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ORIGINAL PAPER

From pollution to solution: How environmental protection tax shapes green technological innovation?

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Abstract

This study examines the influence of environmental protection taxes on the advancement of green technological innovation within heavily polluted Chinese firms, a critical aspect in promoting sustainable development within heavily polluted Chinese firms from 2010 to 2022. Moreover, this study examines the moderating role of green subsidies on the relationship between environmental protection taxes and green innovation among heavily polluted Chinese firms. The findings suggest that environmental protection taxes exhibit a positive and significant impact on green technological innovation, with this impact being further amplified by government environmental subsidies. Additionally, the research reveals that environmental protection taxes predominantly influence practical technology innovation rather than creative innovation. Among environmental components protection taxes, exhaust gas taxation emerges as the most effective, while wastewater taxation proves to be the least effective. Furthermore, the heterogeneity analysis suggests that SOEs, especially those with higher firm ages, lower ownership concentration level, and operating in less marketized environments are more inclined to enhance their green innovation efforts in response to EPT. Moreover, this research also finds a U-shaped curve between EPT and GTI, and further quantile analysis ascertains that the positive EPT effect is more pronounced at higher tax levels. This paper contributes to the existing literature on environmental policy and green innovation, offering practical implications and recommendations for stakeholders, including policymakers, managers, and investors, on optimizing the design and implementation of environmental protection taxes and fostering green technological innovation.

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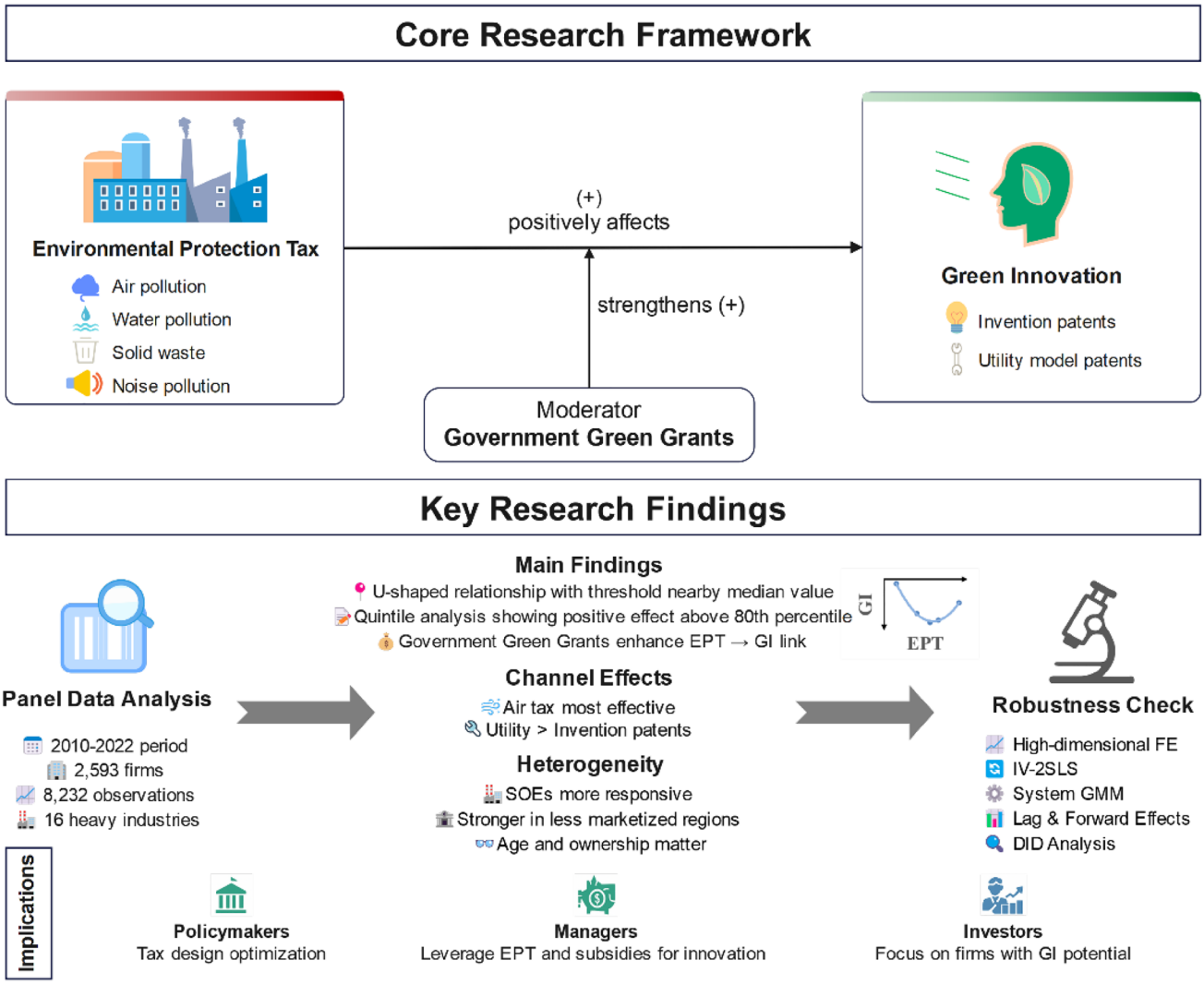
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Graphical Abstract



Keywords Green tax · Environmental subsidies · Green technology innovation · Pigou's theorem · "Double dividend" hypothesis · Heavily polluting firms

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Introduction

Heavily polluting firms have long stood at the intersection of economic growth and environmental degradation. In both developed and emerging economies, these firms contribute significantly to industrial output, infrastructure development, and job creation. In China, the contribution of heavy industry to national GDP remains indispensable. However, this contribution comes at a steep ecological cost: according to the Ministry of Ecology and Environment (2023),[1] industrial emissions—especially from exhaust gases and solid waste—are among the most significant sources of environmental pollution nationwide (see Fig. 1). As illustrated in industry structure data (Fig. 2), heavily polluting sectors continue to dominate China's industrial base, reflecting a persistent dependency on high-emission production models.

This structural reality presents a policy paradox: how can China maintain its economic momentum while delivering

[1] https://english.mee.gov.cn/Resources/Reports/bomeaesoc/202410/P020241031366042359372.pdf

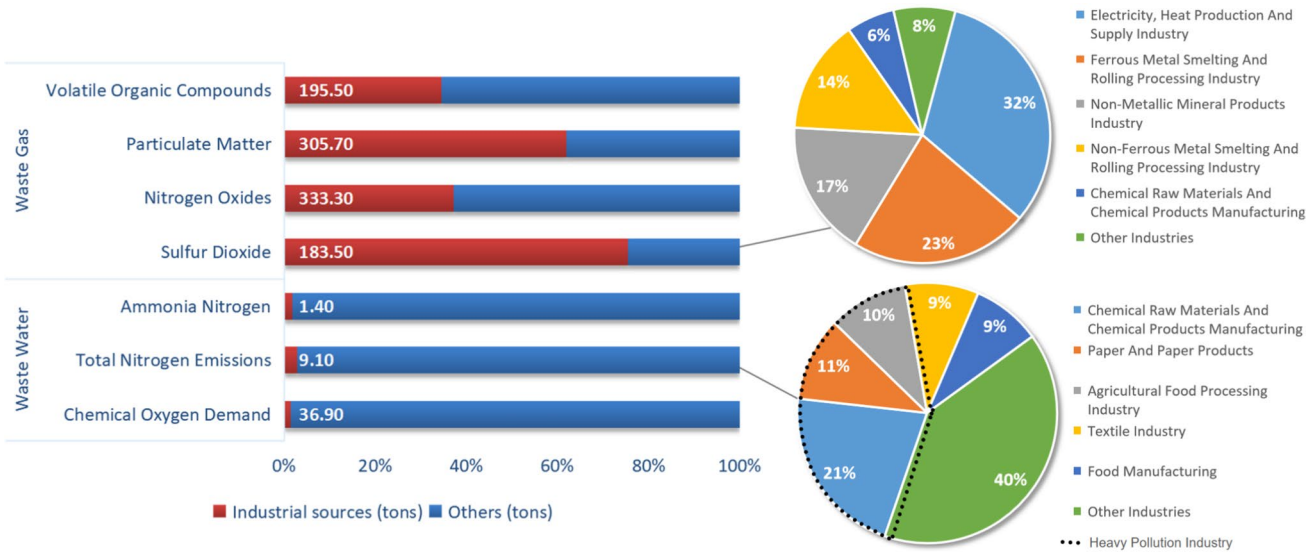


Fig. 1 The proportion of industrial waste water and exhaust gas emissions and the proportion of pollution in heavy polluting industries. *Note* This figure illustrates the overview of water and gas pollutant emissions. On the left side of the illustration, the amount of pollution is displayed along with the percentage of emissions produced by industrial companies. On the right side, the pie charts show the proportions of major contributing industries in sulfur dioxide and total nitrogen emissions, respectively. (Data Source: Ministry of Ecological Environment of the People's Republic of China)

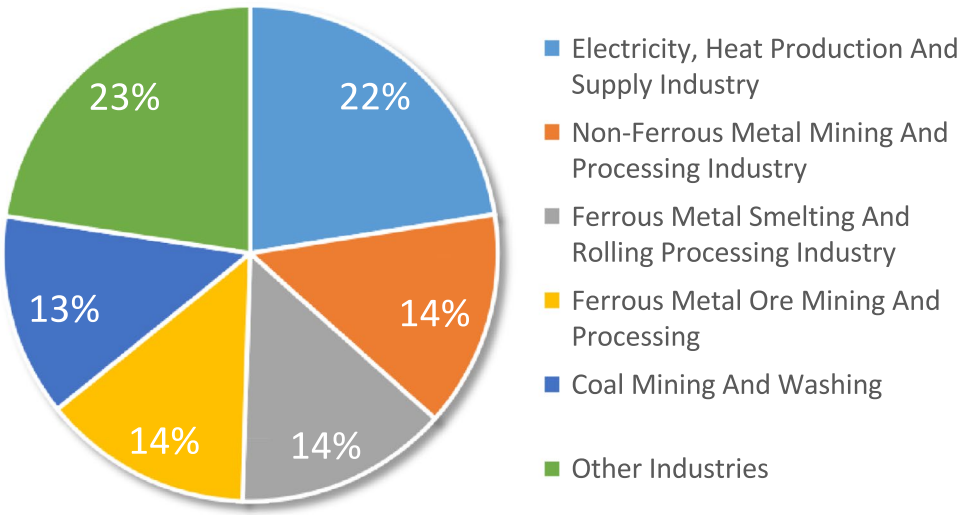


Fig. 2 General Industrial Solid Waste Generation. *Note* This figure illustrates proportions of major contributing industries in solid waste generation. (Data Source: Ministry of Ecological Environment of the People's Republic of China)

on its ambitious environmental goals? The answer, increasingly, lies in the promotion of green technological innovation (GTI)—a process that facilitates industrial upgrading, reduces environmental externalities, and enhances competitiveness through cleaner, more efficient technologies (Lee et al. 2022). GTI has been recognized as a core enabler of sustainable development and ecological transformation (Fang et al. 2024; Han et al. 2024; Wang & Fan 2023), offering both environmental and economic dividends. At the firm level, GTI can lower energy costs, create competitive advantages, and open access to green finance and sustainable markets (Aydin & Bozatli 2023; Deng et al. 2023). At the societal level, it enhances public health outcomes and mitigates climate risks, contributing to long-term national welfare (Wei et al. 2023).

Despite these benefits, the adoption of green innovation remains uneven, particularly among China's heavily polluting firms. High upfront costs, long R&D cycles, and uncertain payoffs make GTI an inherently risky investment (Lee et al. 2023). To address these barriers, the Chinese government has increasingly turned to market-based environmental instruments such as the environmental protection tax (EPT).

Enacted in 2018, EPT replaced the older pollutant discharge fee system, aligning environmental regulation more closely with Pigouvian principles that advocate internalizing external costs through taxation (Kallbekken et al. 2011; Pigou 2017). The intent behind EPT is not merely punitive; it seeks to reshape corporate incentives by raising the cost of pollution-intensive operations, thereby encouraging firms to transition toward sustainable business models (He et al. 2023; Wang & Ye 2024).

Yet, the effectiveness of EPT in stimulating green innovation remains underexplored—particularly in China's industrial sectors, where firms exhibit wide variations in ownership structure, financial constraints, and absorptive capacity. While some studies confirm a positive link between environmental taxes and innovation (Han et al. 2024; Porter & Vanderlinde 1995), others highlight possible unintended consequences. EPT can strain firm liquidity and deter R&D investment, especially in smaller or privately owned enterprises lacking access to financial support (Goulder 1995; Karydas & Zhang 2019; Zhou et al. 2023b). These conflicting findings underscore the need for empirical work that unpacks the heterogeneity of EPT's impact across firm types and innovation outcomes.

China provides a compelling context for such an investigation. As the world's second-largest economy and largest carbon emitter, its environmental policy choices have global repercussions. Domestically, China has committed to reaching carbon peak by 2030 and achieving carbon neutrality by 2060—goals that require structural transformation across its industrial base. Bibliometric data from the China Knowledge Network Academic Journals Library (Fig. 3) confirm a surge in scholarly and policy interest in areas like "green innovation," "carbon neutrality," and "environmental taxation." Concurrently, data from the National Bureau of Statistics (Fig. 4) show increased investments in industrial pollution control, especially in air pollution treatment—a key category under the EPT regime.

Furthermore, EPT in China is not implemented in isolation but is often accompanied by government environmental subsidies that aim to stimulate firm-level innovation and support ecological modernization. From a theoretical perspective, these instruments are complementary. While EPT applies financial pressure to discourage pollution, subsidies alleviate innovation risk and signal governmental support, creating a dual mechanism for driving green transformation (Fang et al. 2024; Wang & Fan 2023). According to the double dividend hypothesis, combining taxes and subsidies can improve both environmental outcomes and economic efficiency, especially when revenues are recycled into innovation support programs (Liu & Li 2022; Parry 1998b). Empirical studies increasingly validate this approach: subsidies can help overcome information asymmetries, reduce financing constraints, and encourage firms to engage in longer-term R&D (Liu et al. 2023; Ma et al. 2023).

However, the interaction between EPT and subsidies remains theoretically underdeveloped and empirically underinvestigated. While previous research has examined the isolated effects of taxation or subsidies on innovation (Dimos & Pugh 2016; Vasileiou et al. 2022), few studies assess their combined impact. Even fewer consider how this relationship varies across types of green innovation (e.g., product vs. process), tax categories (e.g., exhaust gas vs. wastewater), and firm-level characteristics such as ownership, age, and governance. Recent work by Jin et al. (2024), Qi et al. (2023) and Liu et al. (2022) calls for more nuanced, micro-level analyses that examine how institutional heterogeneity influences the efficacy of environmental fiscal policies in driving innovation.

