Received: 17 February 2025 | Revised: 30 July 2025 | Accepted: 30 October 2025 | Published online: 9 December 2025

RESEARCH ARTICLE

Green and Low-Carbon Economy
2025, Vol. 00(00) 1-12
DOI: 10.47852/bonviewGLCE52025436

BON VIEW PUBLISHING

Does China's Environmental Protection Tax Improve Corporate ESG Performance? Causal Inference Based on Double Machine Learning

Yuqiang Gao[1], Shengchang Jiao[1], Kaihua Wang[1], Di Yuan[2,*], Malin Song[3], Mengzi Wang[1]

[1] *School of Economics, Qingdao University, China*

[2] *Business School, Shandong University, China*

[3] *School of Statistics and Applied Mathematics, Anhui University of Finance and Economics, China*

Abstract: The environmental protection tax (EPT), a market-based environmental control mechanism, is essential for enhancing the environmental, social, and governance (ESG) performance of corporations. Using a Double Machine Learning (DML) model, this study empirically investigates the impact of EPT on corporate ESG performance using panel data of the Chinese A-share listed companies from 2012 to 2023. The results illustrate that the EPT improves corporate ESG performance. Furthermore, supplementary robustness tests provide confirmation of the incentive impact. Corporate ESG performance can be enhanced by the EPT through two distinct mechanisms: motivating green technological innovation and increasing green total factor productivity. Heterogeneity analysis demonstrates that the effect of the EPT in promoting corporate ESG performance is more evident in non-state-owned firms, eastern and central regions, and firms with a high proportion of institutional investors. The results of this study have some policy implications for environmental protection that might be educational for many developing nations throughout the world.

Keywords: environmental protection tax, corporate ESG performance, green technological innovation, green total factor productivity, double machine learning model

1. Introduction

China's rapid industrialization and urbanization have marked significant economic development milestones [1], but this growth has come with substantial environmental costs. The growth miracle is accompanied by external diseconomies in the production process of firms, manifested in the overconsumption of resources and the massive growth of pollutant emissions, which do great harm to the ecological environment [2]. Since the 1970s, environmental degradation has become increasingly serious, awakening people's awareness of environmental protection. Simultaneously, governments have been urged to take immediate action to address the problem [3, 4]. To accomplish the mutually harmonious development of the economy and environment, it is necessary to integrate green development principles into corporate governance and operations [5, 6]. As China's first independent environmental tax, the environmental protection tax (EPT) is not aimed at increasing tax revenues but at compelling and encouraging enterprises to promote energy conservation and reduce pollution emissions. The two bear a close correlation with each other.

EPT probably support corporate environmental, social, and governance (ESG) performance by enhancing their environmental, social, and governance practices. From the environmental perspective, the EPT can enhance polluting enterprises' awareness of environmental protection. Under strict environmental supervision, the internalization of environmental protection costs increases significantly, incentivizing firms to upgrade their production processes through increased investment in technological innovation [7, 8]. From the standpoint of social responsibility, the EPT's implementation will also have a favorable effect on business practices. In terms of governance, introducing the EPT can enhance the corporate ESG self-supervision and governance mechanisms. The EPT can motivate firms to establish ESG self-monitoring systems, such as setting up specialized committees for top-down environmental governance. The EPT can actively guide heavy-polluting firms to build and upgrade their ESG governance systems. Incorporating environmental or even ESG assessments into performance appraisals can enhance ESG disclosure and improve the performance of heavy-polluting firms.

ESG performance reflects a new concept of coordinated development [9] and is positively recognized by the capital market and institutional investors. The capital market provides positive feedback to enterprises with better ESG disclosure [10, 11]. In addition, an increasing number of institutional investors are directing their attention to ESG [12].

China's initiatives and achievements in environmental protection are significant on the world stage. China's biggest challenge is striking a balance between environmental protection and economic expansion [13]. The EPT is one of the programs the Chinese government has implemented to improve the state of the environment since it places a high priority on environmental preservation [14]. Studying China's EPT helps us understand the real effects of these policies and the internal mechanisms through which they work [15]. Secondly, China's

***Corresponding author:** Di Yuan, Business School, Shandong University, China. Email: di_yuan@sdu.edu.cn

market size and industrial structure are of unique importance for the introduction and effectiveness of the EPT [16]. A detailed study of China's EPT provides insight into the challenges and opportunities of implementing environmental protection policy in a large-scale economy. Finally, as China is an essential link in the global supply chain, many multinational enterprises have established production bases there [17]. Analyzing China's EPT is helpful for us to understand these multinational responsibilities and practical actions in addressing environmental challenges. This provides lessons for global enterprises to work together to enhance their ESG performance [18].

Therefore, this paper's goal is to investigate the underlying mechanisms and determine if EPT enhances company ESG performance. This study makes three additions to the body of knowledge and real-world applications. First, it enriches the underdeveloped research on EPT and corporate ESG performance by applying the Double Machine Learning (DML) method, which ensures more robust causal inference than conventional approaches. Second, it looks at how EPT influences ESG performance, with a particular emphasis on green total factor productivity and green technical innovation. Third, it provides practical implications by identifying heterogeneous effects across ownership structures, institutional investor presence, and regional characteristics, offering policy guidance for improving ESG performance in emerging markets like China.

2. Literature Review

In recent years, China has achieved remarkable progress in enhancing environmental governance, and the EPT stands out as a pivotal reform in this field. Before 2018, the pollutant discharge fee system was plagued by weak enforcement and excessive discretion on the part of local governments, which frequently compromised its effectiveness. To tackle these problems, the EPT was implemented in 2018, converting environmental levies into a tax regime backed by legal enforcement. Notably, the EPT enables governments to determine tax rates within a legally prescribed range, which takes into account regional variations in environmental goals and economic circumstances. This policy adjustment not only signified the formal establishment of China's independent environmental tax system but also introduced regional differences in enforcement intensity, providing a valuable context for exploring how environmental regulation influences corporate behavior.

Within the body of existing literature, the function of ESG considerations can generally be categorized into three domains. The first domain centers on advancing the ESG evaluation system. A well-developed ESG indicator system has the capacity to guide enterprises more comprehensively and accurately in optimizing their corporate strategies and achieving environmentally sustainable development [19]. Variations in ESG ratings may exert an impact on the economic outcomes of corporate ESG practices [20]. The second category of research focuses on how ESG grading systems affect the economy. This line of research examines how a company's ESG performance affects its debt cost [21], stock price crash risk, financial performance [22], customer structure and operational activities [23], CEO green experience [24], and investment decisions [25]. The third area is dedicated to identifying and explaining the factors that influence ESG considerations. Existing studies have found that the expansion of bank branches [26], institutional heterogeneity [27], digital finance [28], the mixed-ownership reform of state-owned enterprises (SOEs) [29], and a positive social environment [30] have a significant impact. However, establishing a high-quality institutional environment is crucial for improving corporate ESG performance [31]. Thus, it is essential to emphasize the core position of the environmental regulatory framework when analyzing the complex factors related to corporate ESG performance.

With respect to the implementation effect of the EPT, the existing literature holds two contrasting viewpoints. The first viewpoint argues that the introduction of the EPT is of great importance. At the enterprise level, it indicates that green production has become a mandatory obligation for enterprises in their development process [32]. Previous research has demonstrated that putting the EPT into practice can notably boost companies' environmental investments [8], promote their technological innovation [33], enhance their competitiveness [34], affect their profitability, debt capacity [35], and risk level, accelerate the green transformation [36], improve energy use efficiency [37], drive industrial structure upgrading [38], reduce pollutant emissions [15, 39, 40], and improve regional air quality [41–43]. It successfully accomplishes a win-win scenario of economic development and environmental preservation in this way [44–46]. To reduce tax burdens and build a positive corporate image, enterprises tend to optimize their production processes through green transformation, thereby improving their environmental and social performance. Consequently, the EPT has the potential to enhance corporate ESG performance [47].

The second viewpoint, suggests that EPT has not delivered the expected economic effects. Its impact on enterprise performance is not obvious, and it even increases enterprises' costs [48, 49]. For enterprises highly reliant on resource consumption, the EPT has even reduced their corporate performance [50] and hindered their investment in environmental protection [51]. Furthermore, the EPT may trigger adjustments in the industrial structure [52]. Some high-pollution and high-emission industries may be more severely affected, which could lead to the closure of some enterprises [53]. Meanwhile, the tax rate design of the EPT may be either too high or too low for enterprises in different industries, which affects its actual effectiveness in environmental governance [54]. These issues highlight the need for a more comprehensive design of the EPT as a policy tool to simultaneously promote environmental protection.

