, H. (2022). How has China's low-carbon city pilot policy influenced its CO2 abatement costs? Analysis from the perspective of the shadow price. *Energy Econ.* 115, 106353. doi:10.1016/j.eneco.2022.106353

Yu, F., Han, F., and Cui, Z. (2015). Evolution of industrial symbiosis in an eco-industrial park in China. *J. Clean. Prod.* 87, 339–347. doi:10.1016/j.jclepro.2014.10.058

Yu, J., Liu, P., Shi, X., and Ai, X. (2023a). China's emissions trading scheme, firms' R&D investment and emissions reduction. *Econ. Analysis Policy* 80, 1021–1037. doi:10.1016/j.eap.2023.09.039

Yu, J., Liu, P., Fu, D., and Shi, X. (2023b). How do power shortages affect CO2 emission intensity? firm-level evidence from China. *Energy* 282, 128927. doi:10.1016/j.energy.2023.128927

Zhang, N., Huang, X., and Qi, C. (2022). The effect of environmental regulation on the marginal abatement cost of industrial firms: evidence from the 11th five-year plan in China. *Energy Econ.* 112, 106147. doi:10.1016/j.eneco.2022.106147

Zhang, B., Yu, L., and Sun, C. (2023). How do the national eco-industrial demonstration parks affect urban total factor energy efficiency? Evidence from a quasi-natural experiment. *Energy Econ.* 126, 107018. doi:10.1016/j.eneco.2023.107018

Zheng, J.-H., Gao, Y.-Y., and Hu, X.-W. (2008). Enterprise agglomeration, technological upgrading, and economic performance: an empirical analysis of the agglomeration effects in development zones. *Econ. Res.* 05, 33–46. Available online at: https://erj.ajcass.com/#/issue?id=111737&year=2008&issue=5.

Zhou, M., Lu, Y., Du, Y., and Yao, X. (2018). The establishment of development zones and regional manufacturing upgrading. *China Ind. Econ.* 03, 62–79. doi:10.19581/j.cnki.ciejournal.2018.03.004