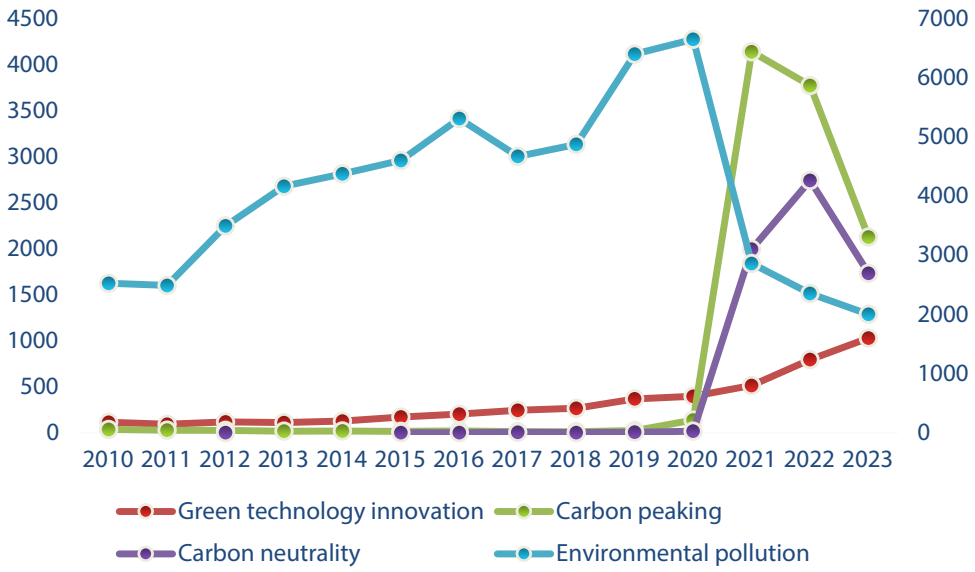


Fig. 3 Number of literatures on different topics over the years. *Note* This figure illustrates the overall trend of literature in environmental topics. Basically, four fields are identified in the literature, "green technology innovation", "carbon peaks", "carbon neutrality", and "environmental pollution". (Data Source: CNKI database)

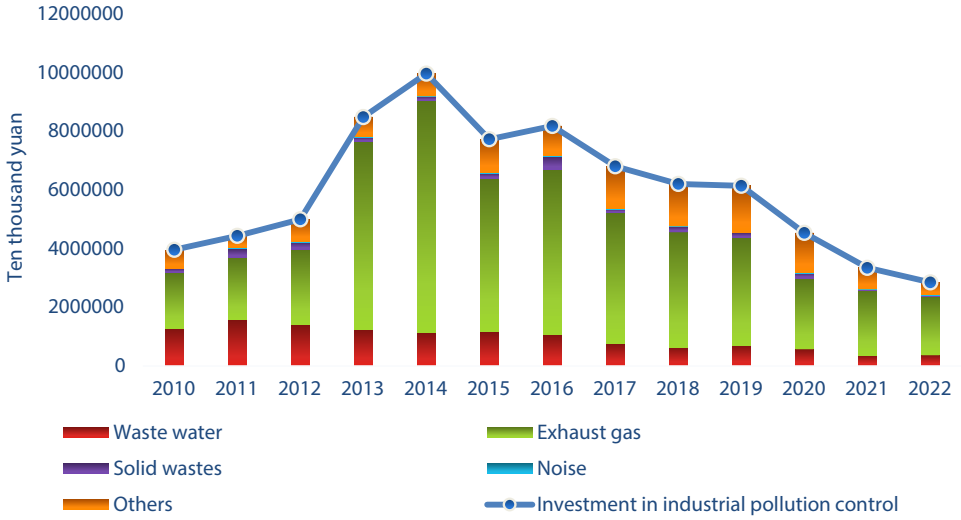


Fig. 4 The investment in the completion of industrial pollution control. *Note* This figure illustrates the yearly trend of investment in the treatment of pollution by showing the investment in water, gas, solid, noise, others, and total level. (Data Source: National Bureau of Statistics)

This study aims to fill these critical gaps by examining how EPT affects green technological innovation in heavily polluting Chinese firms with 8232 firm year observations from 2010 to 2022, and how this relationship is moderated by the presence of government green subsidies. Our contributions are fourfold: (1) We provide firm-level empirical evidence on how EPT impacts different types of green innovation—highlighting whether the tax stimulates practical (incremental) innovation more than creative (radical) innovation; (2) We evaluate the moderating role of green subsidies, offering new insights into how subsidies and taxes jointly influence innovation behavior; (3) We identify nonlinear dynamics, revealing a U-shaped relationship between EPT and GTI—suggesting that while moderate tax levels may hinder innovation, higher levels generate stronger responses; (4)We conduct heterogeneity analysis across firm types, showing that SOEs, older firms, and those operating in less marketized environments are more responsive to EPT in terms of innovation performance.

This study contributes to the literature in four significant ways. First, it provides large-scale firm-level evidence on the differentiated effects of EPT across innovation types and environmental tax categories. Second, it introduces the moderating role of green subsidies into the EPT–innovation nexus, bridging a key gap in the literature on integrated environmental fiscal policies. Third, it identifies nonlinear dynamics and firm heterogeneity, offering actionable insights for more targeted and effective environmental regulation. Finally, it informs both domestic and international policy discussions on how emerging economies can leverage fiscal tools to accelerate their industrial green transformation.

The remainder of this paper is structured as follows: "Literature Review and Hypotheses Development" section reviews relevant literature and formulates hypotheses; "Research Design" section describes data sources, variable construction, and empirical methodology; "Empirical Results" section presents empirical results and robustness checks; "Discussion and Implications" section offers policy and theoretical implications; and "Conclusion and Limitations" section concludes with limitations and directions for future research.

Literature review and hypotheses development

Environmental protection tax and green technological innovation

The environmental protection tax (EPT) represents a cornerstone of modern environmental fiscal policy and is theoretically grounded in the classical Pigouvian framework (Pigou 2017), which advocates for the internalization of external costs through taxation. By raising the financial cost of pollution, EPT encourages firms to adopt cleaner technologies, optimize resource use, and invest in green innovation. In recent years, EPT has emerged as a key instrument in China's ecological modernization agenda, replacing the more discretionary pollution discharge fees with a legally binding, nationwide tax structure beginning in 2018. This institutional reform aims to realign industrial development with ecological sustainability and green growth goals (Long et al. 2022; Shi et al. 2023). At the macroeconomic level, a broad body of empirical evidence confirms that environmental taxes can effectively reduce emissions without undermining long-term economic growth (Abdullah & Morley 2014; Saleem et al. 2020). In particular, recent cross-country studies suggest that environmental taxation fosters technological upgrading by incentivizing eco-innovation and stimulating demand for clean technologies (Aydin & Bozatli 2023; Deng et al.

2023; Han et al. 2024). EPT also indirectly facilitates the diffusion of foreign environmental technologies, especially in economies with low marginal tax rates and supportive trade environments (Chen et al. 2023).

However, the effects of EPT on firm-level innovation behavior—especially in pollution-intensive industries—are far more nuanced and context-dependent. On the one hand, EPT may function as a catalytic force, pushing firms to develop or adopt green technologies to reduce regulatory costs and align with societal expectations (Lee et al. 2022). On the other hand, taxes increase production costs and can reduce internal cash flow, particularly for firms that already operate under financial constraints. This tension has been described as the "double-edged sword" of environmental taxation (Bai et al. 2019; Mahmood et al. 2022). While regulation can stimulate innovation by introducing new constraints, it can also suppress innovation if the costs exceed firms' capacity to adapt (Karydas & Zhang 2019; Zhou et al. 2023a).

Green Technological Innovation (GTI), sometimes referred to as eco-innovation, involves the design and implementation of new or significantly improved products, processes, or practices that reduce environmental harm and enhance sustainability (Castellacci & Lie 2017; Kemp & Pearson 2007; Lee et al. 2022). Scholars frequently distinguish between green product innovation—such as energy-efficient goods or low-carbon materials—and green process innovation, which includes cleaner production systems and energy-saving workflows (Begum et al. 2022; Lee et al. 2023; Tariq et al. 2017). Recent research also differentiates between radical (creative) and incremental (practical) green innovations, noting that the latter may be more immediately feasible for firms under cost pressure (Deng et al. 2023; Wang & Yu 2021).

The existing literature often treats the relationship between EPT and innovation as linear and homogeneous across firms. However, such assumptions are increasingly questioned. Several scholars argue that the influence of environmental taxes on innovation may follow a nonlinear pattern. For example, modest taxes may be insufficient to justify costly R&D investments, while excessively high taxes may lead to production cuts or offshoring rather than innovation. Only at intermediate or high-but-absorbable tax levels do firms begin to see innovation as a more viable compliance mechanism (Gerstlberger et al. 2014; Goulder 1995; Liu et al. 2020). This framework justifies testing for nonlinear or U-shaped effects, as suggested by more recent innovation–regulation studies (Jiang et al. 2023; Song et al. 2020; Wei et al. 2023).

Moreover, the impact of EPT is likely to vary substantially across firms and industries, depending on firm-specific capabilities, institutional constraints, and exposure to environmental regulation. Heavily polluting firms are not a homogeneous group: they differ in their ownership structure (e.g., SOEs vs. private firms), financial constraints, governance quality, and regional regulatory context (Jin et al. 2024; Liu & Li 2022). For instance, SOEs may respond more positively to EPT due to stronger policy alignment, political incentives, or access to public innovation subsidies (Tang et al., 2023), whereas private firms may be more sensitive to tax burden and capital cost, especially in highly competitive markets (Long et al. 2022).

China's unique fiscal decentralization system adds another layer of complexity. Because environmental tax revenues are shared between central and local governments, local enforcement intensity can vary dramatically across regions (Jia et al. 2020). This heterogeneity creates differential innovation incentives and enforcement risk, which may in turn influence the scale and type of green innovation undertaken by firms operating in different provinces or industrial parks (He et al. 2023).

Another underexplored dimension is the effectiveness of different EPT components—such as taxes on exhaust gas, wastewater, noise, or solid waste. Firms may respond more proactively to tax categories that are more stringently enforced, publicly visible, or economically material to their operations. Yet few studies disaggregate EPT by pollution type or analyze which tax mechanisms are more innovation-inducing (Fan et al. 2023; Wang & Ye 2024).

Given these complexities, the relationship between EPT and GTI should be understood as both nonlinear and heterogeneous, shaped by institutional, financial, and technological asymmetries across firms. This necessitates a research framework that accounts for varying innovation responses across different tax intensities, innovation types, and firm profiles. Accordingly, this study seeks to fill these gaps by empirically examining the direction, magnitude, and conditional effects of EPT on green innovation outcomes in Chinese heavily polluting firms.

Thus, we advance a dual-direction hypothesis structure, acknowledging the potential for both innovation-inducing and innovation-inhibiting effects of EPT:

H1$_A$ *EPT raises the green technological innovation capabilities of enterprises within China's heavily polluting industries.*

H1$_B$ *EPT reduces the green technological innovation capabilities of enterprises within China's heavily polluting industries.*

Environmental subsidies, EPT and green technological innovation

Green technological innovation (GTI) is increasingly viewed as a dual-purpose mechanism—enhancing corporate competitiveness while contributing to broader

environmental sustainability goals (Arenhardt et al. 2016; Takalo & Tooranloo 2021; Zhou et al. 2023b). For firms, GTI supports market expansion, cost efficiency, and long-term resilience through eco-friendly production and low-carbon technologies (Arenhardt et al. 2016). For governments, it serves as a strategic lever for achieving national climate goals, industrial upgrading, and compliance with global environmental commitments. Despite its strategic importance, the widespread adoption of green innovation faces several market failures—primarily due to the externality nature of innovation. As Roper et al. (2013), Li et al. (2022) and Han et al. (2024) emphasize, green innovations generate social benefits (e.g., cleaner air, reduced carbon emissions) that are not fully captured by the innovating firm. This mismatch between private and social returns leads to underinvestment in green R&D, particularly in capital-intensive and high-risk sectors such as heavy industry. To correct this distortion, governments often introduce environmental subsidies that provide financial support, reduce innovation risk, and compensate for innovation spillovers (Li et al. 2022; Lin & Zhu 2019).

From the lens of externality theory, subsidies address persistent inefficiencies in resource allocation, especially where innovation requires large upfront costs and delayed returns. In parallel, signal theory posits that receiving a government subsidy can function as a quality signal to external stakeholders—including investors, consumers, and partners—suggesting that the firm has strong green potential or policy alignment (Kleer 2010; Wang & Fan 2023). This signaling effect can attract complementary resources such as human capital, technical expertise, and private capital, thereby strengthening the firm's innovation ecosystem.

Environmental subsidies also mitigate some of the potential downsides of regulatory mechanisms such as environmental taxes. According to the double dividend hypothesis, environmental tax reforms can yield two simultaneous benefits: reducing environmentally harmful activities (the first dividend) and improving the overall efficiency of the tax system when revenues are recycled into innovation incentives (the second dividend) (Parry 1998a; Yi et al. 2021). Thus, integrating green subsidies with EPT can create a balanced incentive structure—where firms are discouraged from polluting through tax burdens, while simultaneously encouraged to innovate through fiscal support.

Empirical evidence increasingly supports this dual-instrument model. Lin and Zhu (2019) find that environmental subsidies enhance green innovation through increased R&D funding, knowledge sharing, and risk mitigation. Bai et al. (2019) show that well-managed firms with higher tax contributions are more likely to receive subsidies, which in turn promotes technology development. Shi et al. (2023) report that firms benefiting from both EPT and government support tend to adopt cleaner technologies at a faster rate. Moreover, green subsidies are particularly valuable in offsetting the crowding-out effect of EPT on internal innovation budgets—a concern especially relevant for firms with weak financial flexibility or limited access to external capital (Zhou et al. 2023a, 2023b).

However, the effectiveness of subsidies as a moderating force is not unconditional. Several studies caution that subsidies can also produce unintended consequences. Rent-seeking behavior, where firms manipulate government relationships to secure funding without engaging in substantive innovation, can reduce policy efficacy (Dimos & Pugh 2016; Liu et al. 2020). Information asymmetry between firms and policymakers may lead to misallocation of funds, with low-efficiency or even non-innovative projects receiving subsidies (Du et al. 2024). Additionally, subsidies may disproportionately favor larger or state-linked firms, leaving smaller or private firms underfunded due to lack of political access or information gaps (Yu et al. 2016).

In this regard, the moderating role of green subsidies in shaping the EPT–GTI relationship is complex and contingent on multiple contextual factors. While well-targeted subsidies can amplify the innovation-stimulating effects of EPT by reducing innovation costs and improving firm capacity, poorly implemented subsidies may dilute incentives, foster moral hazard, or reinforce structural inequalities in innovation access.

Given these conflicting theoretical mechanisms and empirical observations, this study posits a dual-directional hypothesis to empirically assess the conditional impact of government environmental subsidies on the EPT–GTI relationship:

H12$_A$ *Government environmental subsidies positively influence the relationship between green taxes and the green technological innovation capacity of enterprises in China's heavy pollution industry*

H2$_A$ *Government environmental subsidies negatively influence the relationship between green taxes and the green technological innovation capacity of enterprises in China's heavy pollution industry*.

Research design

Sample selection and data sources

In accordance with the 2012 industry classification guidelines set forth by the China Securities Regulatory Commission (CSRC) and previous literature (Song et al. 2022), this study focuses on data from companies within 16 heavily polluted industries [see Table 1] spanning from 2010 to 2022. The

Table 1 List of heavily polluted industries

No.	Classification of industry	Obs.
1	Coal mining and dressing	210
2	Petroleum and natural gas extraction	38
3	Ferrous metals mining and dressing	26
4	Nonferrous metals mining and dressing	151
5	Textile industry	331
6	Leather, hide, feather, and their products and shoe-making	70
7	Paper-making and paper products	264
8	Petroleum processing, coking, and nuclear fuel processing	135
9	Chemical raw materials and chemical products manufacturing	2044
10	Pharmaceutical manufacturing	2086
11	Chemical fiber manufacturing	215
12	Non-metal mineral products	720
13	Smelting and pressing of ferrous metals	312
14	Non-ferrous metals smelting and rolling processing	667
15	Metal products	563
16	Power and heat generation and supply	400
Total		8232

research is structured into three principal segments: firstly, it examines the effect of Environmental Performance Taxation (EPT) on the capacity for green scientific and technological innovation (GTI) within enterprises and the role of government environmental subsidies (GRA); secondly, it delves into the mechanisms of influence at the taxation and green innovation strata; and thirdly, it investigates the state ownership heterogeneity and examines how internal, external, and other influences affect this heterogeneity. The data compilation primarily sources from the green patent listings disseminated by the World Intellectual Property Organization (WIPO) and the CSMAR database. In the data cleansing process this paper excludes companies with irregular trading patterns, including those designated as ST (special treatment), ST* (at risk of delisting), and PT (particular transfer), as well as firms lacking complete data on pivotal variables like EPT and GRA. The study employs the linear estimation method to fill in missing data,[2] resulting in a dataset comprising 8232 firm year observations. Furthermore, the primary continuous variables undergo winsorization at the 1% and 99% thresholds, and some variables with large numbers or counts are coped via logarithmic transformation.

