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HOW DOES ENVIRONMENTAL TAX REFORM DRIVE CORPORATE INNOVATION TO GREEN TECHNOLOGIES? QUASI-NATURAL EXPERIMENTAL EVIDENCE FROM CHINA

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Abstract. How to motivate enterprises to formulate green technology (GT) innovation is crucial for promoting green development and minimizing pollution control costs. This research employs a quasi-experimental approach to analyze the impact of environmental tax reform (ETR) on corporate innovation decisions. First, we construct a two-sector model within a single enterprise, where the enterprise produces goods using GT and non-green technology (NGT) respectively. ETR influences a company's innovation choices by the relative market value, R&D intensity, and productivity of products manufactured using GT and NGT under profit maximization. Second, we test our model using 2012-2023 manufacturing firms' data, and the empirical results confirm our theoretical predictions. Third, we perform robustness tests to exclude the impact of subsidies, command and control environmental supervision and the COVID-19 epidemic. Fourth, we conduct heterogeneity analysis in polluting level and market competition. Finally, this study uses two instrumental variables (IVs) to validate our main regression results: the interaction between regional water area and industrial chemical oxygen demand, and the proportion of days affected by temperature inversion. This study contributes to the literature related to innovation choices under environmental policy and has implications for directing firms' innovation to GT.

Keywords: corporate innovation choices, green technological innovation, non-green technological innovation, environmental tax reform, manufacturing firms, quasi-natural experiment.

JEL Classification: O30, O32, Q55.

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1. Introduction

In recent years, policy makers and scholars have paid more attention to how to control and limit pollution emissions while accelerating the comprehensive green transformation of economic and social development (Gu & Yuan, 2024; Wang et al., 2024; Hu et al., 2023a). Numerous studies focus on the effects of environmental policies on technological advancements, especially in environmentally-friendly technologies (Gugler et al., 2024; Barbieri et al., 2023). Liu et al. (2021) found that the Air Pollution Control policy effectively upgrades production technology, resulting in a decrease in the employment rate of low skilled labor. Xie et al.

(2022) discovered that power price and renewable energy policies facilitate the development of wind and solar power technologies. Nesta et al. (2014), using data from OECD countries, found that renewable energy policies foster green innovation.

However, the literature has paid relatively little attention to corporate innovation choices be- tween green technologies (GT) and non-green technologies (NGT), focusing predominantly on one type of technological innovation between the two or view technological innovation as a whole for research (Gugler et al., 2024; Barbieri et al., 2023). Innovation choices reflect firms' strategic responses when facing environmental policy interventions and R&D constraints (Hu et al., 2023d; Liu et al., 2023a). Environmental policy intervention is costly. Compared to NGT, GT are environ- mentally friendly and have a direct positive impact on reducing pollution emissions and conserving resources (Yao et al., 2021; Chen et al., 2024). Therefore, studying how to motivate companies to voluntarily choose green technology innovation is of great significance for promoting social and economic development.

In 2018, China's government implemented environmental tax reform (ETR). The ETR has two distinct features. First, ETR adopts "tax differentiation"[1]. Some provinces, autonomous regions and municipalities (PRMs)[2] increase taxes rate based on the pollution fee system, and the taxes rate in other PRMs[3] are consistent with the pollution fee. The ETR increases the cost of firms if these firms are in PRM with an increased tax rate and still use non-green technologies to produce final products (Wu & Tal, 2018). Because enterprises using non-green technologies for production will emit more pollutants, results in higher tax. Second, the ETR replaces the environmental fee by an environmental tax and is legally binding and has stricter enforcement mechanisms than the pollution fee system (Karydas & Zhang, 2019). Hence, this study aims to analyze whether and how the ETR would motivate companies to innovate in green technologies.