In summary, against the backdrop of the green economy and sustainable development, the EPT and ESG have become key issues that have attracted widespread attention globally. This paper reviews the literature on the EPT and ESG and offers insights into the interrelationships and mutual influences between these two fields. Previous studies have adopted difference-in-differences (DID) models for research [7, 55] but have lacked nonlinear studies at the micro-enterprise level. Additionally, compared with other causal inference methods, the parallel trend test in DID models requires more sample data, which easily leads to the neglect of inherent differences between different samples, and thus results in biased assessments of policy effects. Therefore, a more diverse and advanced causal inference method is needed. To close this research gap, the DML approach is used in this work.

3. Theoretical Analysis and Research Hypothesis

Environmental performance is significantly influenced by the implementation of the EPT. Neoclassical environmental economics posits that the EPT internalizes the environmental costs incurred by firms by taxing emitted pollutants. This encourages enterprises to upgrade environmental protection to a strategic position in their corporate structure, formulate business strategies aligned with green and sustainable development objectives, pursue technological innovations [56], and enhance productivity [57]. Consequently, firms are motivated to optimize their production methods to curtail energy consumption and diminish pollutant emissions, thereby augmenting their overall environmental performance. From the standpoint of social responsibility, stakeholder theory suggests that an enterprise's performance is closely linked to how it responds to the demands of its stakeholders. The implementation of EPT leads to heightened societal scrutiny of firms' environmental behavior and green sustainable development strategies. This increased scrutiny fosters a positive social reputation, creating conditions conducive to sustainable operations

[58]. Firms demonstrating commendable environmental behavior and social responsibility gain consumer preference, as evidenced by a higher willingness to purchase products from such enterprises [59]. This enhances their competitive market standing. Additionally, by improving their social performance, firms can build closer political affiliations, making it easier to obtain government policy support or preferential measures. From a governance perspective, implementing the EPT enhances the mechanisms for monitoring and managing corporate ESG considerations. While the transformation of corporate shareholders' management awareness and the refinement of the ESG self-monitoring system require time, the long-term effects are substantial. The EPT compels firms to increase their awareness of environmental and social responsibilities, thereby improving their overall ESG performance by directly impacting the "E" and "S" dimensions.

Hypothesis 1: The EPT can significantly improve corporate ESG performance.

The EPT compels enterprises to mitigate pollution by internalizing the external costs associated with it. This policy creates a direct financial incentive to adopt more sustainable practices. Green technological innovation (GTI) emerges as a crucial strategy for balancing corporate profitability with environmental sustainability, leading to a comprehensive transformation of production methodologies. Such transformation is pivotal for enhancing corporate ESG performance and aligning ecological preservation with economic interests [60]. To reduce tax burdens, enterprises will seek methods to mitigate pollution emissions, including improving production processes, adopting environmentally friendly production technologies, and optimizing energy efficiency. Through investments in green technological innovations, enterprises can more effectively manage their environmental responsibilities, a critical component of ESG. According to Farooq et al. [61], using green, innovative technology makes it easier to control negative externalities in operations and manufacturing, which promotes sustainable growth. Under the EPT regime, the heightened costs associated with emissions incentivize firms to invest in technological innovation, thereby bolstering their ESG performance through enhanced environmental sustainability. Moreover, the predictability of the EPT reduces uncertainty, further stimulating innovative activities that contribute to overarching ESG objectives. By investing in practical green production and operations, enterprises can sustain their competitive advantages while concurrently augmenting their ESG performance. This, in turn, promotes consensus-building initiatives aimed at accumulating green capital and attracting innovators [62]. Ultimately, these endeavors foster improved environmental performance for firms, a pivotal element of their ESG strategy.

Hypothesis 2: By stimulating GTI, the EPT has a positive influence on corporate ESG performance.

The EPT plays a crucial role in enhancing corporate ESG performance by boosting their green total factor productivity (GTFP). Historically, China's economic growth relied heavily on factor inputs [63]. However, this growth model has been proven inefficient and environmentally detrimental [64, 65]. To achieve sustainable, high-quality, and green economic growth, a transition towards enhancing GTFP is imperative [66, 67]. In our analytical framework, GTFP serves as a pivotal mechanism. Compelling evidence underscores the significant impact of EPT on GTFP [68]. Motivated by EPT, enterprises are expected to recalibrate their factor input structures towards producing goods with lower energy consumption and pollution [69]. This strategic shift in factor inputs yields substantial benefits, enabling firms to adopt long-term sustainability strategies. By integrating advanced production techniques with optimized factor inputs, firms can address challenges stemming from resource inefficiencies inherent in factor-driven production models [70]. This approach not only facilitates market share acquisition and operational performance enhancement but also generates a compensatory innovation effect, thereby ultimately increasing the GTFP. Enterprises must optimize production resource efficiency to fully comply with EPT requirements [8, 71], thereby compelling them to elevate their GTFP. Increased GTFP drives industrial structure optimization, upgrades energy consumption patterns [72], improves overall resource utilization efficiency [73], and promotes environmentally sustainable production practices [72]. Furthermore, the pursuit of GTFP motivates firms to develop enduring strategies encompassing emission reduction, supply chain management improvements, and governance structure enhancements, contributing to the long-term sustainability of firms within the governance dimension (G) of ESG. This alignment with ESG principles highlights how enhancing GTFP through EPT implementation can drive comprehensive improvements in enterprises' environmental stewardship, social responsibility, and governance practices.

Hypothesis 3: The EPT promotes corporate ESG performance by increasing firms' GTFP.

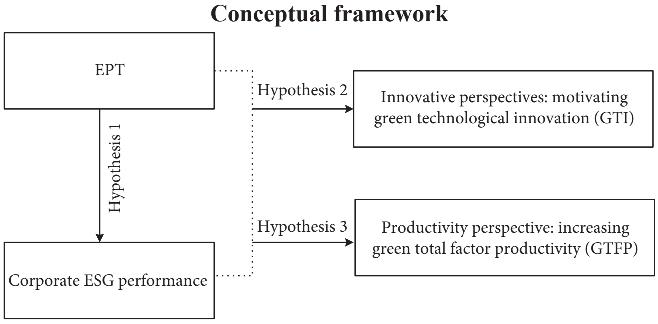
The path exploration for the EPT is able to basically form the logical model below, as depicted in Figure 1.

4. Methodology and Data

4.1 Methodology

This research examines how implementing EPT can affect corporate ESG performance. To date, the majority of relevant research has examined effect assessment using conventional causal inference models. However, such models have many limitations. For instance, the DID model's parallel trend test has to be more stringent when applied to the sample data. Propensity score matching (PSM) involves a great deal of subjective willingness to select variables. In an effort to mitigate the shortcomings of conventional causal inference frameworks, a number of scholars have begun to focus on the use of machine learning in the field of causal inference [74], and the DML model is one of these. The core idea of DML lies in enhancing the accuracy and robustness of causal effect estimation by decomposing complex causal inference problems into two independent prediction tasks and leveraging the powerful capabilities of modern machine learning algorithms. Specifically, it initially utilizes a set of covariates (X) to predict both the outcome variable (Y) and the treatment variable (Event) separately, thereby obtaining their respective prediction residuals. These residuals represent the portions of Y and Event that are not explained by X, effectively eliminating the potential influence of X on Y and Event. Subsequently, by performing a regression analysis on these two residuals, DML is able to directly estimate the net causal effect of the treatment variable on the outcome variable Y. Furthermore, the DML model reduces rule bias in

Figure 1
Conceptual framework



machine learning-based estimation by utilizing the ideas of instrumental variable functions, two-stage residual regression, and sample split fitting. Thus, it ensures the unbiasedness of the disposal coefficient estimator with small samples. Wang et al. [75] argue that DML provides more conservative and robust results than PSM. The results of the study proved that environmental courts significantly promote corporate green innovation. As a new non-parametric approach, DML provides more concrete evidence than the traditional PSM approach. This is because, even though PSM estimates non-linear effects, it uses a linear model in estimating propensities. In contrast, DML does not constrain any linear process and includes both linear and non-linear effects. On this basis, this study uses a DML model to conduct empirical research. The exact build process is as shown in Equations (1) to (8):

The first step is the construction of a partially linear DML model, which is as follows:

$$Y_{\mathrm{it}+1} = \theta_0 Event_{it} + g(X_{it}) + U_{it} \tag{1}$$

$$E(U_{it}|\mathrm{Event}_{it}, X_{it}) = 0 \tag{2}$$

where i is the firm; t is the year; and Y_{it} denotes the explained variable, which is the corporate ESG performance; $Event_{it}$ denotes the disposition variable, the policy variable of "EPT"; θ is the disposal factor that is the key focus of this paper. X_{it} is the set of high-dimensional control variables that use machine learning algorithms to estimate the specific form $\hat{g}(X_{it})$. U_{it} is the error term, which has a conditional mean of 0. Estimating Equations (1) and (2) gives an estimate of the coefficient of dispositions as:

$$\hat{\theta}_0 = \left(\tfrac{1}{n}\sum_{\mathrm{i}\in I,\mathrm{t}\in T} Event_{it}^2\right)^{-1} \tfrac{1}{n}\sum_{\mathrm{i}\in I,\mathrm{t}\in T} Event_{it}\left(Y_{it+1} - \hat{g}(X_{it})\right) \tag{3}$$

where n is the sample size.