[2] For instance, EPT is a seasonal variable from the database, and we take the values of Q4 each year. However, in the dataset we have access to, the 2022 year only has the Q1 observations. Therefore, for each firm, we conduct a linear regression of the Q1 observations on the Q4 ones and estimate the 2022 year-end values accordingly, where negative estimations are excluded from the sample.

Variable measurement

Dependent variable: green innovation (GTI)

Current academic conversations feature numerous research methodologies and analytical frameworks related to advancements in green technology, both within domestic and international contexts (Desheng et al. 2021; Johnstone et al. 2012; Levinsohn & Petrin 2003; Olley & Pakes 1992; Seru 2014). These studies predominantly assess the inputs and outputs of technological innovation, employing methods such as the Olley-Pakes (OP) and Levinsohn-Petrin (LP) to measure green total factor productivity. Alternatively, they evaluate green total factor productivity via the dual pathways of green process innovation and green product innovation or through the metric of green patent applications and grants.

Patent classifications encompass invention patents, utility model patents, and design patents. However, due to the absence of design patents in the International Patent Classification (IPC), this analysis considers only invention and utility model patents. Invention patents are characterized by their higher inventive and technical thresholds, whereas utility models are less innovative, safeguarding only the shape and structure of products. Scholars typically employ quantitative, proportional, and logarithmic measures to quantify the extent of green innovation. This study posits that the count of green patents, both applied for independently and in conjunction, serves as a more accurate reflection of a firm's green innovation capabilities (Zhou et al. 2023a). Consequently, this metric is utilized as the dependent variable for empirical analysis. Furthermore, green invention patents and utility model patents are designated as the primary explanatory variables for analyzing the channeling effect.

Independent variable: environmental protection tax (EPT)

Since 2018, China has undertaken a tax reform initiative, transitioning from sewage charges to Environmental Performance Taxation (EPT). This research draws upon Fang et al. (2023) for the selection of data pertaining to sewage charges and the specific EPT levied on publicly traded companies within heavily polluting industries. These core explanatory variables primarily address emissions related to atmospheric and water pollutants, solid waste, and noise pollution (Wang et al. 2018). Moreover, the model incorporates the four constituents of EPT as substitutes for the independent variables traditionally employed in channel effect analysis.

Moderating variable: environmental subsidy (GRA)

Corporate research and development (R&D) endeavors are typified by substantial investment, protracted development periods, elevated risk, and societal advantages that

frequently surpass the private benefits accrued by the corporations themselves, thereby exhibiting pronounced positive externalities. This disparity often results in a lack of sufficient motivation for companies to allocate resources to R&D, culminating in investment levels that fall considerably short of the ideal (Han et al. 2024). To rectify this market inefficiency, it is imperative for governmental entities to enact subsidies for businesses engaged in R&D and innovation, or to establish advantageous policies that encourage such firms to invest in R&D activities (Shao & Hua 2023). Within the context of this research, the logarithmic transformation of government environmental subsidies (GRA) is employed as a moderating variable.

Control variables

Drawing from extant scholarly works (Desheng et al. 2021; Wang et al. 2022; Zhou et al. 2023c) that investigate the impact of environmental taxes and governmental environmental subsidies on corporate green technology innovation, this study incorporates a set of 12 variables to account for enterprise heterogeneity. These control variables include: firm size (SIZE), leverage ratio (LEV), Tobin's Q (TobinQ), KZ index (KZ), R&D expenditure (RD), firm age (AGE), ownership concentration (OWN), number of board members (DIR), count of female directors (FemD), ESG ratings (ESG), nature of property rights (SOE), and degree of marketization (MAR). Additionally, this research employs industry and year fixed effects to mitigate the impacts from industry-specific and temporal confounding factors on the regression outcomes. Descriptions of variables are delineated in Table 2.

Modeling

This study endeavors to elucidate the influence of environmental protection taxes and green subsidies on green technology innovation within sectors characterized by significant pollution. It employs the methodology developed by Correia (2016) to construct a multidimensional fixed-effect linear regression model, which offers a more nuanced analytical framework compared to conventional models. For instance, random effect models such as Hausman–Taylor approach have strict assumptions that part of explanatory variables are uncorrelated with individual effects, which may not hold in this study (Hausman & Taylor 1981), and although the pooled OLS model is more advantageous at information utilization of the whole sample, it fails to consider the confounding individual and temporal factors that could result in biased estimations (Hausman & Taylor 1981). In contrast, the fixed-effect model is more capable to accurately capture individual and temporal variations, which is crucial when analyzing large panel data (Simen 2010). Additionally, the multidimensional fixed-effect model addresses many of the limitations of conventional fixed-effect models, such as possible lack of convergence and being limited to only two or three sets of fixed effects. The developed equations are as follows:

$$\mathrm{GPAT}_{i,t} = \alpha_0 + \alpha_1 \mathrm{EPT}_{i,t} + \mu_i + \omega_t + \varepsilon_{i,t} \tag{1}$$

$$\mathrm{GPAT}_{i,t} = \alpha_0 + \alpha_1 \mathrm{EPT}_{i,t} + \alpha_i \mathrm{control}_{i,t} + \mu_i + \omega_t + \varepsilon_{i,t} \tag{2}$$

In Eqs. (1) and (2), the μ_i and ω_t represent, respectively, individual and time effect, $\varepsilon_{i,t}$ is the residual, α_0 is the constant, α_1 and α_i are effect coefficients to be estimated. $\mathrm{GPAT}_{i,t}$ represents the number of patents of green technology innovation level of firm i in year t. $\mathrm{EPT}_{i,t}$ is the corporate environment protection tax (lnTax), and $\mathrm{control}_{i,t}$ includes the company's financial, management-level, and macro-level control variables.

Beyond the influence exerted by environmental protection tax (EPT) on corporate green innovation capabilities (GTI), green subsidies also play a pivotal role in shaping green innovation outcomes. This study broadens the scope of the benchmark regression model to delve deeper into the interplay among governmental subsidies (GRA), EPT, and GTI.

$$\begin{aligned}\mathrm{GPAT}_{i,t} = {} & \alpha_0 + \alpha_1 \mathrm{EPT}_{i,t} + \alpha_2 \mathrm{GRA}_{i,t} + \alpha_3 \mathrm{EPT}_{i,t} \\ & * \mathrm{GRA}_{i,t} + \alpha_i \mathrm{control}_{i,t} + \mu_i + \omega_t + \varepsilon_{i,t}\end{aligned} \tag{3}$$

where $\mathrm{GRA}_{i,t}$ represents the logarithm of the government's green subsidy, $\mathrm{EPT}_{i,t} * \mathrm{GRA}_{i,t}$ is the interaction term of $\mathrm{EPT}_{i,t}$ and $\mathrm{GRA}_{i,t}$, and the definitions of other variables are consistent with Eq. (1).

Channeling analysis

The categorization of green innovation patents encompasses both utility model patents and invention patents. Concurrently, environmental taxes predominantly target emissions from air and water pollutants, solid waste, and noise pollution. In light of this, this study constructs analytical models that consider the distinct categories of patents and the various environmental taxes. This approach facilitates a nuanced channel effect analysis within the framework of the benchmark regression, which is articulated as follows:

$$\mathrm{GIN}_{i,t} = \alpha_0 + \alpha_1 \mathrm{EPT}_{i,t} + \alpha_i \mathrm{control}_{\mathrm{i,t}} + \mu_i + \omega_t + \varepsilon_{i,t} \tag{4}$$

$$\mathrm{GUT}_{i,t} = \alpha_0 + \alpha_1 \mathrm{EPT}_{i,t} + \alpha_i \mathrm{control}_{i,t} + \mu_i + \omega_t + \varepsilon_{i,t} \tag{5}$$

$$\mathrm{GPAT}_{i,t} = \alpha_0 + \alpha_1 \mathrm{AIR}_{i,t} + \alpha_i \mathrm{control}_{i,t} + \mu_i + \omega_t + \varepsilon_{i,t} \tag{6}$$

Table 2 Variable descriptions

Variable type	Variable name	Symbol	Description
Dependent variable	Green innovation	GTI	Total number of green patents (invention + utility)
Independent variable	Environmental protection tax	EPT	The word green tax is actual payment of pollution charges, also called environmental protection taxes. It is calculated as ln(Environmental protection tax)
Channel variable: GTI	Green invention patents	GIN	Green invention patent (independent + joint)
	Green utility patents	GUT	Green utility model patent (independent + joint)
Channel variable: EPT	Air pollutant tax	AIR	Green taxes on air pollution which is calculated as ln(air pollutant tax)
	Water pollutant tax	WATER	Green taxes on water pollutant which is calculated as ln(water pollutant tax)
	Solid waste tax	SOLID	Green taxes on solid waste which is calculated as ln(solid waste tax)
	Noise pollution tax	NOISE	Green taxes on noise pollution. which is calculated as ln(noise pollution tax)
Moderator	Government green grants	GRA	ln(The amount of environmental protection subsidy detail item in the current period, which include tax subsidies, soft loans, and grants + 1)
Control variable: firm level	Firm size	SIZE	ln(Total Assets)
	Leverage	LEV	Total asset / Total Liability
	Tobin's Q	TobinQ	Tobin's Q is defined as the capital market value of the firm divided by the replacement value of its assets
	KZ index	KZ	KZ index reflects the degree of corporate financing constraints, where each year of the sample was classified according to net operating cash flow/total assets at the beginning of the year, cash dividends/total assets at the beginning of the year, cash holdings/total assets at the beginning of the year, asset-liability ratio and Tobin's Q. See article for detailed analysis
	R&D expense	RD	ln(R&D expense)
Control variable: management level	Firm's age	AGE	The current year—firm listed year + 1
	Ownership concentration	OWN	Ownership concentration is average of proportion of shares held
	Director number	DIR	Director number
	Female director number	FemD	Female director number
	ESG rating	ESG	Huazheng ESG rating
	State ownership	SOE	Non-state-owned enterprises = 0, state-owned enterprises = 1
Control variable: macro level	Marketization	MAR	Marketization is a restructuring process that enables state enterprises to operate as market-oriented firms by changing the legal environment in which they operate. This is achieved through reduction of state subsidies, organizational restructuring of management (corporatization), decentralization and in some cases partial privatization
Others	Industry effect	Industry	Dummy variables, industry fixed effects
	Year effect	Year	Dummy variables, year fixed effects

Note The table presents the descriptive statistics of all the variables included in the study

$$\mathrm{GPAT}_{i,t} = \alpha_0 + \alpha_1 \mathrm{WATER}_{\mathrm{i,t}} + \alpha_i \mathrm{control}_{i,t} + \mu_i + \omega_t + \varepsilon_{i,t} \quad (7)$$

$$\mathrm{GPAT}_{i,t} = \alpha_0 + \alpha_1 \mathrm{SOLID}_{i,t} + \alpha_i \mathrm{control}_{i,t} + \mu_i + \omega_t + \varepsilon_{i,t} \quad (8)$$

$$\mathrm{GPAT}_{i,t} = \alpha_0 + \alpha_1 \mathrm{NOISE}_{i,t} + \alpha_i \mathrm{control}_{i,t} + \mu_i + \omega_t + \varepsilon_{i,t} \quad (9)$$

where $\mathrm{GIN}_{i,t}$ represents green invention patens and $\mathrm{GUT}_{i,t}$ represents green utility model patents. $\mathrm{AIR}_{i,t}$, $\mathrm{WATER}_{i,t}$, $\mathrm{SOLID}_{i,t}$ and $\mathrm{NOISE}_{i,t}$ represent air pollution, water pollutants, solid waste, and noise pollution, respectively. A detailed study framework is illustrated in Fig. 5.

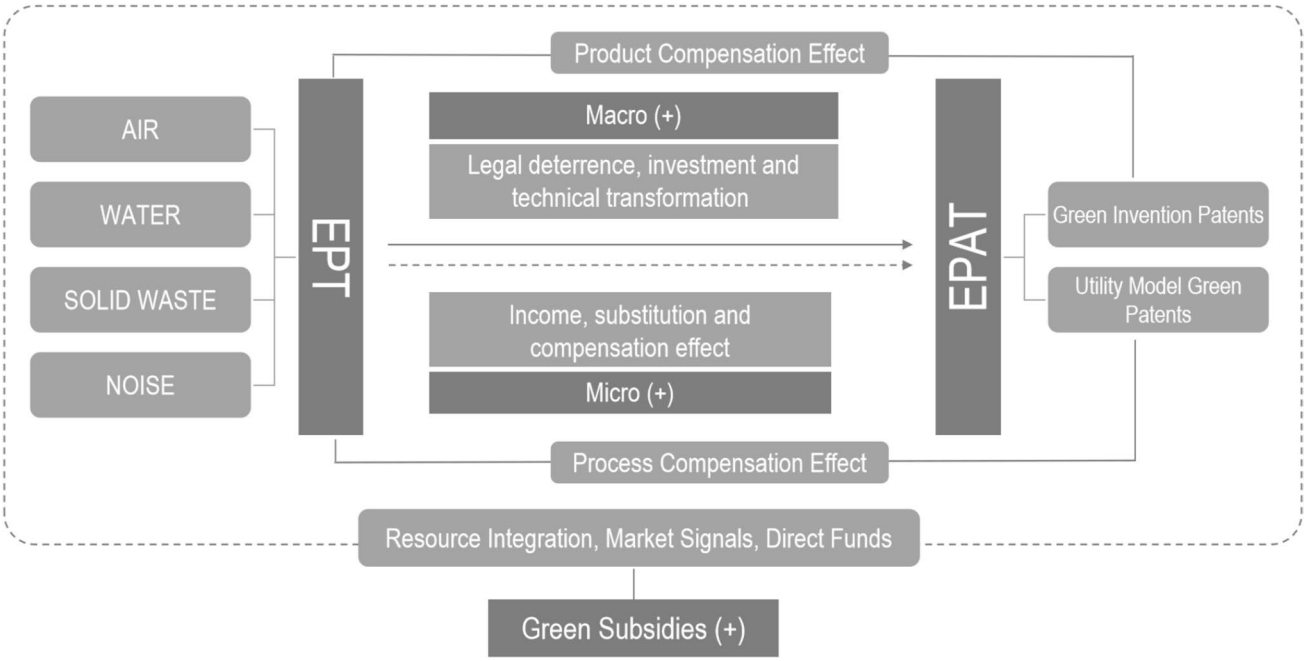


Fig. 5 Study framework. Source: By author/s

Empirical results

Descriptive statistics

Table 3 delineates the descriptive statistics for the variables under examination.[3] In Panel C, the overview statistics of the full sample are listed. The standard deviation for GTI is 11.27, with a range spanning from 0 to 82, indicating substantial variability in green technology innovation levels across firms within China's heavily polluted industries, and suggesting instances of technological discontinuity. The average Environmental Performance Taxation (EPT) stands at 14.01, with a range from 9.10 to 21.02, which suggests a moderate imposition of EPT across these enterprises.

Also, this research examines the descriptive statistics of low EPT and high EPT groups in Panel A and Panel B, which are classified according to the mean value of EPT. The average GTI levels vary significantly across groups, where the average is 1.33 in low EPT group while 7.91 in high EPT group, preliminarily verifying our baseline conjecture. Other control variables basically hold consistent across groups with, with slight differences in several variables like KZ and AGE, ensuring the validity of subsequent statistical estimation.

With regard to the subcategories of GTI, in Panel C, the maximum values of GIN and GUT are 52 and 40, respectively, with standard deviations of 6.63 and 5.74 correspondingly. This disparity suggests a preference for invention patents over utility model patents in China, potentially pointing to a monopolistic trend in inventive capabilities. For EPT, regulations targeting heavy polluters encompass AIR, WATER, SOLID, and NOISE categories. According to Panel C, these factors have similar mean values in the sample (12.96, 12.09, 12.96, and 12.04), indicating a uniform taxation approach to different types of emissions.