To examine whether and how the ETR affects the innovation choices of firms between GT and NGT, we propose a simple two-sector model within a single firm. The two sectors, utilizing GT and NGT respectively, produce a unique final product, respectively. The outputs from the two sectors are competitive and substitutable. The relative proportion of GT and NGT is influenced by their relative market value, R&D intensity, and productivity under profit maximization. When the ETR is implemented, rms using NGT face increased costs due to higher tax rates. Consequently, the relative market value, R&D intensity, and productivity of GT versus NGT change. The ETR thus alters the competitive dynamics between GT and NGT within a firm.

We consider the ETR as a quasi-experiment and construct a Difference-in-Difference (DID) model to analyze its effects on firms' innovation choices (Shahzad et al., 2022; Huang et al., 2022; Liu et al., 2022). Utilizing data from listed manufacturing firms over the 2012–2023 period, we empirically test the impact of ETR on innovation decisions. Firstly, we find that ETR incentivizes firms to innovate more in GT compared to NGT. This result remains consistent even after creating a comparable control group using the Propensity Score Matching (PSM) method, constructing a placebo treatment group using the bootstrapping method, and setting a false policy implementation time. Secondly, we control for the effects of command-and-control (C&C) environmental regulations (Kemp & Pontigolio, 2011), innovation subsidy (Hu et al., 2023d) and COVID-19 (Tsiotas & Tselios, 2022). Thirdly, we find the innovation choice

[1] https://www.chinatax.gov.cn/chinatax/n810219/n810780/c2949707/content.html

[2] Beijing, Hebei, Henan, Chongqing, Sichuan, Yunnan, Hainan, Hunan, Guizhou, Shanxi, Guangxi, Guangdong.

[3] Tianjin, Shanghai, Shandong, Jiangsu, Hubei, Zhejiang, Liaoning, Jilin, Jiangxi, Fujian, Shaanxi, Xinjiang, Ningxia, Qinghai,Inner Mongolia, Gansu, Anhui, Heilongjiang, Tibet.

is different in different polluting-level industries and different market competition Fourthly, we use the interaction of each provinces water area with national industrial chemical oxygen demand (ICOD), and the proportion of days affected by temperature inversion throughout the year as instrumental variables (IVs) for IV estimation (Chen et al., 2018a). Lastly, we incorporate GT and NGT into the model, using operating profit, net profit, R&D spend, number of being cited of patent and total factor productivity (TFP) as dependent variables. Our findings indicate that the increase the relative number of GT and NGT has positive effect of firms' profit. Innovating in GT has a greater positive effect on firms' R&D spend, number of being cited of patent, and TFP compared to NGT. Thus, ETR influences firms' innovation choices through relative R&D intensity, productivity, and market value mechanisms.

Our study contributes to the literature in two key areas. Firstly, we introduce a two-sector model within a single firm to examine rms innovation choices. While existing literature often concentrates solely on innovation in GT to explore the link between environmental policies and technological advancements, our approach recognizes that the adoption of GT is an innovative choice made by companies under environmental policy intervention. Moreover, unlike previous studies that overlook the distinction between GT and NGT, our model distinguishes between the two, acknowledging their inherent differences. By recognizing that even without further policy interventions, firms adoption of green technological innovation is environmentally friendly, our study offers a more detailed understanding of firms innovation behavior.

Secondly, our research helps to test the effectiveness of ETR in China. According to the ETR, firms are obligated to compensate for their pollution emissions. Our findings reveal that the ETR incentivizes firms to choose green technological innovation through rigorous market value mechanisms. This insight offers valuable guidance for policymakers who seek to formulate cost-effective policies. Given the substantial costs associated with policy formulation and implementation, our study suggests that implementing policies that encourage firms to adopt green technological innovation can effectively promote long-term green development while minimizing costs.

This study is structured as follows. Section 2 provides policy context, surveys the literature, and develops a theoretical model. Section 3 describes the research methodology, followed by empirical results in Section 4. Section 5 compares our findings with prior study, and Section 6 concludes.