Their estimation bias can be further examined using the following estimators:

$$\begin{aligned}\sqrt{n}\left(\hat{\theta}_0 - \theta_0\right) &= \left(\tfrac{1}{n}\sum_{\mathrm{i}\in I,\mathrm{t}\in T} Event_{it}^2\right)^{-1} \tfrac{1}{\sqrt{n}}\sum_{\mathrm{i}\in I,\mathrm{t}\in T} Event_{it}U_{it} \\ &+ \left(\tfrac{1}{n}\sum_{\mathrm{i}\in I,\mathrm{t}\in T} Event_{it}^2\right)^{-1} \tfrac{1}{\sqrt{n}}\sum_{\mathrm{i}\in I,\mathrm{t}\in T} Event_{it}\left[g(X_{it}) - \hat{g}(X_{it})\right]\end{aligned} \tag{4}$$

where $a = \left(\frac{1}{\mathrm{n}}\sum_{\mathrm{i}\in \mathrm{I},\mathrm{t}\in \mathrm{T}} Event_{it}^2\right)^{-1} \frac{1}{\mathrm{n}}\sum_{\mathrm{i}\in I,\mathrm{t}\in T} Event_{it}U_{it}$, obeys a normal distribution with mean 0, and $b = \left(\frac{1}{\mathrm{n}}\sum_{\mathrm{i}\in \mathrm{I},\mathrm{t}\in \mathrm{T}} Event_{it}^2\right)^{-1} \frac{1}{\sqrt{n}} \sum_{\mathrm{i}\in \mathrm{I},\mathrm{t}\in \mathrm{T}} Event_{it}\left[g(X_{it}) - \hat{g}(X_{it})\right]$. It is significant to note that the DML model employs machine learning and its regularization algorithm to evaluate a specific functional form $\hat{g}(X_{it})$, which inevitably introduces a "regularity bias" that prevents the estimator from being too large in variance but also results in it not being unbiased, manifesting in the slower convergence of $\hat{g}(X_{it})$ to $g(X_{it})$. $n^{-\varphi g} > n^{-1/2}$, and thus, since n is infinite and b is infinite, $\hat{\theta}_0$ has difficulty converging to θ_0.

We constructed the following auxiliary regression to speed up convergence and make the disposal coefficient estimates satisfy small-sample unbiasedness.

$$\mathrm{Event}_{\mathrm{it}} = m(X_{it}) + V_{it} \tag{5}$$

$$E(V_{it}|X_{it}) = 0 \tag{6}$$

where $m(X_{it})$ is the regression function of the disposition variable on the high-dimensional control variable, again requiring a machine learning algorithm to estimate its specific form $\widehat{m}(X_{it})$. V_{it} is the error term with a conditional mean of zero. The procedure is as follows: First, a machine learning algorithm is used to estimate the auxiliary regression $\widehat{m}(X_{it})$ and take its residuals $V_{it} = Event_{it} - \widehat{m}(X_{it})$. Second, the same machine learning algorithm is used to assess, changing the form of the main regression to $Y_{it+1} - \hat{g}(X_{it}) = \theta_1 Event_{it}U_{it}$; Finally, $\widehat{V}_{it}$ will be regressed as an instrumental variable for to get unbiased coefficient estimates:

$$\hat{\theta}_1 = \left(\tfrac{1}{n}\sum_{\mathrm{i}\in I,\mathrm{t}\in T} \widehat{V}_{it}Event_{it}\right)^{-1} \tfrac{1}{n}\sum_{\mathrm{i}\in I,\mathrm{t}\in T} \widehat{V}_{it}\left(Y_{it+1} - \hat{g}(X_{it})\right) \tag{7}$$

Similarly, Equation (7) is approximated as:

$$\begin{aligned}\sqrt{n}\left(\hat{\theta}_1 - \theta_1\right)\left[E\left(V_{it}^2\right)\right]^{-1} \tfrac{1}{\sqrt{n}}\sum_{\mathrm{i}\in I,\mathrm{t}\in T} V_{it}U_{it} + \left[E\left(V_{it}^2\right)\right]^{-1} \\ \tfrac{1}{\sqrt{n}}\sum_{\mathrm{i}\in I,\mathrm{t}\in T}\left[m(X_{it}) - \widehat{m}(X_{it})\right]\left[g(X_{it}) - \hat{g}(X_{it})\right]\end{aligned} \tag{8}$$

In the context where the variable $\left[E\left(V_{it}^2\right)\right]^{-1} \frac{1}{\sqrt{n}}\sum_{\mathrm{i}\in I,\mathrm{t}\in T} V_{it}U_{it}$ corresponds to a normal distribution with a mean of 0, the convergence rate of the variable $\left[E\left(V_{it}^2\right)\right]^{-1} \frac{1}{\sqrt{n}}\sum_{\mathrm{i}\in I,\mathrm{t}\in T}\left[m(X_{it}) - \widehat{m}(X_{it})\right]\left[g(X_{it}) - \hat{g}(X_{it})\right]$ is contingent upon both the convergence rates of $\widehat{m}(X_{it})$ to $m(X_{it})$ and $\hat{g}(X_{it})$ to $g(X_{it})$, denoted as $n^{-(\varphi_g+\varphi_{\mathrm{m}})}$, owing to the utilization of two machine learning estimations. Compared to the convergence pattern outlined in Equation (4), the pace at which the variable converges to 0 is expedited, thereby facilitating the acquisition of unbiased estimates for coefficients of dispositions.

In comparison with conventional causal inference models like DID and PSM, the DML approach boasts several distinct advantages. First, DML effectively tackles the "curse of dimensionality"—it leverages machine learning algorithms to process a large volume of control variables, which in turn lowers the risk of omitted variable bias. Second, DML is capable of accommodating potential non-linear relationships among the treatment variable, covariates, and outcome variable. This feature enhances estimation accuracy in complex real-world scenarios where linear associations rarely hold. Third, DML incorporates sample splitting and orthogonalization strategies into its framework. These strategies help alleviate overfitting issues and guarantee valid inference results even when working with finite sample sizes. Owing to these methodological merits, DML can generate more robust and unbiased estimates of the causal effect exerted by the EPT on corporate ESG performance. This represents a notable improvement over traditional linear models, which typically depend on more stringent parametric assumptions to yield results.

4.2 Variables and data description

4.2.1. Explained variable

The explanatory variable used in this study is corporate ESG scores, which are obtained from the Bloomberg database and reflect a company's ESG performance.

4.2.2. Explanatory variable

The variable "post" functions as an indicator variable, taking a value of 1 if the year is after 2018, and 0 otherwise. Given that the EPT predominantly targets industries characterized by substantial pollution, the experimental group in this study comprises listed enterprises operating in the heavy pollution industry, where the variable "treat" takes the value of 1. In contrast, the control group consists of enterprises in the non-heavy pollution industry, where the variable "treat" is assigned the value of 0.

4.2.3. Control variables

By using regularization methods, the DML model successfully tackles the problem of high-dimensional control variables. The variable selection methodology of Huang and Lei [76], Gu et al. [77], and He et al. [78] are referenced to ensure the precision of the EPT effect estimates. Furthermore, considering data availability from prefecture-level municipalities, this paper incorporates controls for a variety of factors that might affect ESG performance. The control variables encompass firm size (Size), gearing ratio (Lev), net profit margin on assets (ROA), shareholding ratio of the first largest shareholder (Top1), growth rate of operating income (Growth), two jobs in one (Dual), nature of equity (SOE), presence of the four major auditing firms (Big4), susceptibility to losses (Loss), Tobin's Q (TobinQ), institutional investor shareholding (INST), regional GDP per capita (GDP), and the share of the secondary industry (Secondary industry). Additionally, this study includes quadratic terms for each control variable in the regression model to improve the accuracy of the fitted model. For a more thorough examination, firm-fixed and time-fixed impacts are also taken into account.