Regarding control variables, in Panel C, the average logarithm of firm size is 22.41, with a range from 19.21 to 28.64, reflecting significant diversity in firm sizes within the sample. The leverage ratio (LEV) has an average of 0.41, with a standard deviation of 0.20, signifying a relatively low leverage and minor variation across the industry. Tobin's Q averages at 1.97, with a standard deviation of 1.24 and extremes of 0.82 and 7.96. The KZ index averages at 0.75, ranging from − 6.12 to 6.50, where a negative KZ index indicates a preference for equity financing over bank credit, and a higher index suggests greater financing constraints. The mean R&D expenditure (RD) is 17.96, which is within expected norms. The average firm age (AGE) is 17.39 years, with a span from 3 to 31 years, illustrating a mix of both nascent and established firms in the sector. The ownership concentration (OWN) peaks at a value of 91.70 indicating that the largest shareholders possess more than ninety percent of the shares within enterprises.

[3] For the completeness of the research, we have also conducted the summarization of panel data using "xtsum" in Stata, which reports the between and within statistics, and presented in Appendix A1. The results are showing that most variable vary significantly across firms while insignificantly within the same focal company, with KZ and FemD as exceptions.

Table 3 Descriptive statistics

Variable	Obs.	Mean	SD	Min	Median	Max
Panel A: low-EPT sample						
GTI	4,538	1.33	4.07	0.00	0.00	70.00
EPT	4,538	12.97	0.73	9.10	13.08	14.01
GIN	4,538	0.72	3.14	0.00	0.00	52.00
GUT	4,538	0.60	1.67	0.00	0.00	40.00
AIR	4,538	11.92	0.73	8.02	12.03	13.09
WATER	4,538	11.06	0.76	7.29	11.17	12.37
SOLID	4,538	11.92	0.73	8.11	12.03	13.08
NOISE	4,538	11.00	0.82	6.41	11.10	12.68
GRA	1,471	12.59	1.76	5.99	12.70	17.69
SIZE	4,538	21.57	0.71	19.21	21.56	24.73
LEV	4,538	0.33	0.18	0.05	0.31	0.90
TobinQ	4,538	2.28	1.34	0.82	1.83	7.96
KZ	4,538	0.54	2.43	− 6.12	0.69	6.50
RD	4,538	17.37	1.15	8.34	17.52	20.77
AGE	4,538	15.07	7.34	3.00	14.00	31.00
OWN	4,538	56.69	14.43	22.62	57.27	91.70
DIR	4,538	8.32	1.35	5.00	9.00	15.00
FemD	4,538	1.41	1.10	0.00	1.00	4.00
ESG	4,538	72.44	4.71	57.60	72.75	83.98
MAR	4,538	9.26	1.80	3.25	9.51	11.49
Panel B: high-EPT sample						
GTI	3,694	7.91	15.46	0.00	2.00	82.00
EPT	3,694	15.29	1.07	14.01	15.02	21.02
GIN	3,694	3.88	8.97	0.00	1.00	52.00
GUT	3,694	4.11	7.95	0.00	1.00	40.00
AIR	3,694	14.23	1.07	12.81	13.98	20.08
WATER	3,694	13.37	1.09	11.74	13.12	19.39
SOLID	3,694	14.23	1.07	12.82	13.96	19.93
NOISE	3,694	13.32	1.16	9.94	13.08	19.30
GRA	1,653	14.24	2.00	7.51	14.25	21.42
SIZE	3,694	23.44	1.16	20.58	23.26	28.64
LEV	3,694	0.49	0.18	0.05	0.50	0.90
TobinQ	3,694	1.59	0.99	0.82	1.28	7.96
KZ	3,694	1.00	2.23	− 6.12	1.35	6.50
RD	3,694	18.69	1.69	7.72	18.89	24.08
AGE	3,694	20.23	6.88	3.00	21.00	31.00
OWN	3,694	59.58	15.75	22.62	59.56	91.70
DIR	3,694	9.14	1.95	5.00	9.00	15.00
FemD	3,694	1.20	1.07	0.00	1.00	4.00
ESG	3,694	73.73	5.10	57.60	73.71	83.98
MAR	3,694	9.05	1.75	3.25	9.24	11.49
Panel C: full sample						
GTI	8,232	4.28	11.27	0.00	0.00	82.00
EPT	8,232	14.01	1.46	9.10	13.83	21.02
GIN	8,232	2.14	6.63	0.00	0.00	52.00
GUT	8,232	2.18	5.74	0.00	0.00	40.00
AIR	8,232	12.96	1.46	8.02	12.78	20.08
WATER	8,232	12.09	1.47	7.29	11.92	19.39
SOLID	8,232	12.96	1.46	8.11	12.79	19.93
NOISE	8,232	12.04	1.52	6.41	11.87	19.30

Table 3 (continued)

Variable	Obs.	Mean	SD	Min	Median	Max
GRA	3,124	13.46	2.06	5.99	13.47	21.42
SIZE	8,232	22.41	1.32	19.21	22.19	28.64
LEV	8,232	0.41	0.20	0.05	0.40	0.90
TobinQ	8,232	1.97	1.24	0.82	1.56	7.96
KZ	8,232	0.75	2.35	-6.12	1.01	6.50
RD	8,232	17.96	1.56	7.72	17.97	24.08
AGE	8,232	17.39	7.58	3.00	17.00	31.00
OWN	8,232	57.99	15.10	22.62	58.28	91.70
DIR	8,232	8.69	1.69	5.00	9.00	15.00
FemD	8,232	1.31	1.09	0.00	1.00	4.00
ESG	8,232	73.02	4.93	57.60	73.15	83.98
MAR	8,232	9.17	1.78	3.25	9.44	11.49

Note This table presents the descriptive statistics. Panel A and Panel B subdivide the sample into two groups according to the values of EPT (environmental protection tax level), and Panel C shows the descriptive statistics of the full sample. GTI refers to the number of green patents (green technology innovation); EPT refers to environmental protection EPT; GIN refers to the number of green invention patents; GUT refers to the number of green utility model patents; GRA refers to the amount of governmental environmental protection subsidy; AIR, WATER, SOLID, and NOISE represent the amount of environmental protection taxes on exhaust gas, waste water, solid waste and noise, respectively; SIZE refers to the natural logarithm of enterprises' total assets; LEV refers to the leverage ratio; TobinQ refers to the Tobin's Q; KZ is the financing constraint index; RD refers to R&D expenses; AGE refers to the company's age; OWN refers to the ownership concentration; DIR and FemD represent the number of directors and female directors, respectively; SOE is a dummy variable and takes 1 if the companies are state-owned, otherwise takes 0; ESG is the Huazheng ESG rating; MAR represents the degree of market orientation. All variables are defined in Table 2

Pairwise correlation matrix

Table 4 presents the results of the pairwise correlation analysis, and Table 5 demonstrates the results of White's test. The analysis indicates a positive and significant correlation between GTI and EPT. This suggests that Environmental Performance Taxation (EPT) is conducive to the advancement of green technology innovation within China's heavily polluting industries. Additionally, the maximum Variance Inflation Factor (VIF) recorded is 5.66 and the White's test is significant, which confirms the absence of multicollinearity and heteroscedasticity concerns, thereby validating the suitability of the variables for regression analysis.

Regression analysis and robustness test

Table 6 showcases the two-way fixed-effect regression analysis, which probes the influence of Environmental Performance Taxation (EPT) on green technology innovation (GTI). The regressions are conducted by adding control variables step by step, which is more capable to illustrate the effect consistency of EPT. Column (1) delineates outcomes without control variables (3.337***), revealing a significantly positive coefficient for EPT. When control variables are included [columns (2)–(4)], the coefficients drop in their magnitude, while still remain significant and positive, indicating a valid positive correlation between heightened environmental tax intensity and increased green technology innovation. These results lend empirical support to *hypothesis* $H1_A$. From an economic perspective, EPT serves not only as a legal deterrent for emissions but also as a financial catalyst for technological transformation within enterprises, reducing green costs and stimulating green technological innovation (Carrion-Flores et al. 2006; He et al. 2023). Furthermore, in line with previous work (Martínez-Ros & Kunapatarawong 2019; Song et al. 2020; Wang et al. 2023; Wu & Hu 2020; Zeng et al. 2021), we observe significantly positive coefficients on SIZE (3.532***), TobinQ (0.433***), RD (0.756***), ESG (0.086***), OWN (0.033***), and MAR (0.133**), suggesting that increases in firm size, Tobin's Q, research and development, ownership concentration, and marketization levels are conducive to fostering green technology innovation.

Table 7 elucidates the robustness of the basic regression results. Columns (1) and (2) detail the outcomes of the two-stage least squares (2SLS) instrumental variable regressions[4]. In column (1), we adopt the Batik instrumental variable approach and includes the interaction of 1-year

[4] The correlation coefficients between the error term and constructed instruments (Bartik-style, 1-year lag, industrial average, and provincial average) are -0.0087, 0.0337, 0.0082, and 0.0330, respectively, indicating that there is no significant relationship between the instruments and the error term.

Table 4 Correlation and VIF analyses

	GTI	EPT	SIZE	LEV	TobinQ	KZ	RD	AGE	OWN	DIR	FemD	ESG	MAR	VIF
GTI	1	0.468***	0.480***	0.240***	−0.315***	0.053***	0.354***	0.114***	0.089***	0.135***	−0.078***	0.150***	−0.016*	
EPT	0.488***	1	0.871***	0.448***	−0.507***	0.093***	0.583***	0.311***	0.154***	0.241***	−0.114***	0.168***	−0.066***	5.45
SIZE	0.534***	0.885***	1	0.455***	−0.574***	0.113***	0.590***	0.325***	0.145***	0.265***	−0.099***	0.187***	−0.115***	5.66
LEV	0.174***	0.420***	0.431***	1	−0.375***	0.691***	0.148***	0.326***	−0.073***	0.167***	−0.123***	−0.113***	−0.171***	2.73
TobinQ	−0.168***	−0.379***	−0.418***	−0.277***	1	−0.125***	−0.218***	−0.154***	−0.132***	−0.140***	0.083***	−0.090***	0.062***	1.25
KZ	0.037***	0.063***	0.086***	0.666***	−0.002	1	−0.063***	0.265***	−0.214***	0.066***	−0.106***	−0.208***	−0.163***	2.08
RD	0.319***	0.560***	0.548***	0.089***	−0.141***	−0.089***	1	0.050***	0.089***	0.099***	−0.002	0.215***	0.124***	1.76
AGE	0.097***	0.285***	0.304***	0.331***	−0.056***	0.265***	0.010	1	−0.265***	0.215***	−0.154***	−0.094***	−0.307***	1.59
OWN	0.213***	0.236***	0.236***	−0.070***	−0.105***	−0.216***	0.141***	−0.265***	1	0.036***	−0.023**	0.148***	0.056***	1.28
DIR	0.185***	0.290***	0.322***	0.199***	−0.121***	0.073***	0.104***	0.213***	0.059***	1	0.052***	0.054***	−0.180***	1.17
FemD	−0.066***	−0.117***	−0.102***	−0.119***	0.054***	−0.110***	0.004	−0.154***	−0.027***	0.067***	1	0.016*	0.112***	1.06
ESG	0.168***	0.197***	0.223***	−0.122***	−0.089***	−0.201***	0.232***	−0.095***	0.148***	0.062***	0.023**	1	0.067***	1.11
MAR	0.032***	−0.030***	−0.085***	−0.166***	−0.003	−0.149***	0.163***	−0.283***	0.039***	−0.167***	0.097***	0.073***	1	1.15

Note This table presents the results of pairwise correlation analysis and VIF test. The Pearson correlation coefficients are listed on the bottom left, the Spearman correlation coefficients are listed on the top right, and the VIFs are shown on the far right. GTI refers to the number of green patents (green technology innovation); EPT refers to environmental protection EPT; SIZE refers to the natural logarithm of enterprises' total assets; LEV refers to the leverage ratio; TobinQ refers to the Tobin's Q; KZ is the financing constraint index; RD refers to R&D expenses; AGE refers to the company's age; OWN refers to the ownership concentration; DIR and FemD represent the number of directors and female directors, respectively; SOE is a dummy variable and takes 1 if the companies are state-owned, otherwise takes 0; ESG is the Huazheng ESG rating; MAR represents the degree of market orientation. All variables are defined in Table 2

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 5 White test

Source	chi2	df	*p*
Heteroskedasticity	2952.53	90	0.000
Skewness	1081.33	12	0.000
Kurtosis	110.8	1	0.000
Total	4144.66	103	0.000

lag and first difference values as the first instrument and the 1-year lag value as the second instrument (Bartik 2006). In column (2), we choose the industrial average (excluding the focal firm) and provincial average (excluding the focal firm) as instruments, which captures the confounding factors at regional and industrial levels (Gormley & Matsa 2014). Both sets of instrumental variables are related to the endogenous independent variable while not necessarily influencing the

Table 6 baseline regression analysis

	(1) GTI	(2) GTI	(3) GTI	(4) GTI
EPT	3.337***	0.415**	0.496***	0.469***
	(27.365)	(2.356)	(2.852)	(2.689)
SIZE		3.434***	3.482***	3.532***
		(14.802)	(14.163)	(14.209)
LEV		−6.865***	−6.776***	−6.669***
		(−7.956)	(−7.900)	(−7.821)
TobinQ		0.414***	0.430***	0.433***
		(5.052)	(5.196)	(5.215)
KZ		0.320***	0.397***	0.394***
		(5.714)	(6.806)	(6.776)
RD		0.877***	0.792***	0.756***
		(8.439)	(7.607)	(7.204)
ESG		0.102***	0.087***	0.086***
		(4.718)	(3.992)	(3.951)
AGE			−0.082***	−0.078***
			(−3.878)	(−3.660)
OWN			0.033***	0.033***
			(4.561)	(4.562)
DIR			0.127	0.138
			(1.453)	(1.578)
FemD			−0.329***	−0.332***
			(−3.439)	(−3.472)
MAR				0.133**
				(2.370)
Constant	−42.566***	−99.964***	−100.803***	−102.265***
	(−25.775)	(−23.104)	(−22.855)	(−22.496)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	9501	8232	8232	8232
R^2	0.31	0.38	0.39	0.39
Adj. R^2	0.31	0.38	0.39	0.39
F	748.861	131.257	92.251	84.471

Note This table presents the results of baseline regression analysis of EPT on GTI. Column (1) is the univariate regression model. Columns (2) to (4) are the two-way fixed effect regressions with gradual additions of firm-level financial control variables, management-level control variables, and the market effect control variable. GTI refers to the number of green patents (green technology innovation); EPT refers to environmental protection tax; SIZE refers to the natural logarithm of enterprises' total assets; LEV refers to the leverage ratio; TobinQ refers to the Tobin's Q; KZ is the financing constraint index; RD refers to R&D expenses; AGE refers to the company's age; OWN refers to the ownership concentration; DIR and FemD represent the number of directors and female directors, respectively; SOE is a dummy variable and takes 1 if the companies are state-owned, otherwise takes 0; ESG is the Huazheng ESG rating; MAR represents the degree of market orientation. All variables are defined in Table 2