2. Theoretical analysis

2.1. Policy background and literature review

The ETR was implemented in January 2018, which means that China's nearly 40-year-old pollution discharge fees came to an end and was replaced by environmental tax. As the 19th tax category in China, the environmental tax is the first time that the Chinese government has imposed an environmental protection tax on polluting enterprises. There are four notable details of the ETR. Firstly, this ETR aims to establish a more robust and effective mechanism to reduce pollution and promote greener practices within industries (Hu et al., 2023b). Unlike the previous pollution discharge fee system, the environmental tax is legally binding and subject to stricter enforcement mechanisms (Hu et al., 2023c). The ETR solves the problems of insufficient enforcement rigidity and local government intervention in the past pollution fee system. Secondly, environmental tax is a local revenue in order to promote environmental protection and improvement in various regions, and increase investment in environmental protection. The sharing ratio will change from the previous pollution fee income being divided between the central and local governments in a 1:9 ratio to the income from environmental protection tax. Third, the ETR adheres to a guiding mechanism that combines reverse constraints and positive incentives of "more emissions, more payments, less emissions, less payments, and no emissions, no payments". Four, environmental taxes are levied on specified air pollutants, water pollutants, solid waste, and industrial noise. The tax rates are designed to vary based on the type and severity of the pollution.

According to official announcements from each provincial and regional municipality (PRMs), 12 PRMs increased their tax rates beyond the previous fee levels. A key feature of the new system is the principle of "tax differentiation", which allows regions with more severe pollution problems or unmet environmental targets to set higher tax rates. This approach aims to provide flexibility and encourage local governments to take more aggressive actions against pollution (Liu et al., 2022). On the one hand, by imposing higher costs on polluting activities, the tax system has motivated companies to invest in greener technologies and practices (Hu et al., 2023b). On the other hand, the tax has generated significant revenue, which is allocated to environmental protection projects, thereby enhancing the government's capacity to address environmental issues (Liu et al., 2022).

The 2023 government work report shows that in the past five years, energy consumption per unit of GDP has decreased by 8.1%, carbon dioxide emissions have decreased by 14.1%, and the average concentration of fine particulate matter (PM2.5) in prefecture level and above cities has decreased by 27.5%. In PRMs that have raised their environmental tax collection standards, the average comprehensive score of corporate environmental responsibility has increased by 7.2% compared to other PRMs. The environmental tax has effectively leveraged polluting enterprises to consciously fulfill their environmental responsibilities. On the one hand, the mechanism of "multiple emissions, multiple payments" serves as a reverse constraint, directly transforming pollution behavior into operational costs for enterprises, thereby directly affecting their market competitiveness. On the other hand, the positive incentive policy of "less emissions, less payments, no emissions, no payments" encourages enterprises to pay attention to environmental benefits and in- novate in green technologies. According to statistics from the State Administration of Taxation, the green investment of industrial enterprises in China will grow rapidly in 2023, with the purchase of environmental protection and governance services increasing by 17.7%, and the proportion of high energy consuming manufacturing in the manufacturing industry dropping to 30.7%.

Innovation choices reflect firms' strategic decisions for profit maximization in response to pol- icy changes or market dynamics, encompassing aspects such as innovation type and approach. Liu et al. (2023a) found that executives tend to prefer exploitative innovation (non-intervention innovation) over explorative innovation (intervention innovation). Liu et al. (2023c) examined the effects of the development gap between emerging economies and developed regions on countries' innovation strategies. When the gap is large, countries tend to choose imitative innovation; otherwise, they opt for independent innovation.