4.2.4. Mechanism variables

GTI: The World Intellectual Property Organization's (WIPO) list of green patents is used to determine the categorization number of green patents in order to calculate GTI. The State Intellectual Property Office's (SIPO) official website is used to manually search listed companies' international patent classification numbers and match them to the different kinds of green technology innovative patents. As a measure of GTI, the number of authorized green utility model patents owned by the sample businesses each year is first obtained, then incremented by one, and lastly transformed into a natural logarithm.

GTFP: The non-radial Slacks-Based Measure–Malmquist-Luenberger (SBM-ML) index is employed to gauge the total factor productivity of firms. It combines the SBM efficiency measurement model introduced by Tone [79], which incorporates non-expected outputs, with the GTFP index ML proposed by Chung et al. [80].

4.3 Data

The corporate ESG performance data is sourced from Bloomberg, GTI data from the State Intellectual Property Office (SIPO) of China, and the remaining data from CSMAR. Since the EPT went into force on January 1, 2018, the experimental period of its introduction is defined as 2018–2023. Chinese A-share listed companies covering the years 2012–2023 make up the whole research sample. The data processing steps are outlined below: (1) excluding samples with missing ESG and control variable data; (2) eliminating ST firms; (3) applying the Winsorization technique to all continuous variables at the 1% quantile; and (4) lagging control variables by one period. All control variables are adjusted with a one-period lag. Additionally, we take the natural logarithm of select control and mechanism variables, adding 1 for scale standardization. The descriptive data for every indication are shown in Table 1.

5. Empirical Results

5.1 Benchmark regression

With the data divided at a 1:4 ratio, this study uses the DML model to assess how the EPT affects company ESG performance. The Random Forest technique is used to carry out the primary and auxiliary regressions. The baseline regression results are shown in Table 2, and the benchmark model includes firm fixed effects, temporal fixed effects, and a complete set of control variables.

The regression outcomes reveal that the EPT significantly enhances corporate ESG performance at the 1% significance level. Even after incorporating the quadratic terms of control variables, this positive effect remains robust. This indicates that after accounting for potential

Table 1
Descriptive statistics of variables

Variable classification	Variable	Descriptions	N	Mean	Std. dev.	Min	Max
Explained variables	ESG	ESG	13873	31.610	10.130	6.198	78.412
	E	E	13873	11.887	15.170	0.000	89.731
	S	S	13873	15.371	8.657	0.514	82.708
	G	G	13873	68.013	13.112	15.021	89.856
Explanatory variable	treat×post	Policy dummy variables	13873	0.096	0.295	0.000	1.000
Control variables	Size	Enterprise size	13873	22.205	1.296	19.903	26.231
	Lev	The ratio of debt to asset	13873	0.419	0.206	0.054	0.899
	Roa	Return on assets	13873	0.041	0.066	-0.249	0.223
	Top1	The share ratio of the largest shareholder	13873	0.377	0.163	0.084	0.780
	Growth	Enterprise's ability to grow in the future	13873	0.169	0.383	-0.502	2.402
	Dual	Two jobs in one	13873	0.295	0.456	0.000	1.000
	Soe	Nature of Property right	13873	0.506	0.500	0.000	1.000
	Big4	Big Four accounting firms	13873	0.125	0.331	0.000	1.000
	Loss	Firm loss	13873	0.110	0.313	0.000	1.000
	TobinQ	TobinQ	13873	1.933	1.329	0.828	8.441
	Shareholding	Institutional investor shareholding	13873	0.501	0.222	0.019	0.912
	GDP	Take the logarithm of regional GDP per capita +1	13873	11.379	0.495	9.954	12.223
	Secondary industry	Value of secondary industry/GDP	13873	40.266	11.607	15.830	64.370
Mechanism variables	GTFP	Green total factor productivity	13873	1.008	0.079	0.854	1.148
	GTI	Green technology innovation	13873	0.923	1.213	0.000	6.346

Table 2
Results for benchmark regressions

	(1) ESG	(2) ESG	(3) E	(4) S	(5) G
Treat×post	1.700*** (0.261)	1.705*** (0.262)	4.271*** (0.526)	0.619** (0.241)	0.202 (0.187)
Time FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Quadratic term	No	Yes	Yes	Yes	Yes
Control variable	Yes	Yes	Yes	Yes	Yes
Obs	13873	13873	13873	13873	13873

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are robust standard errors for coefficient estimates. The same below.

non-linear relationships and high-dimensional covariates, the EPT still exerts a stable promotional influence on corporate ESG performance.

A deeper analysis of each ESG sub-dimension shows that EPT has a notably positive impact on both environmental (E) and social (S) scores, whereas its effect on the governance (G) dimension is statistically non-significant. This trend underscores that the EPT primarily drives improvements in corporate behaviors related to environmental protection and social responsibility—an outcome that aligns with the tax's design goal of internalizing environmental externalities and motivating enterprises to reduce pollution.

The significant improvement in the "E" dimension reflects the EPT's policy efficacy in promoting cleaner production among heavy-polluting enterprises, boosting their investments in pollution control, and encouraging enhancements in resource utilization efficiency. As for the positive effect on the "S" dimension, it can be explained by the heightened stakeholder pressure and incentives for corporate reputation management under stricter environmental regulations. These factors drive enterprises to improve employee welfare, strengthen product responsibility, and increase engagement with local communities.

In contrast, the non-significant impact on the governance (G) dimension is reasonable. The EPT primarily targets environmental performance and does not directly affect internal corporate governance mechanisms. Changes to governance structures usually require more time and internal organizational adjustments, and such structures are less responsive to external environmental taxes in the short term.

Overall, these results lend credence to Hypothesis 1. Promoting corporate ESG performance—primarily by enhancing enterprises' environmental and social responsibilities. This offers micro-level evidence that market-oriented environmental policies can improve corporate sustainability practices without exerting adverse effects on firms' governance structures.

5.2 Robustness tests

5.2.1. Replacement of explanatory variables

This study uses the strategy of substituting the explanatory factors to ensure the conclusions are robust. Table 3, column (1) displays the results of substituting CSI ESG ratings data for the original explanatory factors. The significance test findings and the direction of the coefficients remain consistent when compared to the benchmark regression results, demonstrating the high degree of dependability of the conclusions.

5.2.2. Considering province-time interaction fixed effects

In the governance structure of the Chinese government, the provinces play an essential role. As administrative nodes, their policy formulation and implementation have far-reaching implications for the country. Cities in the same province tend to exhibit a certain degree of similarity in policy environment, geographic location, history, and culture. Table 3 shows the specific results of the regressions when considering province-time interaction fixed effects.

5.2.3. Excluding the effect of parallel policy

Before the implementation of EPT, some other environmental regulatory policies were introduced in China. One notable example is the newly revised Environmental Protection Law, which was promulgated and implemented in 2015. To ensure accurate effect estimates of EPT, this paper controls the newly revised policy. The policy dummy variable "environmental protection" is therefore created in this research to be included in the regression analysis. The policy effect of EPT remains significant even when the impact of parallel policies is excluded, and the original conclusions remain robust.

5.2.4. Replacement of the estimation model

The regression estimation above uses a partially linear regression (PLR) model constructed by the DML machine, and a more general interaction model is constructed based on the DML approach for robustness testing.

The primary regression changes and auxiliary regression changes used in this analysis are shown in Equations (9) to (11).

$$Y_{\mathrm{it+1}} = g(Event_{it}, X_{it}) + U_{it} \tag{9}$$

$$Event_{it} = m(X_{it}) + V_{it} \tag{10}$$

The estimates of the coefficients of the disposition effect from the interactive model are:

$$\hat{\theta}_1 = E[g(Event_{it} = 1, X_{it}) - g(Event_{it} = 0, X_{it})]. \tag{11}$$

The specific regression results are presented in Table 3. These coefficients remain significantly positive at the 1% level, indicating robust results.

Table 3
Results for robustness tests

	Replacement of explanatory variables	Interaction model	Province×year	SVM	Gradboost	Lassocv	K8	K3	Excluding relevant policies
Treat×post	0.095*** (0.027)	5.879*** (0.620)	1.753*** (0.262)	7.911*** (0.303)	2.001*** (0.272)	1.013*** (0.196)	1.732*** (0.263)	3.826*** (0.243)	3.826*** (0.243)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	16869	13873	13873	13873	13873	13873	13873	13873	13873

5.2.5. Replacing machine learning model parameters

This paper conducts robustness tests from two dimensions to avoid the influence of bias arising from the DML model settings on the study's conclusions. First, change the machine learning algorithms employed in the analysis, that is to say, replace the random forest algorithm with support vector machines (SVM), gradient boosting (GradBoost), and least absolute shrinkage and selection operator (Lasso). Second, adjust the original sample segmentation ratio from 1:4 to 1:2 and 1:7, respectively. The adjustment aims to throw light on the possible effects of distinct split proportions on the results.