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 7 Baseline robustness test

	(1) GTI	(2) GTI	(3) GTI	(4) GTI	(5) GTI	(6) GTI
L.GTI			0.564***			
			(24.562)			
EPT	0.689***	9.363***	0.553**	0.407**		
	(3.464)	(4.032)	(2.444)	(2.291)		
L.EPT					0.619***	
					(3.130)	
F.EPT						0.514***
						(3.103)
SIZE	3.567***	−3.846**	2.080***	3.383***	3.627***	3.558***
	(13.450)	(−1.979)	(2.795)	(13.808)	(14.082)	(13.634)
LEV	−7.500***	−14.089***	−8.529*	−6.032***	−7.305***	−6.994***
	(−7.916)	(−6.503)	(−1.892)	(−7.146)	(−7.738)	(−7.453)
TobinQ	0.456***	0.369***	0.785*	0.381***	0.468***	0.396***
	(4.891)	(3.591)	(1.827)	(4.523)	(5.018)	(4.382)
KZ	0.447***	0.929***	0.614***	0.371***	0.425***	0.405***
	(6.875)	(6.087)	(2.874)	(6.428)	(6.578)	(6.347)
RD	0.751***	−0.202	1.169***	0.732***	0.757***	0.662***
	(6.570)	(−0.758)	(3.006)	(7.049)	(6.637)	(6.098)
ESG	0.086***	0.040	0.162**	0.090***	0.085***	0.086***
	(3.641)	(1.466)	(1.982)	(4.046)	(3.585)	(3.901)
AGE	−0.094***	−0.212***	0.298***	−0.062***	−0.095***	−0.096***
	(−4.167)	(−5.029)	(3.041)	(−2.893)	(−4.199)	(−4.147)
OWN	0.026***	0.007	0.040	0.023***	0.027***	0.029***
	(3.360)	(0.671)	(1.182)	(3.077)	(3.387)	(3.776)
DIR	0.140	0.105	−0.284**	0.146*	0.141	0.097
	(1.464)	(1.108)	(−2.090)	(1.704)	(1.481)	(1.026)
FemD	−0.343***	−0.213*	0.315	−0.348***	−0.346***	−0.378***
	(−3.246)	(−1.891)	(0.624)	(−3.545)	(−3.282)	(−3.653)
MAR	0.144**	−0.114	0.018	0.180	0.148**	0.186***
	(2.365)	(−1.188)	(0.152)	(1.075)	(2.442)	(3.209)
Constant			−90.552***	−98.309***	−105.761***	−101.174***
			(−6.683)	(−21.246)	(−22.470)	(−21.059)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov. FE	No	No	No	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7208	8232	7225	8045	7223	7005
R^2				0.418	0.404	0.392
Adj. R^2				0.413	0.401	0.389
F	80.01			83.171	79.814	71.342
Kleibergen-Paap rk LM	1308.63***	62.64***				
Cragg-Donald Wald F	3300***	36.36***				
Hansen J	1.892	1.962	127.19			
AR(1)			−6.28***			
AR(2)			1.50			

Note This table presents the results of robustness tests for baseline regressions. Columns (1) and (2) presents 2sls IV regression results, where the instrumental variables in column (1) are Bartik instrument and one-year lag values of EPT, and those in column (2) are the industrial and provincial average levels of EPT; Column (3) lists the results using systematic GMM approach and considers the one-year lag effect of GTI; Column (4) presents the high-dimensional fixed effect regression model by controlling provincial-, industry-, and year-fixed effects; Columns (5) and (6) adopt the one-year lag and one-year forward values of EPT to replace EPT in the models. GTI refers to the number of green patents (green technology innovation); EPT refers to environmental protection tax; GIN refers to the number of green invention patents; GUT refers to the number of green utility model patents; GRA refers to the amount of governmental environmental protection subsidy; AIR, WATER, SOLID, and NOISE represent the amount of environmental protection taxes on exhaust gas, waste water, solid waste and noise, respectively; SIZE refers to the natural logarithm of enterprises' total assets; LEV refers to the leverage ratio; TobinQ refers to the Tobin's Q; KZ is the financing con-

Table 7 (continued)

straint index; RD refers to R&D expenses; AGE refers to the company's age; OWN refers to the ownership concentration; DIR and FemD represent the number of directors and female directors, respectively; SOE is a dummy variable and takes 1 if the companies are state-owned, otherwise takes 0; ESG is the Huazheng ESG rating; MAR represents the degree of market orientation. All variables are defined in Table 2

***$p<0.01$, **$p<0.05$, *$p<0.1$

dependent and omitted variables, satisfying the relevance and exogeneity requirements (Berkowitz et al. 2012). According to Table 7, both regressions exhibit positive and significant coefficients for EPT (0.689*** and 9.363***), albeit with different magnitudes. The test statistics are showing that both regressions reject the under-identification (LM statistics) and weak IV (F statistics) hypotheses, and do not reject the over-identification Hansen J test, confirming the validity of our IV-2SLS regressions.

The subsequent column (3) introduces the system GMM model, which adds 1-year lag values of the dependent variable (L.GTI) as the independent variable, making the model more valid to analyze dynamic panel data (Blundell & Bond 1998). The results yield a significantly positive impact of EPT (0.553***), reassuring the validity of *hypothesis* $H1_A$. The rejection of AR(1) test and inability to reject AR(2) confirm the homoskedasticity condition of residuals in the model. And the result of Hansen J test shows that the instruments are not overidentified, further confirming the robustness of the GMM model.

Column (4) alters the model specification of the baseline regression by adding the provincial fixed effect. The results of this high-dimensional fixed-effect model (0.619***) are consistent with the baseline regression, confirming the previous conclusion.

Columns (5) and (6) introduce lagged and forward EPT as the independent variable, respectively, with both yielding coefficients (0.619***, 0.514***, respectively) that align with the foundational regression results. From a statistical standpoint, this approach addresses data endogeneity, thereby enhancing the explanatory power and precision of the regression analysis.

The consistently positive coefficients across these models affirm the validity of baseline results. The effectiveness of the GMM and IV-2SLS approaches in addressing issues of reverse causality and endogeneity are testified via different tests, thereby enhancing the reliability and robustness. Additionally, the IV-2SLS model indicates that the relationship between innovation and EPT manifests through two primary effects: firstly, the income advantage in the region and industry, where the relative cost efficiency of environmentally friendly products in the face of heightened environmental costs compels higher-emission firms to adopt greener practices (Capozza & Samson 2019); secondly, the substitution effect inside the company, where EPT increases the price disparity among firms' products, mitigating substitution effects and enabling market share capture. Firms are thus incentivized to refine their production and governance structures, striving to develop products that are either low-taxed or exempt from environmental taxes (Kosonen 2012). This strategy not only reduces the environmental tax burden but also establishes a sustainable cost-reduction mechanism. Through technological innovation, firms can decrease their emissions, lower their EPT obligations, and achieve green production. The savings accrued can then be reinvested into further technological innovation, creating a virtuous cycle. These findings corroborate *hypothesis* $H1_A$, indicating that in China's heavily polluted industries, a more robust taxation power bolsters the capacity for environmental protection innovation.

Difference-in-difference (DID) analysis

Following Chen et al. (2025) and Wu et al. (2024), this paper chooses high-pollution industry firms in high environmental protection tax level regions as the treatment group, and firms in lower tax level regions as the controlled group. And according to the Chinese Government Website, *Implementation Regulations of the Environmental Protection Tax Law of the People's Republic of China* was effective from January 1st, 2018. Therefore, we choose 2018 as the policy year. In terms of model settings, column (1) displays the fundamental DID model with *Treat* indicating the treatment group, *Time* indicating the policy year, and their interaction term *Treat*×*Time*. In addition, column (2) shows the time-varying DID model, where the interaction term of *Treat* with each observation year is included to examine the policy effectiveness. Finally, column (3) presents the results of DID after entropy balancing, an approach to match values the covariates in treated and control groups (Hainmueller 2012). The results are suggesting a positive and significant DID effect (1.168***), even after the entropy balancing (1.711***). In column (2) and Fig. 6, the results are indicating that the treatment effects are insignificant before 2017, and becomes positively significant in and after 2017. This could be due to the existence of the time lag before the release of the government document after the issuance of the scheduled policy proposal; therefore, firms could receive the signal before the policy release. To conclude, we find a significant and positive policy effect of the environmental protection tax

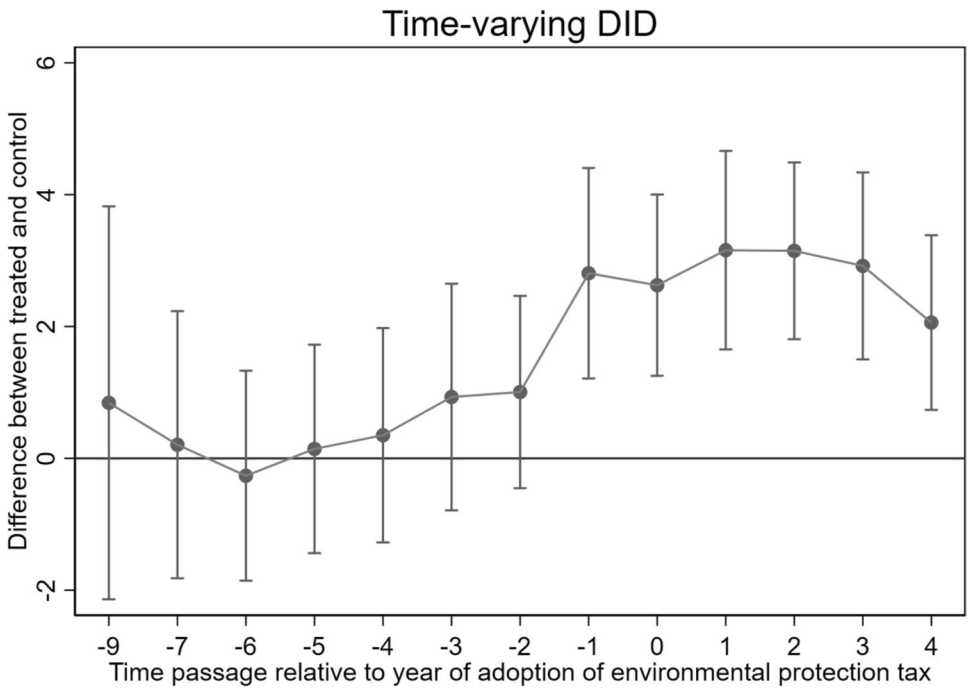


Fig. 6 Multi-year DID. *Note* This figure visualizes the results of time-varying DID [Table 8, column (2)] by plotting the coefficients of Treat × Year(i) and adding the 90% level confidence interval

reform regulation, which mitigates the endogeneity issue and supports the baseline conclusion (Table 8)[5].

Moderating impact and robustness analysis

Table 9 elucidates the moderating effects of government environmental subsidies (GRA) on the relationship between Environmental Performance Taxation (EPT) and green patent applications (GTI). Similar to the baseline regressions, this research adds control variables step by step from column (1) to column (4). The results are showing positive and significant coefficients of the interaction terms (0.5***, 0.391***, 0.376***, and 0.374***, respectively), revealing a positive and strengthening regulating effect of GRA in the nexus between EPT and GTI. Also, in Table 10, this paper adopts IV-2SLS, GMM, and high-dimensional fixed-effect models as robustness tests. The results validate the above findings (0.395***, 0.393***, and 0.350***, respectively), indicating that government subsidies can significantly enhance the positive impact of EPT on GTI, particularly in firms receiving substantial government grants, thus affirming Hypothesis $H2_A$. These findings reinforce the notion that government subsidies can lower financial barriers and encourage the adoption of green products, thereby increasing firms' propensity to engage in green innovation (Zhan et al. 2018). Furthermore, when coupled with EPT reforms, the ability of enterprises to secure environmental subsidies not only signals market confidence but also alters competitive dynamics, incentivizing peers to prioritize technological innovation (Wang & Fan 2023).

Channeling analysis

Table 11 provides a comprehensive analysis of the channel effects of Environmental Performance Taxation (EPT) on green technology innovation (GTI), examining the impact across different patent types and environmental tax categories. Columns (1) and (2) explore the influence of EPT on green invention patents (GIN) and utility model green patents (GUT), respectively. The findings reveal that EPT exerts a more pronounced positive impact on GUT, with a significant coefficient of 0.303, compared to GIN, which has a coefficient of 0.212. This suggests that EPT encourages businesses to invest in utility model innovations since the associated costs and challenges, as well as the examination criteria, are less stringent in comparison with invention patents, making it easier for enterprises to practically promote the operational processes and effectively reduce the pollutant emissions (Andersson et al. 2009; Hub 2024).

Columns (3) to (6) assess the specific impacts of different environmental tax components—AIR, WATER, SOLID, and NOISE. The regression coefficients demonstrate a significant positive effect across all categories, with AIR exhibiting the strongest incentive for environmental innovation and WATER the weakest. This variation is likely due to the direct correlation between waste discharge fees, emission levels, and the operational costs of heavily polluting industries. Firms are thus motivated to undertake transformative

[5] https://www.gov.cn/zhengce/content/2017-12/30/content_5251797.htm

Table 8 DID analysis

	(1) GTI	(2) GTI	(3) GTI
Treat	1.168***		1.711***
	(3.018)		(4.463)
Time	−0.740		−1.434
	(−0.995)		(−1.528)
Treat × Time	1.368**		0.778*
	(2.457)		(1.661)
SIZE	3.817***	3.808***	5.443***
	(18.538)	(19.481)	(33.147)
LEV	−6.101***	−6.198***	−11.046***
	(−7.382)	(−7.752)	(−11.083)
TobinQ	0.416***	0.372***	0.668***
	(5.032)	(4.890)	(5.193)
KZ	0.362***	0.372***	0.556***
	(6.359)	(6.832)	(7.368)
RD	0.837***	0.847***	0.943***
	(8.223)	(8.375)	(9.418)
ESG	0.086***	0.088***	0.107***
	(3.976)	(4.078)	(4.217)
AGE	−0.061***	−0.064***	−0.118***
	(−2.905)	(−3.366)	(−5.768)
OWN	0.035***	0.036***	0.054***
	(4.919)	(5.061)	(5.803)
DIR	0.133	0.136	0.195***
	(1.531)	(1.576)	(2.651)
FemD	−0.341***	−0.345***	−0.200*
	(−3.575)	(−3.604)	(−1.759)
MAR	0.026	0.041	0.268***
	(0.477)	(0.771)	(2.712)
Treat × Year.2010		0.842	
		(0.465)	
Treat × Year.2011		0.207	
		(0.168)	
Treat × Year.2012		−0.264	
		(−0.272)	
Treat × Year.2013		0.143	
		(0.149)	
Treat × Year.2014		0.351	
		(0.355)	
Treat × Year.2015		0.930	
		(0.891)	
Treat × Year.2016		1.006	
		(1.135)	
Treat × Year.2017		2.808***	
		(2.893)	
Treat × Year.2018		2.626***	
		(3.142)	
Treat × Year.2019		3.158***	
		(3.449)	
Treat × Year.2020		3.148***	
		(3.862)	
Treat × Year.2021		2.920***	
		(3.387)	
Treat × Year.2022		2.060**	
		(2.557)	
Constant	−102.959***	−103.705***	−144.421***
	(−24.758)	(−25.419)	(−46.660)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	8250	8250	8250
R^2	0.40	0.39	0.50
Adj. R^2	0.39	0.39	0.50
F	44.041	44.629	156.986

Note This table presents the results of DID (Difference-in-Difference) analysis. Following Chen et al. (2025) and Wu et al. (2024), this paper chooses high-pollution industry firms in high environmental protection tax level regions as the treatment group, and firms in lower tax level regions as the controlled group. And according to the Chinese Government Website, Implementation Regulations of the Environmental Protection Tax Law of the People's Republic of China was effective from January 1st, 2018. Therefore, we choose 2018 as the policy year. In the table, column (1) shows the results of baseline DID; column (2) presents the results of Time-varying DID for each observation year; column (3) presents the results of DID after entropy balancing (Hainmueller 2012). EPT refers to environmental protection tax; SIZE refers to the natural logarithm of enterprises' total assets; LEV refers to the leverage ratio; TobinQ refers to the Tobin's Q; KZ is the financing constraint index; RD refers to R&D expenses; AGE refers to the company's age; OWN refers to the ownership concentration; DIR and FemD represent the number of directors and female directors, respectively; SOE is a dummy variable and takes 1 if the companies are state-owned, otherwise takes 0; ESG is the Huazheng ESG rating; MAR represents the degree of market orientation. All variables are defined in Table 2

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

actions or technological breakthroughs to mitigate these costs and ensure sustainable operations. The analysis underscores the pivotal role of exhaust gas charges within the tax sub-program in stimulating environmental innovation, while highlighting the relatively lesser influence of wastewater taxes. Overall, the study affirms the critical role of EPT in fostering green technological advancements within heavily polluting sectors.