According to the China National Intellectual Property Administration, GT encompass emerging technologies designed to reduce consumption, decrease pollution, enhance ecological systems, promote ecological civilization, and achieve harmonious coexistence between humans and nature. Unlike NGT, GT have direct and significant effects on reducing or halting the consumption of natural resources and are environmentally friendly. Existing literature has explored the impact of environmental policies on green technological innovation (Gugler et al., 2024; Hu et al., 2023d). For instance, Hu et al. (2023d) identified "green washing" behavior under green credit policies, where firms increase patenting activities without corresponding increases in innovation inputs, thus boosting the quantity but not its quality. Similarly, Gugler et al. (2024) demonstrated that environmental taxes, regulations, and R&D subsidies positively influence green innovation using a cross-country dataset. Blind et al. (2017) investigated the influence of regulation on innovation efficiency under varying levels of market uncertainty, finding that regulation enhances innovation efficiency in low-uncertainty markets but diminishes it in high-uncertainty ones. Costantini et al. (2017) analyzed determinants of R&D investment in environmental factors, noting that ER encourages firms' R&D investments in green technologies. Cojoianu et al. (2020) suggested that stringent LER positively influence the creation of new ventures in green technologies, analyzing data from green startups in OECD countries.

However, there is a paucity of literature examining how Chinese firms choose innovation be- tween GT and NGT in response to ETR. Within a firm, innovation competition exists between GT and NGT. Barbieri et al. (2023) found that while environmental policies encourage green patenting, they do not hinder the development of non-green technological foundations essential for green interventions, as observed from 1978 to 2014. Additionally, Cuerva et al. (2014) indicated that implementing Quality Management Systems and differentiation strategies in Spanish Food and Beverage firms promotes green innovation activities more than non-green innovation activities. From a market demand perspective, Rizzi et al. (2022) studied how various types of Point-of-Purchase displays affect the sales of green and non-green products. Moreover, Liu et al. (2023b) discovered that blockchain technology affects product pricing, consequently changing the competitive dynamics between green and non-green products.

2.2. Theoretical model

Referring to the study of Acemoglu et al. (2012), we posit that within firms, a single final product (goods or services) is produced competitively by two distinct sectors, labeled g and n. Sector g employs GT, while sector n utilizes NGT. The overall production function is given by:

$$Y_t = (Y_{gt}^{\frac{\theta-1}{\theta}} + Y_{nt}^{\frac{\theta-1}{\theta}})^{\frac{\theta-1}{\theta}}. \tag{1}$$

Here, $\theta > 1$ represents the elasticity of substitution between GT and NGT, reflecting our expectation that GT will replace the functions of NGT. Given that the final products and are produced competitively, the relative price of the two products is determined by:

$$\frac{P_{gt}}{P_{nt}} = \frac{Y_{gt}}{Y_{nt}}^{-\frac{1}{\theta}}. \tag{2}$$

The outputs Y_{gt} and Y_{nt} are produced by labor and a range of sector-specific technologies:

$$Y_{jt} = L_{jt}^{1-\alpha} \int_0^1 A_{jit}^{1-\alpha} x_{jit}^{\alpha} di, \tag{3}$$

where the share of technologies is α and the share of labor is $1-\alpha$ in the production, $0 < \alpha < 1$. The notation $j = g, n$ denotes two distinct sectors, while $i = GT, NGT$ signifies the types of technologies, and t denotes time. A_{jit} represents the quality of technology. x_{jit} denotes the quantity of technology. The cost of producing one unit of technology in any sector is β. For simplicity, β is normalized to α^2. The wage of labor in any sector is w_t.

Each technology in sector j requires at least one R&D staff member and is successfully developed with probability δ_j. The number of R&D staff working on technologies is s_{jt}. R&D efforts enhance the quality of a technology by a factor of $1+\eta$, where $\eta > 0$. Thus, we have:

$$A_{jit} = \left(1+\eta\delta_j s_{jt}\right) A_{jit-1}. \tag{4}$$

In the study, we define average productivity in sector j, where A_{gt} represents green technology and A_{nt} is non-green technology.