The result remains same whether the machine learning technique is substituted or the sample split ratio is modified. This is enough to demonstrate the validity of the results.

5.3 Transmission mechanism test

The aforementioned research has verified the substantial contribution of EPT to corporate ESG performance. Nevertheless, this paper is likely to focus more on how EPT might promote the growth path of corporate ESG performance. Based on the existing literature, the improvement of corporate ESG performance probably owes to GTI and GTFP. This section employs a causal mediation effect analysis to explore this trajectory, drawing inspiration from Farbmacher et al. [81]. Utilizing a DML model and R software, the examination is conducted through lasso regression to scrutinize the transmission mechanism of EPT on corporate ESG performance. This analysis is approached from an innovation and a productivity perspective, respectively. The detailed outcomes are presented in Table 4. The findings indicate that the total utility exhibits a significantly positive correlation at the 1% significance level across all examined paths. Above all, these results substantiate and reinforce the conclusion that EPT positively influences corporate ESG performance.

5.3.1. Innovative perspectives

Innovation not only serves as the core driver of development but also holds vital importance for enterprises seeking to improve their ESG performance. In this study, the number of green utility patents is increased by one, and the natural logarithm of this adjusted figure is used to gauge GTI. The indirect effect of GTI is significantly positive at the 1% level in both the control and disposal groups. This indicates that the increase in the level of GTI brought about by EPT can significantly improve ESG performance. After divesting the green technology innovation path, the direct effect remains positive and significant at the 1% level for both the disposal and control groups. These results imply that firms achieve green transformation through positive technological innovation, which improves their ESG performance, thus supporting Hypothesis 2.

5.3.2. Productivity perspective

Comparable to the ESG performance of enterprises, GTFP is a comprehensive index that integrates environmental factors into its analytical framework. It measures the extent of green development, including undesirable outputs such as resource utilization and environmental pollution within the entire factor productivity framework, seeking to make economic development live in harmony with the ecological environment. GTFP dramatically affects the future development of firms, which further affects their environmental, social, and governance performance. This study analyzes firms' GTFP as a mechanism variable in a regression analysis. The results reveal that the indirect effects of the disposal and control groups are notably positive at the 1% level. Simultaneously, the direct impact of EPT on corporate ESG performance remains significantly positive. This declares that EPT can improve corporate ESG performance by elevating GTFP, thereby establishing Hypothesis 3.

The mechanism analysis reveals that EPT promotes corporate ESG performance primarily through two channels: GTI and GTFP. Specifically, the positive indirect impacts through GTI verify that the EPT spurs enterprises to boost their investment in green innovation, motivated by the necessity to lower environmental tax expenses and adhere to more stringent environmental rules. This aligns with the Porter Hypothesis, suggesting that appropriate environmental regulation can stimulate innovation and enhance competitiveness. Meanwhile, the GTFP pathway illustrates that EPT compels firms to optimize resource allocation, improve production efficiency, and transition towards more sustainable production processes. This mechanism highlights that EPT does not only impose additional costs but also incentivizes firms to pursue operational efficiency and long-term sustainable growth, thereby improving overall ESG outcomes.

6. Further Analyses

The empirical evidence begins with a systematic study of the impact of policies from a comprehensive perspective using the entire sample. Various robustness tests substantiate the efficiency of EPT in promoting corporate ESG performance. It is imperative to underscore the investigation into whether EPT yields uniform effects across diverse categories of enterprises. The sample is classified based on enterprise ownership, institutional investor shareholding, and regional disparities to probe such distinctions. Apart from presenting the empirical outcomes of heterogeneity grouping tests, the Fisher test is employed.

The specific process of Fisher test is as follows. First, a total of 6349 firms were randomly selected as private enterprises, while the remaining were categorized as state-owned enterprises. Second, the event coefficients of the two sets of samples generated through random sampling are calculated separately, and then the difference between the two coefficients is calculated as $d_{s1} = \theta_{\text{private}} - \theta_{\text{public}}$. Third, steps 1 and step 2 are iterated 100 times to generate 100 statistics of d {d1, d2, d3..., d100}. The number of statistics d that are more significant than the actual observed coefficient difference is counted (denoted as n), and the empirical p-value is calculated as n/100. The coefficient difference between the two sample groups is significant at the 10% level if the empirical p-value is less than 0.1.

6.1. Enterprise ownership heterogeneity

Because SOEs and non-SOEs differ significantly in terms of resources, political backing, and goals, it is essential to examine how EPT affects businesses with various ownership arrangements. Table 5

Table 4
Results for mechanism tests

Variable	total effect	Disposal group direct effect	Control group direct effect	Disposal group indirect effect	Control group indirect effect
GTFP	2.138***	1.798***	1.773***	0.365***	0.340***
	(0.232)	(0.240)	(0.243)	(0.129)	(0.089)
GTI	4.586***	4.485***	4.502***	0.084***	0.101***
	(0.222)	(0.220)	(0.221)	(0.009)	(0.001)

Table 5
Heterogeneity analysis

	Eastern part	Central part	Western part	State-owned	Non-state-owned	High investment ratio	Low investment ratio
Treat×post	2.136***	1.219**	0.638	1.607***	2.225***	1.883***	1.560***
	(0.313)	(0.596)	(0.576)	(0.343)	(0.400)	(0.340)	(0.386)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	8698	2474	2343	5480	5349	6954	6810
Experienced *p*-value		0.00		0.04		0.00	

examines the heterogeneity of the impact of different property rights on the ESG performance of enterprises that employ EPT. The empirical p-value indicates that the difference between the coefficients of the state-owned and non-state-owned samples is significant at the 1% level. This difference can be attributed to SOEs' closer relationships with governmental entities, providing them with resource endowments and less financial pressure. In contrast, non-SOEs are sufficiently incentivized to protect the environment to ensure good relations with the government, reduce financial constraints, and attract more investment.

6.2. Institutional investor shareholding heterogeneity

Institutional investors are the primary audience for securities analysis services. Their focus on ESG issues inevitably attracts analysts' attention to corporate ESG performance. Furthermore, listed firms increasingly emphasize the sustainability of their development, strengthen their commitment to social responsibility, and improve their green corporate governance mechanisms. These actions help establish a broader investor base and enhance corporate valuation. Using the annual industry median as a threshold, firms are classified into those with low and high proportions of institutional investor ownership. The results, presented in Table 5, show a coefficient of 1.883 for the effect of EPT on ESG performance among enterprises with substantial institutional investor ownership, achieving statistical significance at the 1% level. In contrast, firms with a lower institutional investor ownership ratio exhibit an impact coefficient of 1.560 on ESG performance, also achieving statistical significance at the 1% level.

6.3. Regional disparity heterogeneity

According to Lei et al. [82], China's environmental policy framework has notable regional variations in environmental control. Based on geographical location and economic development, this paper divides firms into three regions: eastern, central, and western. The policy coefficient of the western region is positive but insignificant. The political coefficient of eastern region is positive and significant at the 1% level. In comparison, the policy coefficient of the central region is essential at the 5% level and has an empirical p-value of 0.04. One possible reason for this is the higher overall tax burden in the eastern part of the country, where firms face higher tax costs. By improving their ESG performance, firms aim to ease financial constraints and attract investment. Additionally, the eastern and central regions have a higher concentration of talent and more mature funding mechanisms than other regions, providing stronger incentives to innovate. In contrast, in the western region, efforts to reduce environmental pollution have not been effectively implemented, and many enterprises still have significant deficiencies in environmental governance and social responsibility. Therefore, the guidance of EPT can better lead to the optimization and improvement of enterprise management in the western region, thereby enhancing corporate ESG performance.

The heterogeneity analysis further enriches the understanding of EPT's impact. The stronger positive effects observed among non-state-owned enterprises (non-SOEs) suggest that firms with less political backing and greater market exposure are more sensitive to environmental taxation and more motivated to improve ESG performance for market reputation and investment attraction. In contrast, SOEs, often shielded by administrative resources, exhibit weaker responsiveness. Additionally, firms with higher institutional investor ownership demonstrate more pronounced ESG improvements after EPT implementation. Regional heterogeneity results indicate that firms in the eastern and central regions respond more actively to EPT, likely due to higher regulatory pressure, stricter enforcement, and better market conditions for green innovation. The insignificant effect in western regions may reflect weaker regulatory enforcement and limited innovation capacity, suggesting a need for differentiated policy design across regions.