Heterogeneity analysis

The heterogeneity analysis between environmental protection tax (EPT) and green innovation (GTI) adaptation involves examining how different types of firms—specifically State-Owned Enterprises (SOEs) and Non-State-Owned Enterprises (Non-SOEs)—respond to EPT in terms

Table 9 Moderating analysis—government subsidy, EPT, and GTI

	(1) GTI	(2) GTI	(3) GTI	(4) GTI
EPT	−4.647***	−4.538***	−4.367***	−4.379***
	(−4.528)	(−4.298)	(−4.060)	(−4.064)
GRA	−6.828***	−5.408***	−5.198***	−5.168***
	(−6.538)	(−4.846)	(−4.589)	(−4.558)
EPT×GRA	0.500***	0.391***	0.376***	0.374***
	(6.635)	(4.831)	(4.572)	(4.546)
SIZE		1.877***	1.788***	1.849***
		(6.230)	(5.770)	(5.681)
LEV		−4.853***	−4.788***	−4.745***
		(−4.242)	(−4.225)	(−4.183)
TobinQ		0.328***	0.331***	0.338***
		(2.685)	(2.623)	(2.655)
KZ		0.315***	0.334***	0.341***
		(3.466)	(3.552)	(3.614)
RD		0.599***	0.607***	0.579***
		(4.463)	(4.317)	(4.131)
ESG		0.084***	0.085***	0.085***
		(2.921)	(2.937)	(2.918)
AGE			0.010	0.013
			(0.319)	(0.420)
OWN			0.026**	0.025**
			(2.156)	(2.114)
DIR			0.102	0.108
			(0.828)	(0.881)
FemD			−0.244	−0.250
			(−1.497)	(−1.536)
MAR				0.116
				(1.240)
Constant	65.524***	8.127	5.216	3.337
	(4.657)	(0.493)	(0.307)	(0.195)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	3687	3124	3124	3124
R^2	0.262	0.326	0.328	0.328
Adj. R^2	0.256	0.318	0.319	0.319
F	87.68	39.58	29.21	26.97

Note This table presents the results of moderating regressions that investigate the role of GRA in the relationship between GTI and EPT. Column (1) is the regression model that only includes EPT, GTI, and their interaction. Columns (2) to (4) are the two-way fixed effect regressions with gradual additions of firm-level financial control variables, management-level control variables, and the market effect control variable. GTI refers to the number of green patents (green technology innovation); EPT refers to environmental protection tax; GRA refers to the amount of governmental environmental protection subsidy, and EPT×GRA is the interaction term between EPT and GRA; SIZE refers to the natural logarithm of enterprises' total assets; LEV refers to the leverage ratio; TobinQ refers to the Tobin's Q; KZ is the financing constraint index; RD refers to R&D expenses; AGE refers to the company's age; OWN refers to the ownership concentration; DIR and FemD represent the number of directors and female directors, respectively; SOE is a dummy variable and takes 1 if the companies are state-owned, otherwise takes 0; ESG is the Huazheng ESG rating; MAR represents the degree of market orientation. All variables are defined in Table 2

***$p<0.01$, **$p<0.05$, *$p<0.1$

of their green innovation activities. In Table 12, the findings have revealed that the positive correlation between EPT and GTI is predominantly observed within the SOEs sample. This suggests that SOEs are more responsive to EPT, possibly due to their greater social responsibility and more resources in innovating in environmentally friendly ways (Bai et al. 2006; Stone et al. 2022).

Further subsample analyses delve into the nuances of this heterogeneity by considering factors such as ownership concentration, marketization, and firm age. The results indicate that the positive association between EPT and GTI is particularly pronounced in SOEs with lower ownership concentration level and higher ages. This could be because such firms have easier access to capital, more balanced decision-making and efficient resource allocation, which are conducive to higher levels of green innovation (Brown et al. 2012; Liu & Xu 2024; Wu 2023). Similarly, for both SOEs and non-SOEs operating in regions with low marketization—where market forces are less dominant—EPT exhibits greater impact on GTI. This might be due to these firms having more to gain from government incentives like EPT, as they are less influenced by competitive market pressures.

Lastly, the heterogeneity analysis suggests that SOEs, especially those with higher firm ages, lower ownership concentration levels, and operating in less marketized environments, are more inclined to enhance their green innovation efforts in response to EPT (Bai et al. 2019; Zhou et al. 2023a). This reflects the varying impacts of economic and policy instruments across different firm types and market conditions in China (Table 12).

Nonlinearity analysis

This study also examines the quadratic effect of environmental protection taxation (EPT) on green innovation level (GTI). According to the literature, moderate EPT acts as burden to companies which prevent them from emissions; without process and technology upgrading, this could result in a "crowding-out" effect in innovation investment to reduce potential pollution generation (Carrion-Flores et al. 2006; He et al. 2023). Nonetheless, high EPT transmit strong signals through legitimacy, entailing high costs or transformation for companies, thereby acting as a financial catalyst to boost green technological innovation. It also indicates that EPT leads to an "innovation compensation" effect, where the internalization of high environmental management costs into operational expenses drives firms to either eliminate or improve non-environmentally friendly products, prompting companies to pursue environmental technology innovation. The results from Table 13 and Fig. 7 suggest a distinct U-shape curve between EPT and GTI (and its

Table 10 Moderating robustness test

	(1) GTI	(2) GTI	(3) GTI
L.GTI		0.512***	
		(35.320)	
EPT	−4.464***	−4.661***	−4.185***
	(−3.505)	(−3.583)	(−3.710)
GRA	−5.486***	−5.549***	−4.808***
	(−4.251)	(−4.043)	(−4.032)
EPT × GRA	0.395***	0.393***	0.350***
	(4.218)	(4.207)	(4.069)
SIZE	1.969***	1.364***	1.817***
	(5.794)	(2.676)	(5.243)
LEV	−5.736***	−4.339**	−4.449***
	(−4.536)	(−2.088)	(−3.821)
TobinQ	0.408***	0.970***	0.278**
	(2.942)	(2.761)	(2.228)
KZ	0.435***	0.184	0.310***
	(4.217)	(1.242)	(3.274)
RD	0.514***	1.455***	0.545***
	(3.416)	(6.306)	(3.888)
ESG	0.097***	0.055	0.078***
	(3.059)	(1.374)	(2.630)
AGE	0.004	0.218***	0.035
	(0.105)	(3.025)	(1.058)
OWN	0.015	0.005	0.025**
	(1.171)	(0.189)	(2.019)
DIR	0.091	−0.380***	0.036
	(0.680)	(−3.994)	(0.275)
FemD	−0.255	−0.418*	−0.339*
	(−1.437)	(−1.903)	(−1.904)
MAR	0.144	0.121	−0.117
	(1.462)	(1.166)	(−0.457)
Constant		3.200	4.623
		(0.141)	(0.264)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	2790	2798	3052
R^2			0.353
Adj. R^2			0.338
F	25.72		23.81
Kleibergen-Paap rk LM	351.51***		
Cragg-Donald Wald F	5920.11***		
Hansen J	0.130	150.59	
AR(1)		−5.06***	
AR(2)		0.38	

Note This table presents the results of robustness tests on moderating regressions. Column (1) is the 2SLS instrumental variable regression model using Batik instrument and one-year lag values of EPT; column (2) is the GMM approach; column (3) is the high-dimensional fixed effect regression model by controlling provincial-, industry-, and year-fixed effects. GTI refers to the number of green patents (green technology innovation); EPT refers to environmental protection tax; GRA refers to the amount of governmental environmental protection subsidy, and EPT × GRA is the interaction term between EPT and GRA; SIZE refers to the natural logarithm of enterprises' total assets; LEV refers to the leverage ratio; TobinQ refers to the Tobin's Q; KZ is the financing constraint index; RD refers to R&D expenses; AGE refers to the company's age; OWN refers to the ownership concentration; DIR and FemD represent the number of directors and female directors, respectively; SOE is a dummy variable and takes 1 if the companies are state-owned, otherwise takes 0; ESG is the Huazheng ESG rating; MAR represents the degree of market orientation. All variables are defined in Table 2

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

subcategories).[6] This implies that while environmental protection tax initially reduces the inclination for green innovation, firms may be incentivized to invest in green innovation at higher environmental protection tax levels. The above findings are in line with the literature, suggesting a relatively complicate relationship between EPT and GTI in practice. The asymmetric line, take GTI for instance, is at 13.77, which is comparable to the median of EPT (13.83). It suggests the threshold for EPT to act as impetus for GTI, and also reveals that for almost half of the observations in the sample, an increase of EPT results in a lower GTI, while the other half shows opposite results.

Quantile analysis

This study further explores the effect heterogeneity of environmental protection taxation (EPT) on green innovation level (GTI) in different percentiles. Specifically, we apply subsection linear regressions to different quantile intervals according to the values of EPT: 0–20%, 20–40%, 40–60%, 60–80%, and 80–100%. The results further consolidate the findings from nonlinearity test. According to Table 14, the coefficients of EPT are negative and insignificant across all the groups below 80th percentile, and only the 80–100% observations are showing significant and positive results. These could also suggest implicitly that negative effect of environmental protection tax would offset the positive benefits at relatively low tax levels, while the positive impact outweighs only at high EPT levels, complying with the conclusion in the U-shape curve effect and literature (Carrion-Flores et al. 2006; He et al. 2023). The findings in quantile analysis, collectively with the nonlinearity test, underline the nuanced relationship between EPT and GTI in Chinese heavily polluting listed firms. Enterprises strategically adjust their green innovation investment according to the government taxation level, balancing the burdens from pollution and costs from research and development.

[6] For the subcategories of EPT – AIR, WATER, SOLID, and NOISE, the nonlinearity is also checked and plotted in Fig. 8.

Table 11 Channeling analysis

	(1) GIN	(2) GUT	(3) GTI	(4) GTI	(5) GTI	(6) GTI
EPT	0.212**	0.303***				
	(1.997)	(3.370)				
AIR			0.446***			
			(2.604)			
WATER				0.365**		
				(2.271)		
SOLID					0.440**	
					(2.566)	
NOISE						0.420***
						(2.790)
SIZE	1.898***	1.740***	3.551***	3.618***	3.556***	3.573***
	(12.501)	(13.781)	(14.375)	(14.666)	(14.429)	(14.875)
LEV	−4.068***	−3.017***	−6.655***	−6.590***	−6.642***	−6.630***
	(−7.475)	(−7.172)	(−7.799)	(−7.745)	(−7.781)	(−7.861)
TobinQ	0.222***	0.219***	0.433***	0.434***	0.433***	0.434***
	(4.767)	(4.999)	(5.214)	(5.227)	(5.214)	(5.230)
KZ	0.219***	0.205***	0.394***	0.389***	0.392***	0.391***
	(5.959)	(7.037)	(6.757)	(6.687)	(6.735)	(6.788)
RD	0.396***	0.362***	0.759***	0.767***	0.760***	0.760***
	(6.279)	(6.695)	(7.235)	(7.364)	(7.236)	(7.277)
ESG	0.055***	0.032***	0.086***	0.086***	0.086***	0.086***
	(4.263)	(2.770)	(3.962)	(3.976)	(3.958)	(3.954)
AGE	−0.055***	−0.039***	−0.077***	−0.076***	−0.077***	−0.076***
	(−4.289)	(−3.575)	(−3.647)	(−3.591)	(−3.640)	(−3.605)
OWN	0.021***	0.012***	0.033***	0.033***	0.033***	0.033***
	(5.148)	(3.029)	(4.570)	(4.597)	(4.571)	(4.602)
DIR	0.138**	0.032	0.138	0.138	0.138	0.139
	(2.491)	(0.725)	(1.579)	(1.575)	(1.580)	(1.589)
FemD	−0.253***	−0.084*	−0.333***	−0.332***	−0.332***	−0.333***
	(−4.245)	(−1.736)	(−3.479)	(−3.471)	(−3.477)	(−3.484)
MAR	0.152***	−0.023	0.133**	0.135**	0.134**	0.136**
	(4.535)	(−0.760)	(2.376)	(2.409)	(2.383)	(2.425)
Constant	−55.927***	−49.193***	−101.983***	−102.361***	−102.033***	−101.822***
	(−19.548)	(−22.111)	(−22.207)	(−22.077)	(−22.255)	(−22.284)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8232	8232	8232	8232	8232	8232
R^2	0.317	0.387	0.391	0.391	0.391	0.391
Adj. R^2	0.314	0.384	0.388	0.388	0.388	0.388
F	59.36	77.55	84.46	84.39	84.43	84.48

Note This table presents the results of channel effects from different subcategories of EPT on different aspects of GTI. Columns (1) and (2) subdivide GTI into GIN and GUT; columns (3)-(6) examine the effects of subcategories of EPT. GTI refers to the number of green patents (green technology innovation); EPT refers to environmental protection tax; GIN refers to the number of green invention patents; GUT refers to the number of green utility model patents; AIR, WATER, SOLID, and NOISE represent the amount of environmental protection taxes on exhaust gas, waste water, solid waste and noise, respectively; SIZE refers to the natural logarithm of enterprises' total assets; LEV refers to the leverage ratio; TobinQ refers to the Tobin's Q; KZ is the financing constraint index; RD refers to R&D expenses; AGE refers to the company's age; OWN refers to the ownership concentration; DIR and FemD represent the number of directors and female directors, respectively; SOE is a dummy variable and takes 1 if the companies are state-owned, otherwise takes 0; ESG is the Huazheng ESG rating; MAR represents the degree of market orientation. All variables are defined in Table 2

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 12 Heterogeneity analysis

	SOE						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	SOE	Low OWN	High OWN	Low MAR	High MAR	Low AGE	High AGE
EPT	0.922***	0.611**	1.056*	0.650**	−0.123	1.113	0.694*
	(2.704)	(2.487)	(1.732)	(1.983)	(−0.161)	(1.313)	(1.871)
SIZE	5.729***	1.967***	7.446***	3.293***	8.564***	5.482***	4.475***
	(12.318)	(6.102)	(9.653)	(6.795)	(9.361)	(5.044)	(9.231)
LEV	−14.292***	−0.142	−25.727***	−5.134***	−19.355***	−21.527***	−8.727***
	(−7.950)	(−0.109)	(−7.769)	(−2.923)	(−5.545)	(−4.101)	(−4.910)
TobinQ	1.459***	0.499***	1.836***	0.939***	1.836***	1.478**	1.188***
	(6.569)	(3.151)	(4.199)	(4.416)	(4.154)	(2.335)	(5.723)
KZ	1.088***	0.109	1.577***	0.311*	1.408***	0.599*	0.975***
	(7.015)	(0.950)	(5.743)	(1.944)	(5.105)	(1.752)	(5.876)
RD	0.987***	0.587***	1.585***	0.695***	1.778***	3.158***	0.687***
	(5.516)	(4.218)	(5.004)	(4.823)	(4.202)	(5.109)	(3.907)
ESG	0.168***	0.158***	0.113	0.125***	0.105	0.375***	0.213***
	(3.737)	(4.170)	(1.358)	(3.442)	(1.082)	(3.263)	(4.363)
AGE	−0.340***	0.054*	−0.573***	−0.190***	−0.352***		
	(−7.305)	(1.669)	(−8.289)	(−3.102)	(−5.032)		
OWN	−0.003			−0.004	−0.085***	0.031	0.010
	(−0.211)			(−0.266)	(−2.707)	(0.841)	(0.568)
DIR	−0.160	0.036	−0.154	−0.098	0.051	0.020	0.088
	(−1.016)	(0.315)	(−0.627)	(−0.722)	(0.156)	(0.050)	(0.542)
FemD	−0.240	0.088	0.053	−0.018	−0.502	−0.261	−0.266
	(−0.902)	(0.484)	(0.102)	(−0.078)	(−1.044)	(−0.452)	(−0.946)
MAR	0.574***	−0.004	0.663***			−1.195***	0.822***
	(4.875)	(−0.036)	(3.069)			(−3.489)	(6.240)
Constant	−160.431***	−73.338***	−201.726***	−95.328***	−209.211***	−201.790***	−141.801***
	(−20.996)	(−11.233)	(−17.694)	(−10.930)	(−16.394)	(−11.150)	(−17.012)
Ind, FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2971	1513	1457	1740	1231	588	2383
R^2	0.51	0.39	0.57	0.34	0.63	0.74	0.44
Adj. R^2	0.51	0.37	0.56	0.33	0.61	0.72	0.44
F	64.249	24.056	57.231	25.337	46.653	22.852	42.049
	Non SOE						
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Non-SOE	Low OWN	High OWN	Low MAR	High MAR	Low AGE	High AGE
EPT	−0.105	0.061	−0.151	−0.119	−0.073	−0.465***	0.884***
	(−0.711)	(0.344)	(−0.663)	(−0.580)	(−0.370)	(−2.944)	(2.813)
SIZE	1.231***	1.152***	1.231***	1.669***	1.015***	1.655***	0.920***
	(6.626)	(4.501)	(4.740)	(4.693)	(4.765)	(6.961)	(2.962)
LEV	1.392***	1.148*	1.884**	1.985**	1.786***	2.099***	−1.473
	(2.726)	(1.657)	(2.396)	(2.427)	(2.699)	(3.426)	(−1.454)
TobinQ	0.142*	0.140*	0.187	0.107	0.131	0.111*	0.347*
	(1.941)	(1.709)	(1.642)	(1.158)	(1.402)	(1.832)	(1.765)
KZ	−0.074*	0.067	−0.167**	−0.124*	−0.097*	−0.113**	0.052
	(−1.661)	(1.085)	(−2.569)	(−1.739)	(−1.728)	(−2.410)	(0.525)
RD	0.527***	0.607***	0.480***	0.376***	0.587***	0.477***	0.211**

Table 12 (continued)

	Non SOE						
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Non-SOE	Low OWN	High OWN	Low MAR	High MAR	Low AGE	High AGE
	(7.093)	(7.691)	(3.363)	(3.339)	(6.467)	(5.329)	(1.970)
ESG	0.020	0.084***	−0.038	0.030	−0.006	0.034*	−0.033
	(0.967)	(3.648)	(−1.157)	(1.201)	(−0.215)	(1.825)	(−0.586)
AGE	0.033*	0.017	0.041	−0.047**	0.079***		
	(1.950)	(0.968)	(1.516)	(−2.527)	(3.175)		
OWN	0.001			−0.013	0.015	−0.015***	0.003
	(0.115)			(−1.569)	(1.525)	(−2.744)	(0.169)
DIR	0.057	0.009	0.097	−0.034	0.114*	0.124**	−0.263**
	(1.094)	(0.136)	(1.213)	(−0.416)	(1.735)	(2.148)	(−2.265)
FemD	−0.066	0.152	−0.245**	0.204	−0.145*	0.014	−0.258*
	(−0.930)	(1.385)	(−2.570)	(1.536)	(−1.726)	(0.166)	(−1.944)
MAR	−0.062	−0.076	−0.037			−0.077*	0.042
	(−1.430)	(−1.347)	(−0.588)			(−1.787)	(0.381)
Constant	−35.503***	−41.566***	−30.447***	−41.310***	−32.920***	−39.290***	−29.937***
	(−10.938)	(−8.052)	(−7.776)	(−6.027)	(−10.125)	(−8.879)	(−6.414)
Ind, FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5261	2537	2723	1717	3544	3898	1363
R^2	0.15	0.20	0.13	0.22	0.16	0.14	0.25
Adj. R^2	0.14	0.19	0.12	0.20	0.15	0.13	0.23
F	28.558	19.302	12.537	11.454	24.148	19.439	11.275

Note This table presents the results of state ownership heterogeneity and further illustrates the regulating factors from the different aspects such as marketization, leverage ratio, and financial constraint. For instance, column (1) displays the results within the SOE group, and columns (2) and (3) conduct the heterogeneity test of OWN in the SOE group. It is similar for other factors and for the Non-SOE group. GTI refers to the number of green patents (green technology innovation); EPT refers to environmental protection tax; SIZE refers to the natural logarithm of enterprises' total assets; LEV refers to the leverage ratio; TobinQ refers to the Tobin's Q; KZ is the financing constraint index; RD refers to R&D expenses; AGE refers to the company's age; OWN refers to the ownership concentration; DIR and FemD represent the number of directors and female directors, respectively; SOE is a dummy variable and takes 1 if the companies are state-owned, otherwise takes 0; ESG is the Huazheng ESG rating; MAR represents the degree of market orientation. All variables are defined in Table 2

***$p<0.01$, **$p<0.05$, *$p<0.1$

Discussion and implications

The study's findings illuminate the intricate relationship between environmental policy instruments and corporate innovation within China's context, a nation grappling with significant pollution challenges. In the baseline results and DID analysis, this study identifies a positive impact of environmental protection tax and policy impact. And further in nonlinearity test and quantile analysis, a plausible U-shaped effect of EPT is revealed, showing the positive effect of EPT is more pronounced with a relatively high tax level. The positive influence of environmental protection taxes (EPT) on green technological innovation (GTI) underscores the efficacy of fiscal measures in steering firms toward sustainable practices (Jaffe et al. 2002). The amplification of this effect by government subsidies is particularly noteworthy, suggesting that a combination of incentives and penalties can be a potent catalyst for environmental innovation (Brunnermeier & Cohen 2003). The research also sheds light on the differential impact of EPT on product versus process innovation. This distinction is crucial for policymakers, as it suggests that EPT may be more effective in stimulating certain types of innovation over others (Rennings 2000). The finding that exhaust gas taxation is more effective than wastewater taxation in promoting GTI could inform the refinement of tax policies to target specific environmental issues more effectively (Fullerton & Wolverton 2005). The heterogeneity analysis offers a nuanced perspective, revealing that state-owned enterprises (SOEs), particularly those with higher firm ages, lower ownership concentration levels, and operating in less marketized environments, are more responsive to EPT. This suggests that the resource accessibility, social responsibility, management participation,

Table 13 Nonlinearity analysis

	(1) GTI	(2) GIN	(3) GUT
EPT	−29.777***	−17.590***	−13.536***
	(−20.178)	(−17.781)	(−18.802)
EPT_sq	1.081***	0.636***	0.495***
	(20.006)	(17.578)	(18.598)
SIZE	2.487***	1.283***	1.262***
	(10.381)	(8.757)	(10.267)
LEV	−3.920***	−2.450***	−1.759***
	(−5.616)	(−5.493)	(−4.871)
TobinQ	0.132*	0.045	0.081**
	(1.832)	(1.105)	(2.086)
KZ	0.179***	0.093***	0.107***
	(3.414)	(2.797)	(3.961)
RD	0.655***	0.336***	0.315***
	(6.507)	(5.536)	(6.066)
ESG	0.057***	0.038***	0.018*
	(2.762)	(3.100)	(1.679)
AGE	−0.065***	−0.048***	−0.034***
	(−3.279)	(−3.944)	(−3.254)
OWN	−0.003	−0.000	−0.004
	(−0.389)	(−0.097)	(−1.041)
DIR	0.098	0.114**	0.013
	(1.219)	(2.220)	(0.332)
FemD	−0.232***	−0.194***	−0.038
	(−2.598)	(−3.486)	(−0.839)
MAR	0.121**	0.145***	−0.028
	(2.303)	(4.554)	(−0.975)
Constant	136.125***	84.389***	59.882***
	(12.372)	(11.601)	(10.957)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	8232	8232	8232
R^2	0.467	0.394	0.448
Adj. R^2	0.465	0.391	0.446
F	95.12	66.35	84.46

Note This table displays the nonlinearity test on the sample data. GTI refers to the number of green patents (green technology innovation); EPT refers to environmental protection tax, and EPT_sq is its squared term; GIN refers to the number of green invention patents; GUT refers to the number of green utility model patents; SIZE refers to the natural logarithm of enterprises' total assets; LEV refers to the leverage ratio; TobinQ refers to the Tobin's Q; KZ is the financing constraint index; RD refers to R&D expenses; AGE refers to the company's age; OWN refers to the ownership concentration; DIR and FemD represent the number of directors and female directors, respectively; SOE is a dummy variable and takes 1 if the companies are state-owned, otherwise takes 0; ESG is the Huazheng ESG rating; MAR represents the degree of market orientation. All variables are defined in Table 2

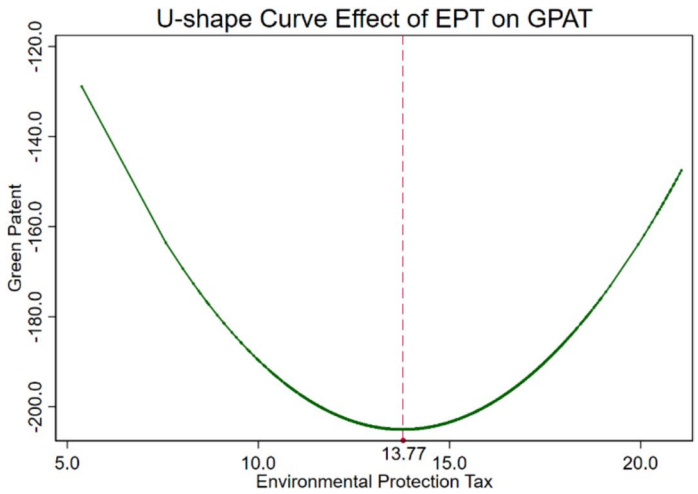
***$p<0.01$, **$p<0.05$, *$p<0.1$

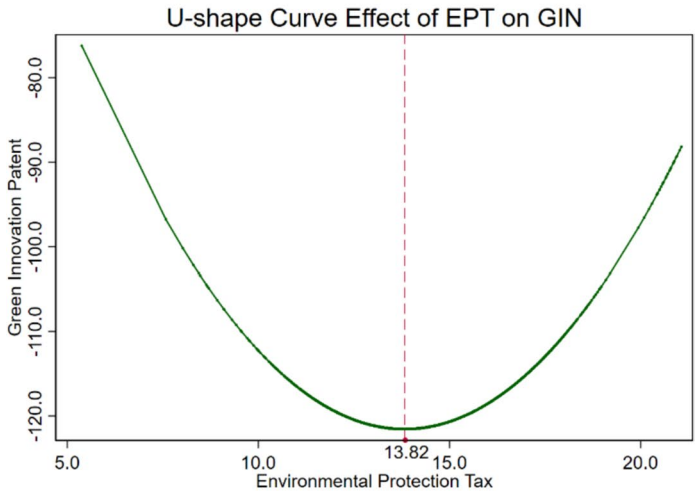
and market pressures faced by firms significantly influence their innovation responses to environmental policies (Ambec et al. 2013).

The research findings can be interpreted through the frameworks of signaling theory, stakeholder theory, and Pigou's theorem, which provide a multifaceted understanding of the dynamics at play in the adoption of green technological innovation (GTI) in response to environmental protection taxes (EPT).

Pigou's theorem provides an economic perspective, arguing that taxes and subsidies can be used to correct market failures due to externalities (Pigou, 2017). The effectiveness of EPT in promoting GTI supports the theorem's assertion that appropriately designed taxes can internalize the external costs of pollution, leading firms to innovate in ways that reduce their environmental impact (Baumol & Oates 1988). However, signaling theory posits that organizations send signals to convey their characteristics or intentions to stakeholders, which is particularly relevant in markets where information asymmetry exists (Spence 1973). The imposition of EPT acts as a signal to the market, indicating a firm's commitment to sustainable practices. Firms that adapt by enhancing their GTI may be perceived as environmentally responsible, potentially attracting investors and customers who value sustainability (Connelly et al. 2011). Moreover, stakeholder theory suggests that organizations must consider the interests of all stakeholders in their decision-making processes (Freeman, 1984). The positive impact of EPT on GTI, especially when amplified by government subsidies, indicates that these policy tools are effective in aligning the interests of firms with those of broader societal stakeholders, including the government and the public, who are concerned with environmental sustainability (Hart & Sharma 2004).

These theoretical perspectives underscore the importance of designing and implementing environmental policies that not only encourage firms to innovate but also align the interests of various stakeholders toward achieving sustainable development goals. The study's implications extend to various stakeholders. Policymakers can leverage these insights to design more targeted and effective environmental tax policies that consider firm heterogeneity. Managers can use this information to strategically position their firms to benefit from environmental policies, while investors may consider a firm's responsiveness to EPT as an indicator of its innovation potential and long-term sustainability. The study's findings highlight the need for nuanced policy instruments that can effectively stimulate GTI across different types of firms and market conditions.





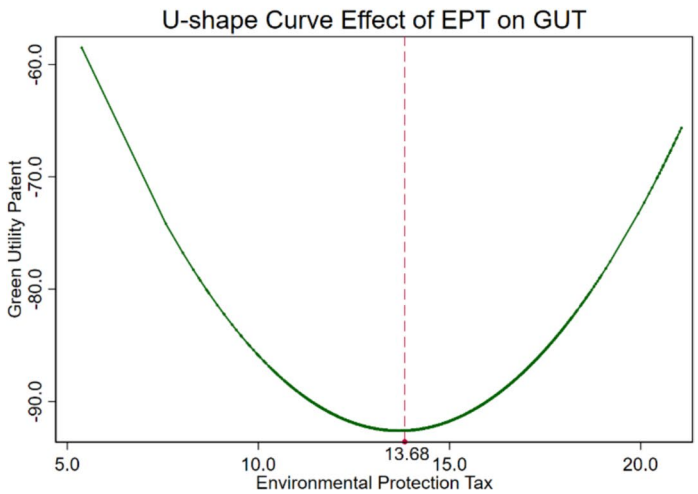


Fig. 7 Non-linearity Test. *Note* This figure illustrates the estimated U-shaped effect of EPT on GTI and its sub-aspects, GIN and GUT. The dotted line shows the location of axis of symmetry in the U-shaped curve

Conclusion and limitations

This research provides compelling evidence that environmental protection taxes (EPT) are a significant driver of green technological innovation (GTI) within heavily polluted Chinese firms. The study's rigorous analysis of panel data based on 8232 firm year observations from 2010 to 2022 underscores the effectiveness of EPT as a policy instrument not only