7. Conclusions and Recommendations

7.1. Conclusions

According to the study, putting EPT into practice greatly enhances company ESG performance, and the empirical findings hold up even after a few robustness tests. Additionally, non-state-owned businesses, businesses with large institutional investor ownership percentages, and businesses in the eastern and central regions are more significantly impacted by the EPT when it comes to improving ESG performance. Furthermore, by strengthening the "E" and "G" aspects, this study demonstrates that EPT enhances corporate ESG performance. Finally, the mechanism test indicates that GTI and GTFP effectively influence EPT to enhance corporate ESG performance. This research concludes that EPT has generated positive effects and is of great practical significance in promoting sustainability of enterprises. It encourages enterprises to undertake social responsibility and actively build ESG-related governance mechanisms.

This study employs a limited set of variables to conduct initial exploration into the microeconomic impacts of the environmental protection tax law, thereby contributing to the literature on factors influencing corporate ESG performance. However, the ESG practices of listed enterprises in China are still nascent, resulting in incomplete disclosures and a lack of crucial data necessary for comprehensive analyses. As China's ESG practices steadily advance, there is a growing imperative to acquire more comprehensive trace data to facilitate more nuanced studies. This direction has been a longstanding focus of the author.

7.2. Policy implications

This study makes the following specific policy proposals to improve the efficacy of China's EPT and advance corporate ESG performance in light of the empirical findings.

First, regulators ought to explore a differentiated EPT design that takes enterprise ownership structures into account. The findings show that non-SOEs respond more strongly to the EPT, whereas SOEs exhibit limited improvements in ESG performance. For this reason, supplementary mechanisms can be introduced for SOEs—such as stricter ESG disclosure rules, deeper internal governance reforms, and environmental incentives tied to performance—to enhance their responsiveness to environmental policies.

Second, the EPT's positive impact is more notable among enterprises with higher institutional investor ownership. Policymakers should encourage institutional investors to participate more actively in corporate governance: this can be done by promoting ESG-oriented investment strategies and reinforcing shareholder activism, which may be achieved through refining green investment guidelines and improving ESG information transparency in capital markets.

Third, considering the significant regional differences in the EPT's effect—its impact is stronger in eastern and central regions but statistically insignificant in western regions—the government needs to pursue a more balanced regional policy approach. In less developed western regions, it is recommended to pair the EPT with additional support measures: increasing government subsidies for green technologies, launching capacity-building programs, and implementing phased adjustments to tax rates. These measures can help avoid imposing excessive financial pressure on local enterprises while facilitating gradual progress in environmental protection.

Finally, to maximize the EPT's policy impact, cross-departmental collaboration between environmental authorities and tax agencies should be strengthened to improve tax collection efficiency and enforcement. Moreover, a dynamic adjustment mechanism for EPT rates should be established, enabling flexible policy responses based on factors like pollution levels, industry traits, and regional development priorities. Such targeted strategies will better align environmental protection objectives with corporate sustainable development, and ensure a more equitable and effective green transition.

Funding Support

This research is supported by the National Social Science Foundation of China (nos. 20BJL074).

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Yuqiang Gao: Conceptualization, Validation, Project administration, Funding acquisition. **Shengchang Jiao:** Conceptualization, Methodology, Software, Investigation, Writing – original draft. **Kaihua Wang:** Formal analysis, Writing – review & editing. **Di Yuan:** Validation, Writing – review & editing, Project administration. **Malin Song:** Supervision. **Mengzi Wang:** Writing – review & editing.

References

[1] Liang, L., Chen, M., & Lu, D. (2022). Revisiting the relationship between urbanization and economic development in China since the reform and opening-up. *Chinese Geographical Science*, *32*(1), 1–15. https://doi.org/10.1007/s11769-022-1255-7

[2] Hassan, A., Yang, J., Usman, A., Bilal, A., & Ullah, S. (2023). Green growth as a determinant of ecological footprint: Do ICT diffusion, environmental innovation, and natural resources matter? *PLOS ONE*, *18*(9), e0287715. https://doi.org/10.1371/journal.pone.0287715

[3] Guo, W., Yang, B., Ji, J., & Liu, X. (2023). Green finance development drives renewable energy development: Mechanism analysis and empirical research. *Renewable Energy*, *215*, 118982. https://doi.org/10.1016/j.renene.2023.118982

[4] Li, L., Zeng, Y., He, Y., Qin, Q., Wang, J., & Fu, C. (2022). Developing village-based green economy in an endogenous way: A case study from China. *International Journal of Environmental Research and Public Health*, *19*(13). https://doi.org/10.3390/ijerph19137580

[5] Mahmood, N., Zhao, Y., Lou, Q., & Geng, J. (2022). Role of environmental regulations and eco-innovation in energy structure transition for green growth: Evidence from OECD. *Technological Forecasting and Social Change*, *183*, 121890. https://doi.org/10.1016/j.techfore.2022.121890

[6] Ye, Y. (2023). Research on the impact of integrated marketing communication on consumers' perceived value from the perspective of green marketing. In *8th International Conference on Financial Innovation and Economic Development*, 742–748. https://doi.org/10.2991/978-94-6463-142-5_84

[7] Li, J., & Li, S. (2022). Environmental protection tax, corporate ESG performance, and green technological innovation. *Frontiers in Environmental Science*, *10*, 982132. https://doi.org/10.3389/fenvs.2022.982132

[8] Liu, G., Yang, Z., Zhang, F., & Zhang, N. (2022). Environmental tax reform and environmental investment: A quasi-natural experiment based on China's Environmental Protection Tax Law. *Energy Economics*, *109*, 106000. https://doi.org/10.1016/j.eneco.2022.106000

[9] Zhang, X. (2023). How does government support promote the relationship between ESG performance and innovation? *Journal of Innovation and Development*, *3*(2), 89–92. https://doi.org/10.54097/jid.v3i2.9391

[10] Moalla, M., & Dammak, S. (2023). Corporate ESG performance as good insurance in times of crisis: Lessons from US stock market during COVID-19 pandemic. *Journal of Global Responsibility*, *14*(4), 381–402. https://doi.org/10.1108/JGR-07-2022-0061

[11] Stroebel, J., & Wurgler, J. (2021). What do you think about climate finance? *Journal of Financial Economics*, *142*(2), 487–498. https://doi.org/10.1016/j.jfineco.2021.08.004

[12] Wang, H. (2024). ESG investment preference and fund vulnerability. *International Review of Financial Analysis*, *91*, 103002. https://doi.org/10.1016/j.irfa.2023.103002

[13] Peng, J., Fu, S., Gao, D., & Tian, J. (2023). Greening China's growth: Assessing the synergistic impact of financial development and technological innovation on environmental pollution reduction—A spatial stirpat analysis. *International Journal of Environmental Research and Public Health*, *20*(6), 5120. https://doi.org/10.3390/ijerph20065120

[14] Xu, L., Yang, L., Li, D., & Shao, S. (2023). Asymmetric effects of heterogeneous environmental standards on green technology innovation: Evidence from China. *Energy Economics*, *117*, 106479. https://doi.org/10.1016/j.eneco.2022.106479

[15] He, Y., Zhao, X., & Zheng, H. (2023c). How does the environmental protection tax law affect firm ESG? Evidence from the Chinese stock markets. *Energy Economics*, *127*, 107067. https://doi.org/10.1016/j.eneco.2023.107067

[16] Qing, L., Alwahed Dagestani, A., Shinwari, R., & Chun, D. (2023). Novel research methods to evaluate renewable energy and energy-related greenhouse gases: Evidence from BRICS economies. *Economic Research-Ekonomska Istraživanja*, *36*(1), 960–976. https://doi.org/10.1080/1331677X.2022.2080746

[17] Guan, D., Wang, D., Hallegatte, S., Davis, S. J., Huo, J., Li, S., …, & Gong, P. (2020). Global supply-chain effects of COVID-19 control measures. *Nature Human Behaviour*, *4*(6), 577–587. https://doi.org/10.1038/s41562-020-0896-8

[18] Vasilyeva, T., Samusevych, Y., Babenko, V., Bestuzheva, S., Bondarenko, S., & Nesterenko, I. (2023). Environmental taxation: Role in promotion of the pro-environmental behaviour. *WSEAS Transactions on Business and Economics*, *20*, 410–427. https://doi.org/10.37394/23207.2023.20.38