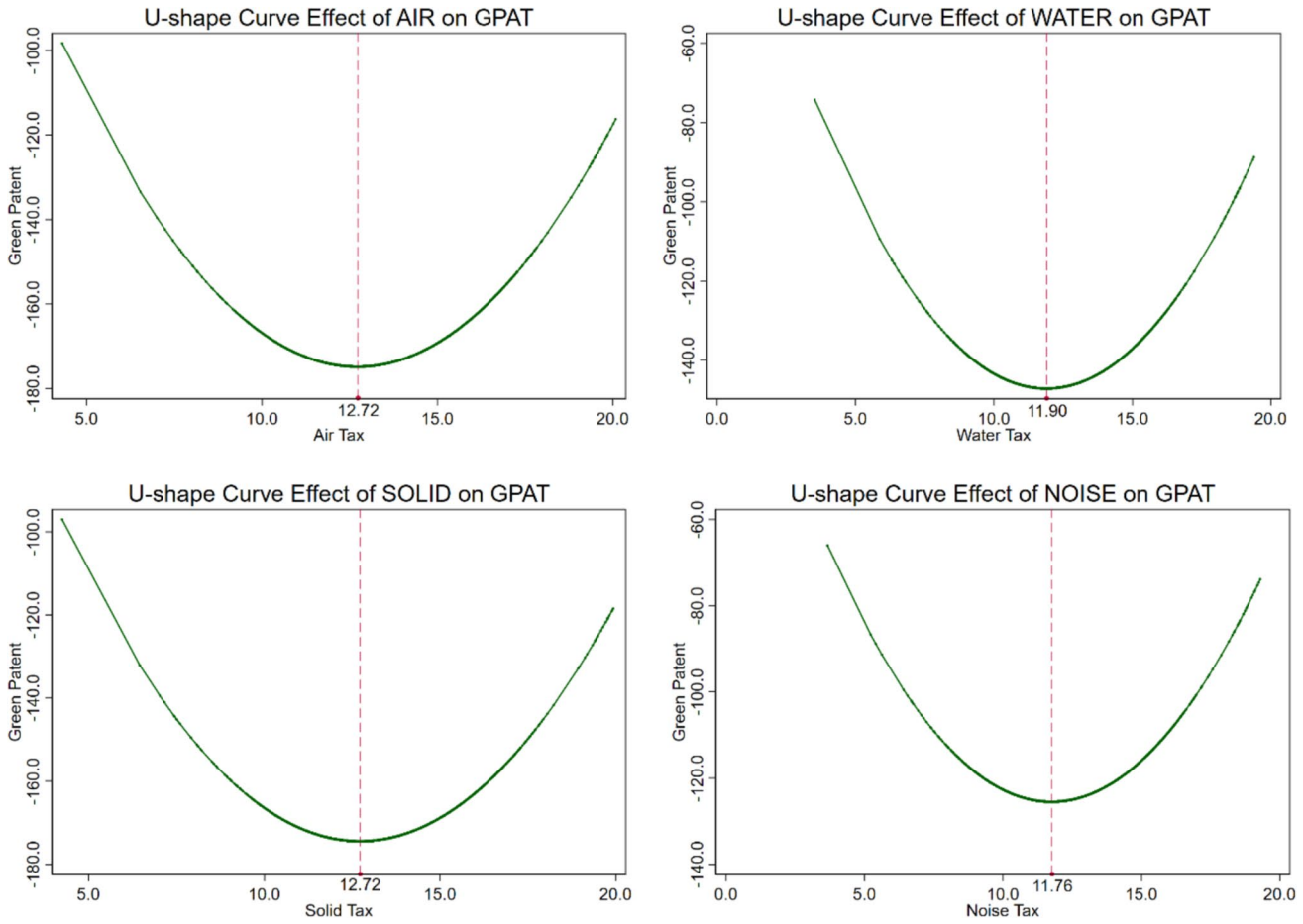


Fig. 8 Non-linearity Test on the Subcategories of EPT. *Note* This figure illustrates the estimated U-shaped effect of the subcategories of EPT (AIR, WATER, SOLID, NOISE) on GTI. The dotted line shows the location of axis of symmetry in the U-shaped curve

for internalizing environmental costs but also for catalyzing innovation toward sustainable development. The positive and significant relationship between EPT and GTI is a testament to the potential of fiscal tools in achieving environmental objectives. Further analyses suggest a complicated U-shaped effect, in which EPT initially inhibit the GTI level and promote GTI after reaching a threshold level. And this conclusion is also verified by the results of quantile analysis, which show that the effect of EPT is only significant over the 80th percentile. It underscores the intensification of policy efforts to strengthen firm green innovation level and reveals the latent strategic adjustment of heavily polluting Chinese firms in response to environmental protection taxation. The amplification of EPT's impact by government subsidies highlights the importance of complementary policy measures in reinforcing firms' commitment to green innovation. The study's insights into the differential effects of EPT on product versus process innovation provide a nuanced understanding of how firms prioritize their innovation efforts in response to environmental taxation. The effectiveness of exhaust gas taxation over wastewater taxation in promoting GTI suggests that the specificity of environmental taxes is crucial in targeting the most pressing environmental issues. Moreover, the heterogeneity analysis reveals that state-owned enterprises, particularly those with higher firm ages, lower ownership concentration levels, and operating in less competitive markets, are more responsive to EPT. This indicates that the impact of EPT is contingent upon firm-specific characteristics and market dynamics.

The findings of this study have significant implications for stakeholders. Policymakers can draw on these insights to refine the design of environmental taxes to maximize their impact on GTI. Managers can leverage the findings to strategically navigate the evolving landscape of environmental regulations. Investors, too, can use the responsiveness of firms to EPT as a gauge for their innovation potential and long-term viability. This research enriches the existing body of literature on environmental policy and green innovation and serves as a foundation for future studies to explore the long-term effects of EPT on GTI across various industries and firm types. It underscores the critical role of targeted fiscal policies in steering heavily polluted industries toward a more sustainable and innovative future.

Table 14 Quantile analysis

	(1)	(2)	(3)	(4)	(5)
	20th	40th	60th	80th	100th
	GTI	GTI	GTI	GTI	GTI
EPT	−0.099	−0.485	−0.595	0.351	4.034***
	(−0.724)	(−0.955)	(−1.517)	(0.607)	(5.572)
SIZE	0.668***	1.085***	0.727***	1.330***	6.061***
	(2.769)	(3.775)	(3.229)	(4.307)	(8.424)
LEV	1.015*	1.059	−0.584	1.736	−15.093***
	(1.796)	(1.460)	(−0.803)	(1.570)	(−4.019)
TobinQ	0.082*	−0.069	−0.094	−0.005	0.462
	(1.910)	(−1.081)	(−1.024)	(−0.053)	(0.816)
KZ	−0.129**	−0.033	0.079	0.119	0.433*
	(−2.361)	(−0.537)	(1.435)	(1.424)	(1.691)
RD	0.272***	0.413***	0.395***	0.812***	1.189***
	(2.859)	(3.855)	(5.271)	(7.561)	(3.833)
ESG	−0.005	0.026	0.017	0.080***	0.259***
	(−0.334)	(1.278)	(0.889)	(2.682)	(3.356)
AGE	0.010	0.041**	0.013	0.015	−0.286***
	(0.720)	(2.185)	(0.752)	(0.625)	(−4.376)
OWN	0.003	0.018***	−0.000	−0.024**	−0.041
	(0.367)	(2.713)	(−0.028)	(−2.457)	(−1.404)
DIR	0.093*	−0.093	0.036	0.096	0.066
	(1.704)	(−1.322)	(0.400)	(1.223)	(0.318)
FemD	−0.162**	−0.104	−0.090	−0.121	−0.184
	(−2.204)	(−1.282)	(−1.138)	(−0.827)	(−0.450)
MAR	0.004	0.127**	0.070	0.066	0.432**
	(0.124)	(2.228)	(1.171)	(0.744)	(1.962)
Constant	−17.611***	−26.873***	−15.006**	−53.998***	−229.086***
	(−3.160)	(−3.818)	(−2.312)	(−6.137)	(−18.245)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	1650	1629	1626	1660	1664
R^2	0.066	0.113	0.105	0.228	0.525
Adj. R^2	0.045	0.092	0.083	0.210	0.514
F	2.571	3.768	5.232	11.46	38.16

Note This table presents the quantile analysis on the data sample. The regressions are conducted on different quantiles of sample, from 0–20% to 80–100%. GTI refers to the number of green patents (green technology innovation); EPT refers to environmental protection tax; SIZE refers to the natural logarithm of enterprises' total assets; LEV refers to the leverage ratio; TobinQ refers to the Tobin's Q; KZ is the financing constraint index; RD refers to R&D expenses; AGE refers to the company's age; OWN refers to the ownership concentration; DIR and FemD represent the number of directors and female directors, respectively; SOE is a dummy variable and takes 1 if the companies are state-owned, otherwise takes 0; ESG is the Huazheng ESG rating; MAR represents the degree of market orientation. All variables are defined in Table 2

***$p<0.01$, **$p<0.05$, *$p<0.1$

This research could be subjected to various limitations. Firstly, the study's focus on heavily polluted industries may not capture the full spectrum of Chinese firms' responses to EPT, potentially limiting the generalizability of the findings. Secondly, the exclusion of firms without green innovation patents or ineligible for government subsidies could introduce selection bias, affecting the representativeness of the results. Thirdly, the period of study does not capture the long-term effects of EPT on GTI, which may evolve as firms adapt to and integrate green technologies more fully into their operations. Fourthly, with regard to the components of EPT, future researches could elaborate on the effect

heterogeneity of different types on taxation on different industries, which would be more specific and contributable to detailed and targeted policy making.

Appendix

See Tables 15 and 16.

Table 15 Descriptive statistics between and within the panel data

Variable		Mean	Std. dev.	Min.	Max.	Obs.
GTI	Overall	4.283	11.275	0.000	82.000	$N=8232$
	Between		9.553	0.000	82.000	$n=1115$
	Within		5.905	−45.917	67.533	T-bar = 7.38296
EPT	Overall	14.009	1.460	9.102	21.023	$N=8232$
	Between		1.357	9.103	20.586	$n=1115$
	Within		0.543	10.911	17.175	T-bar = 7.38296
SIZE	Overall	22.410	1.321	19.213	28.636	$N=8232$
	Between		1.217	19.503	28.505	$n=1115$
	Within		0.457	19.622	24.964	T-bar = 7.38296
LEV	Overall	0.405	0.197	0.053	0.902	$N=8232$
	Between		0.180	0.053	0.885	$n=1115$
	Within		0.091	−0.110	0.949	T-bar = 7.38296
TobinQ	Overall	1.972	1.243	0.819	7.964	$N=8232$
	Between		1.055	0.845	7.964	$n=1115$
	Within		0.772	−1.971	7.829	T-bar = 7.38296
KZ	Overall	0.747	2.354	−6.115	6.498	$N=8232$
	Between		2.136	−6.115	6.484	$n=1115$
	Within		1.524	−8.628	8.280	T-bar = 7.38296
RD	Overall	17.964	1.562	7.720	24.081	$N=8232$
	Between		1.412	8.337	23.639	$n=1115$
	Within		0.831	11.346	23.124	T-bar = 7.38296
AGE	Overall	17.387	7.583	3.000	31.000	N = 8232
	Between		8.810	3.000	31.000	n = 1115
	Within		0.000	17.387	17.387	T-bar = 7.38296
OWN	Overall	57.985	15.102	22.620	91.700	$N=8232$
	Between		13.631	22.620	91.700	$n=1115$
	Within		7.177	15.953	105.468	T-bar = 7.38296
DIR	Overall	8.688	1.694	5.000	15.000	$N=8232$
	Between		1.516	5.000	15.000	$n=1115$
	Within		0.794	3.233	16.465	T-bar = 7.38296
FemD	Overall	1.315	1.090	0.000	4.000	$N=8232$
	Between		0.946	0.000	4.000	$n=1115$
	Within		0.659	−1.399	4.312	T-bar = 7.38296
ESG	Overall	73.016	4.927	57.600	83.980	$N=8232$
	Between		3.405	60.222	82.538	$n=1115$
	Within		3.467	54.337	85.471	T-bar = 7.38296
MAR	Overall	9.169	1.779	3.250	11.494	$N=8232$
	Between		1.729	3.250	11.494	$n=1115$
	Within		0.496	6.829	10.790	T-bar = 7.38296

Note This appendix supplements to Table 3 and shows the summary statistics of major variables between and within the panel. Between values are calculated as $\overline{x}_i$ (the average value of firm i across years in the sample). Within values are calculated as $x_{i,t} - \overline{x}_i + \overline{\overline{x}}$, where $\overline{\overline{x}}$ is the global average, and can take negative values as they are relative indicators. GTI refers to the number of green patents (green technology innovation); EPT refers to environmental protection tax; GIN refers to the number of green invention patents; GUT refers to the number of green utility model patents; GRA refers to the amount of governmental environmental protection subsidy; AIR, WATER, SOLID, and NOISE represent the amount of environmental protection taxes on exhaust gas, waste water, solid waste and noise, respectively; SIZE refers to the natural logarithm of enterprises' total assets; LEV refers to the leverage ratio; TobinQ refers to the Tobin's Q; KZ is the financing constraint index; RD refers to R&D expenses; AGE refers to the company's age; OWN refers to the ownership concentration; DIR and FemD represent the number of directors and female directors, respectively; SOE is a dummy variable and takes 1 if the companies are state-owned, otherwise takes 0; ESG is the Huazheng ESG rating; MAR represents the degree of market orientation. All variables are defined in Table 2

Table 16 Nonlinearity analysis on subcategories of EPT

	(1) GTI	(2) GTI	(3) GTI	(4) GTI
AIR	−27.491***			
	(−20.391)			
AIR_sq	1.081***			
	(20.208)			
WATER		−24.732***		
		(−20.252)		
WATER_sq		1.039***		
		(19.988)		
SOLID			−27.420***	
			(−20.117)	
SOLID_sq			1.078***	
			(19.892)	
NOISE				−21.348***
				(−17.603)
NOISE_sq				0.908***
				(17.397)
SIZE	2.497***	2.625***	2.509***	2.604***
	(10.525)	(11.121)	(10.586)	(11.190)
LEV	−3.912***	−3.938***	−3.931***	−4.336***
	(−5.603)	(−5.617)	(−5.629)	(−6.079)
TobinQ	0.129*	0.153**	0.137*	0.164**
	(1.792)	(2.142)	(1.904)	(2.200)
KZ	0.180***	0.179***	0.179***	0.220***
	(3.415)	(3.395)	(3.408)	(4.140)
RD	0.654***	0.666***	0.657***	0.675***
	(6.503)	(6.681)	(6.543)	(6.694)
ESG	0.058***	0.058***	0.058***	0.058***
	(2.788)	(2.827)	(2.823)	(2.808)
AGE	−0.066***	−0.064***	−0.065***	−0.066***
	(−3.322)	(−3.235)	(−3.289)	(−3.301)
OWN	−0.003	−0.001	−0.002	0.002
	(−0.372)	(−0.122)	(−0.356)	(0.239)
DIR	0.103	0.095	0.096	0.107
	(1.278)	(1.168)	(1.197)	(1.303)
FemD	−0.240***	−0.237***	−0.236***	−0.218**
	(−2.692)	(−2.647)	(−2.649)	(−2.420)
MAR	0.120**	0.121**	0.122**	0.129**
	(2.277)	(2.287)	(2.313)	(2.418)
Constant	105.680***	74.777***	104.902***	53.414***
	(11.055)	(8.930)	(10.820)	(6.217)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	8232	8232	8232	8232
R^2	0.467	0.464	0.467	0.456
Adj. R^2	0.465	0.462	0.464	0.454
F	95.25	94.37	94.79	92.76

Note This appendix shows the further nonlinearity test on the subcategories of EPT, which is showing consistent results. GTI refers to the number of green patents (green technology innovation); AIR, WATER, SOLID, and NOISE represent the amount of environmental protection taxes on exhaust gas, waste water, solid waste and noise, respectively; SIZE refers to the natural logarithm of enterprises' total assets; LEV refers to the leverage ratio; TobinQ refers to the Tobin's Q; KZ is the financing constraint index; RD refers to R&D expenses; AGE refers to the company's age; OWN refers to the ownership concentration; DIR and FemD represent the number of directors and female directors, respectively; SOE is a dummy variable and takes 1 if the companies are state-owned, otherwise takes 0; ESG is the Huazheng ESG rating; MAR represents the degree of market orientation. All variables are defined in Table 2

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Author contributions Dr. Mirza, Mr. Huang, Mr. Zhang and Miss Su contributed significantly to all stages of this research project. Dr. Mirza conceptualized the study, formulated the research design, and supervised the overall project. He also provided critical insights into the theoretical framework and methodology, ensuring alignment with the study's objectives. Dr. Mirza led the analysis and interpretation of the results. Miss Su and Mr. Zhang contributed extensively to data collection, preprocessing, and empirical analysis, ensuring the robustness and accuracy of the findings. Mr Huang and Mr. Zhang contributed extensively to data preprocessing, and empirical analysis, and performed a detailed literature review, contributed to drafting specific sections of the manuscript, and provided revisions to enhance the overall clarity and coherence of the paper. All the authors reviewed and approved the final version of the manuscript for submission and agree to be accountable for all aspects of the work, ensuring its integrity and accuracy.

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Declarations

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