[19] Pislaru, M., Herghiligiu, I. V., & Robu, I.-B. (2019). Corporate sustainable performance assessment based on fuzzy logic. *Journal of Cleaner Production*, *223*, 998–1013. https://doi.org/10.1016/j.jclepro.2019.03.130

[20] Mao, Z., Wang, S., & Lin, Y. (2024). ESG, ESG rating divergence and earnings management: Evidence from CHINA. *Corporate Social Responsibility and Environmental Management*, *31*(4), 3328–3347. https://doi.org/10.1002/csr.2748

[21] Mathath, N., Kumar, V., & Balasubramanian, G. (2024). The effect of Environmental, Social, and Governance disclosure on cost of debt: A life-cycle perspective. *Managerial and Decision Economics*, *45*(4), 1883–1893. https://doi.org/10.1002/mde.4105

[22] Kao, F. C. (2023). How do ESG activities affect corporate performance? *Managerial and Decision Economics*, *44*(7), 4099–4116. https://doi.org/10.1002/mde.3944

[23] Han, S., & Wang, Y. (2024). Reducing dependency: Corporate ESG profiles and customer structure. *Managerial and Decision Economics*, *45*(6), 4053–4071. https://doi.org/10.1002/mde.4224

[24] Deng, M., Tang, H., & Luo, W. (2024). Can the green experience of CEO improve ESG performance in heavy polluting companies? Evidence from China. *Managerial and Decision Economics*, *45*(4), 2373–2392. https://doi.org/10.1002/mde.4149

[25] Avramov, D., Cheng, S., Lioui, A., & Tarelli, A. (2022). Sustainable investing with ESG rating uncertainty. *Journal of Financial Economics*, *145*(2), 642–664. https://doi.org/10.1016/j.jfineco.2021.09.009

[26] Tian, Z., Shen, Y., & Chen, Z. (2024). How does bank branch expansion affect ESG: Evidence from Chinese commercial banks. *Economic Analysis and Policy*, *82*, 502–514. https://doi.org/10.1016/j.eap.2024.03.025

[27] Wang, Y., Lin, Y., Fu, X., & Chen, S. (2023). Institutional ownership heterogeneity and ESG performance: Evidence from China. *Finance Research Letters*, *51*, 103448. https://doi.org/10.1016/j.frl.2022.103448

[28] Mu, W., Liu, K., Tao, Y., & Ye, Y. (2023). Digital finance and corporate ESG. *Finance Research Letters*, *51*, 103426. https://doi.org/10.1016/j.frl.2022.103426

[29] Liu, K., Wang, J., Liu, L, & Huang, Y. (2023). Mixed-ownership reform of SOEs and ESG performance: Evidence from China. *Economic Analysis and Policy*, *80*, 1618–1642. https://doi.org/10.1016/j.eap.2023.10.016

[30] Ortas, E., Gallego-Álvarez, I., & Álvarez, I. (2019). National institutions, stakeholder engagement, and firms' environmental, social, and governance performance. *Corporate Social Responsibility and Environmental Management*, *26*(3), 598–611. https://doi.org/10.1002/csr.1706

[31] Liu, X., Cifuentes-Faura, J., Zhao, S., & Wang, L. (2024). The impact of government environmental attention on firms' ESG performance: Evidence from China. *Research in International Business and Finance*, *67*, 102124. https://doi.org/10.1016/j.ribaf.2023.102124

[32] Yin, Q., Lin, Y., Yuan, B., & Dong, Z. (2023). Does the environmental protection tax reduce environmental pollution? Evidence from a quasi-natural experiment in China. *Environmental Science and Pollution Research*, *30*(48), 106198–106213. https://doi.org/10.1007/s11356-023-29898-4

[33] Xu, Y., Wen, S., & Tao, C.-Q. (2023). Impact of environmental tax on pollution control: A sustainable development perspective. *Economic Analysis and Policy*, *79*, 89–106. https://doi.org/10.1016/j.eap.2023.06.006

[34] Porter, M. E., & Linde, C. V. D. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives*, *9*(4), 97–118. https://doi.org/10.1257/jep.9.4.97

[35] Ren, Y., Hu, G., & Wan, Q. (2024). Environmental protection tax and diversified transition of heavily polluting enterprises: Evidence from a quasi-natural experiment in China. *Economic Analysis and Policy*, *81*, 1570–1592. https://doi.org/10.1016/j.eap.2024.02.031

[36] Su, Y., Zhu, X., Deng, Y., Chen, M., & Piao, Z. (2023). Does the greening of the tax system promote the green transformation of China's heavily polluting enterprises?. *Environmental Science and Pollution Research*, *30*(19), 54927–54944. https://doi.org/10.1007/s11356-023-26027-z

[37] Mandal, S. K. (2010). Do undesirable output and environmental regulation matter in energy efficiency analysis? Evidence from Indian Cement Industry. *Energy Policy*, *38*(10), 6076–6083. https://doi.org/10.1016/j.enpol.2010.05.063

[38] Lin, C., Cui, G., & Sun, Y. (2023). Labor allocation: How environmental regulation promotes industrial structure. *Managerial and Decision Economics*, *44*(4), 1995–2003. https://doi.org/10.1002/mde.3795

[39] He, P., & Zhang, B. (2018). Environmental tax, polluting plants' strategies and effectiveness: Evidence from China. *Journal of Policy Analysis and Management*, *37*(3), 493–520. https://doi.org/10.1002/pam.22052

[40] Liu, L., & Zhou, S. (2023). Environmental regulation, public environmental concern, and pollution reduction. *Managerial and Decision Economics*, *45*(8), 5231–5248. https://doi.org/10.1002/mde.4011

[41] Han, F., & Li, J. (2020). Assessing impacts and determinants of China's environmental protection tax on improving air quality at provincial level based on Bayesian statistics. *Journal of Environmental Management*, *271*, 111017. https://doi.org/10.1016/j.jenvman.2020.111017

[42] Li, X., & Deng, G. (2021). Research on the Effect of an environmental protection tax policy on haze control in China—Empirical analysis based on provincial panel data. *Sustainability*, *14*(1), 41. https://doi.org/10.3390/su14010041

[43] Xue, W., Wang, L., Yang, Z., Xiong, Z., Li, X., Xu, Q., & Cai, Z. (2023). Can clean heating effectively alleviate air pollution: An empirical study based on the plan for cleaner winter heating in northern China. *Applied Energy*, *351*, 121923. https://doi.org/10.1016/j.apenergy.2023.121923

[44] Dagestani, A. A., Shang, Y., Schneider, N., Cifuentes-Faura, J., & Zhao, X. (2023). Porter in China: A quasi-experimental view of market-based environmental regulation effects on firm performance. *Energy Economics*, *126*, 106966. https://doi.org/10.1016/j.eneco.2023.106966

[45] Xiao, X., & Liu, Y. (2023). Is China's environmental governance model a win-win for energy conservation and economic development? *Emerging Markets Finance and Trade*, *59*(2), 324–337. https://doi.org/10.1080/1540496X.2022.2101360

[46] Zhang, M., & Huang, M. (2023). Study on the impact of informal environmental regulation on substantive green innovation in China: Evidence from PITI disclosure. *Environmental Science and Pollution Research*, *30*(4), 10444–10456. https://doi.org/10.1007/s11356-022-22868-2

[47] Chen, G., Wei, B., & Dai, L. (2022). Can ESG-responsible investing attract sovereign wealth funds' investments? Evidence from Chinese listed firms. *Frontiers in Environmental Science*, *10*, 935466. https://doi.org/10.3389/fenvs.2022.935466

[48] Jiang, Z., Xu, C., & Zhou, J. (2023). Government environmental protection subsidies, environmental tax collection, and green innovation: Evidence from listed enterprises in China. *Environmental Science and Pollution Research*, *30*(2), 4627–4641. https://doi.org/10.1007/s11356-022-22538-3

[49] Mardones, C., & Ortega, J. (2023). The individual and combined impact of environmental taxes in Chile − A flexible computable general equilibrium analysis. *Journal of Environmental Management*, *325*, 116508. https://doi.org/10.1016/j.jenvman.2022.116508

[50] Long, F., Lin, F., & Ge, C. (2022). Impact of China's environmental protection tax on corporate performance: Empirical data from heavily polluting industries. *Environmental Impact Assessment Review*, *97*, 106892. https://doi.org/10.1016/j.eiar.2022.106892

[51] Cheng, Z., Chen, X., & Wen, H. (2022). How does environmental protection tax affect corporate environmental investment? Evidence from Chinese listed enterprises. *Sustainability*, *14*(5), 2932. https://doi.org/10.3390/su14052932

[52] Du, K., Cheng, Y., & Yao, X. (2021). Environmental regulation, green technology innovation, and industrial structure upgrading: The road to the green transformation of Chinese cities. *Energy Economics*, *98*, 105247. https://doi.org/10.1016/j.eneco.2021.105247

[53] Huang, Y., Haseeb, M., Usman, M., & Ozturk, I. (2022). Dynamic association between ICT, renewable energy, economic complexity and ecological footprint: Is there any difference between E-7 (Developing) and G-7 (Developed) countries? *Technology in Society*, *68*, 101853. https://doi.org/10.1016/j.techsoc.2021.101853

[54] Wolde-Rufael, Y., & Mulat-weldemeskel, E. (2023). Effectiveness of environmental taxes and environmental stringent policies on CO2 emissions: The European experience. *Environment, Development and Sustainability*, *25*(6), 5211–5239. https://doi.org/10.1007/s10668-022-02262-1

[55] He, P., Zhang, S., Wang, L., & Ning, J. (2023a). Will environmental taxes help to mitigate climate change? A comparative study based on OECD countries. *Economic Analysis and Policy*, *78*, 1440–1464. https://doi.org/10.1016/j.eap.2023.04.032

[56] Ouyang, X., Li, Q., & Du, K. (2020). How does environmental regulation promote technological innovations in the industrial sector? Evidence from Chinese provincial panel data. *Energy Policy*, *139*, 111310. https://doi.org/10.1016/j.enpol.2020.111310

[57] Rao, M., Vasa, L., Xu, Y., & Chen, P. (2023). Spatial and heterogeneity analysis of environmental taxes' impact on China's green economy development: A sustainable development perspective. *Sustainability*, *15*(12), 9332. https://doi.org/10.3390/su15129332

[58] Novitasari, M., Wijaya, A. L., Agustin, N. M., Gunardi, A., & Dana, L. (2023). Corporate social responsibility and firm performance: Green supply chain management as a mediating variable. *Corporate Social Responsibility and Environmental Management*, *30*(1), 267–276. https://doi.org/10.1002/csr.2353

[59] Iqbal, A., Kazmi, S. Q., Anwar, A., Ramish, M. S., & Salam, A. (2023). Impact of green marketing on green purchase intention and green consumption behavior: The moderating role of green concern. *Journal of Positive School Psychology*, *7*(2).

[60] Saqib, N., Usman, M., Ozturk, I., & Sharif, A. (2024). Harnessing the synergistic impacts of environmental innovations, financial development, green growth, and ecological footprint through the lens of SDGs policies for countries exhibiting high ecological footprints. *Energy Policy*, *184*, 113863. https://doi.org/10.1016/j.enpol.2023.113863

[61] Farooq, U., Wen, J., Tabash, M. I., & Fadoul, M. (2024). Environmental regulations and capital investment: Does green innovation allow to grow? *International Review of Economics & Finance*, *89*, 878–893. https://doi.org/10.1016/j.iref.2023.08.010

[62] Fernandes, C. I., Veiga, P. M., Ferreira, J. J. M., & Hughes, M. (2021). Green growth versus economic growth: Do sustainable technology transfer and innovations lead to an imperfect choice?. *Business Strategy and the Environment*, *30*(4), 2021–2037. https://doi.org/10.1002/bse.2730

[63] He, Y., Li, X., Huang, P., & Wang, J. (2022). Exploring the road toward environmental sustainability: Natural resources, renewable energy consumption, economic growth, and greenhouse gas emissions. *Sustainability*, *14*(3), 1579. https://doi.org/10.3390/su14031579

[64] Kostakis, I., & Arauzo-Carod, J.M. (2023). The key roles of renewable energy and economic growth in disaggregated environmental degradation: Evidence from highly developed, heterogeneous and cross-correlated countries. *Renewable Energy*, *206*, 1315–1325. https://doi.org/10.1016/j.renene.2023.02.106

[65] Yang, J. (2023). Factor price distortion among regions in China and its influence on China's economic growth. *PLOS ONE*, *18*(4), e0284191. https://doi.org/10.1371/journal.pone.0284191

[66] Gong, Y., & Xu, F. (2023). Research on the measurement and spatial spillover effects of green total factor productivity in western regions. *Journal of Research in Social Science and Humanities*, *2*(4), 119–130. https://doi.org/10.56397/JRSSH.2023.04.15

[67] Shen, Y., Guo, X., & Zhang, X. (2023). Digital financial inclusion, land transfer, and agricultural green total factor productivity. *Sustainability*, *15*(8), 6436. https://doi.org/10.3390/su15086436

[68] Jin, W., Gao, S., & Pan, S. (2023). Research on the impact mechanism of environmental regulation on green total factor productivity from the perspective of innovative human capital. *Environmental Science and Pollution Research*, *30*(1), 352–370. https://doi.org/10.1007/s11356-022-22120-x

[69] Peng, J., Xie, R., Ma, C., & Fu, Y. (2021). Market-based environmental regulation and total factor productivity: Evidence from Chinese enterprises. *Economic Modelling*, *95*, 394–407. https://doi.org/10.1016/j.econmod.2020.03.006

[70] Luan, B., Zou, H., Chen, S., & Huang, J. (2021). The effect of industrial structure adjustment on China's energy intensity: Evidence from linear and nonlinear analysis. *Energy*, *218*, 119517. https://doi.org/10.1016/j.energy.2020.119517

[71] Lin, Y., Liao, L., Yu, C., & Yang, Q. (2023). Re-examining the governance effect of China's environmental protection tax.

Environmental Science and Pollution Research, *30*(22), 62325–62340. https://doi.org/10.1007/s11356-023-26483-7

[72] Liang, C., & Wang, Q. (2023). The relationship between total factor productivity and environmental quality: A sustainable future with innovation input. *Technological Forecasting and Social Change, 191*, 122521. https://doi.org/10.1016/j.techfore.2023.122521

[73] Du, Y., & Li, M. (2024). The impact of enterprise digital transformation on carbon reduction—Experience from listed companies in China. *IEEE Access*, *12*, 15726–15734. https://doi.org/10.1109/ACCESS.2024.3349615

[74] Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., & Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal*, *21*(1), C1–C68. https://doi.org/10.1111/ectj.12097

[75] Wang, X., Bian, Y., & Zhang, Q. (2023). The effect of cooking fuel choice on the elderly's well-being: Evidence from two non-parametric methods. *Energy Economics*, *125*, 106826. https://doi.org/10.1016/j.eneco.2023.106826

[76] Huang, L., & Lei, Z. (2021). How environmental regulation affect corporate green investment: Evidence from China. *Journal of Cleaner Production*, *279*, 123560. https://doi.org/10.1016/j.jclepro.2020.123560

[77] Gu, Y., Ho, K. -C., Yan, C., & Gozgor, G. (2021). Public environmental concern, CEO turnover, and green investment: Evidence from a quasi-natural experiment in China. *Energy Economics*, *100*, 105379. https://doi.org/10.1016/j.eneco.2021.105379

[78] He, X., Jing, Q., & Chen, H. (2023). The impact of environmental tax laws on heavy-polluting enterprise ESG performance: A stakeholder behavior perspective. *Journal of Environmental Management*, *344*, 118578. https://doi.org/10.1016/j.jenvman.2023.118578

[79] Tone, K. (2004). Dealing with undesirable outputs in DEA: A Slacks-Based Measure (SBM) approach. *GRIPS Research Report Series I*, *2004*, 44–45.

[80] Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management*, *51*(3), 229–240. https://doi.org/10.1006/jema.1997.0146

[81] Farbmacher, H., Huber, M., Lafférs, L., Langen, H., & Spindler, M. (2022). Causal mediation analysis with double machine learning. *The Econometrics Journal*, *25*(2), 277–300. https://doi.org/10.1093/ectj/utac003

[82] Lei, P., Tian, X., Huang, Q., & He, D. (2017). Firm size, government capacity, and regional environmental regulation: Theoretical analysis and empirical evidence from China. *Journal of Cleaner Production*, *164*, 524–533. https://doi.org/10.1016/j.jclepro.2017.06.166

How to Cite: Gao, Y., Jiao, S., Wang, K., Yuan, D., Song M., & Wang, M. (2025). Does China's Environmental Protection Tax Improve Corporate ESG Performance? Causal Inference Based on Double Machine Learning. *Green and Low-Carbon Economy*. https://doi.org/10.47852/bonviewGLCE52025436