$$A_{jt} = \int_0^1 A_{jit} di. \tag{5}$$

Combining Eqs. (4) and (5), we can know average productivity in sector j evolving over time:

$$A_{jt} = \left(1+\eta\delta_j s_{jt}\right) A_{jt-1}. \tag{6}$$

Achieving market equilibrium for labor and R&D staff necessitates that labor demand and R&D staff are equal to the total labor supply and total R&D staff, respectively. For simplicity, we normalize total labor supply and total R&D staff to 1 without loss of generality.

$$L_{gt} + L_{nt} = L_t = 1; \tag{7}$$

$$s_{gt} + s_{nt} = s_t = 1. \tag{8}$$

The firms' output is Y_{jt} The profit-maximization problem can be written as:

$$\pi_{jt} = P_{jt} Y_{jt} - w_t L_{jt} - \int_0^1 \beta x_{jit} di. \tag{9}$$

Initially, we address the first-order condition concerning x_{jit} to derive the iso-elastic inverse demand curve for technology i in sector j:

$$x_{jit} = \left(\frac{\alpha P_{jt}}{\beta}\right)^{\frac{1}{1-\alpha}} A_{jit} L_{jt} = \left(\frac{P_{jt}}{\alpha}\right)^{\frac{1}{1-\alpha}} A_{jit} L_{jt}. \tag{10}$$

Subsequently, by integrating Eq. (10), we address the first-order condition concerning L_{jt} to ascertain the relative price of the final good produced by GT and NGT:

$$\frac{P_{gt}}{P_{nt}} = \left(\frac{A_{gt}}{A_{nt}}\right)^{-(1-\alpha)}. \tag{11}$$

Third, we combine Eq. (2) and $Y_{jt} = \left(\frac{P_{jt}}{\alpha}\right)^{\frac{1}{1-\alpha}} A_{jit} L_{jt}$ and obtain the relative labor demand:

$$\frac{L_{gt}}{L_{nt}} = \left(\frac{A_{gt}}{A_{nt}}\right)^{-(1-\alpha)}. \tag{12}$$

Consequently, the relative number of GT and NGT is governed by the ratio

$$\frac{x_{gt}}{x_{nt}}=\frac{\int_0^1 x_{git}di}{\int_0^1 x_{nit}di}=(\frac{P_{gt}}{P_{nt}})^{\frac{1}{1-\alpha}}\frac{L_{gt}}{L_{nt}}\frac{A_{gt}}{A_{nt}}. \tag{13}$$

Equation (13) indicates that an increase in this ratio leads to a shift of R&D efforts from NGT to GT. The relative abundance of GT and NGT is influenced by the relative price effect $(\frac{P_{gt}}{P_{nt}})^{\frac{1}{1-\alpha}}$, labor allocation $\frac{L_{gt}}{L_{nt}}$, and relative productivity effect $\frac{A_{gt}}{A_{nt}}$. Relative price effect reflects the relative market value, and labor allocation reflects relative R&D intensity.

We account for the presence of an ETR. Firms employing non-green technologies for producing final goods are subject to paying an environmental protection tax for pollutant emissions. The profit-maximization problem for firms utilizing technology i in sector n at time t to produce output Y_{nt} can be:

$$\pi_{jt}=\left(P_{jt}-\tau\right)Y_{jt}-w_t L_{jt}-\int_0^1 \beta x_{jit}di, \tag{14}$$

where τ is tax of unit final product. The profit-maximization problem of the firms using technology i in sector g at time t to produce output Y_{gt} is as before. We address the first-order condition concerning x_{jit} to derive the iso-elastic inverse demand curve for technology i in section j after the ETR.

$$x_{jit}=(\frac{\alpha\left(P_{jt}-\tau\right)}{\beta})^{\frac{1}{1-\alpha}}A_{jit}L_{jt}=(\frac{P_{jt}}{\alpha})^{\frac{1}{1-\alpha}}A_{jit}L_{jt}. \tag{15}$$

If firms use green technologies to product after the ETR, it does not need to bear additional taxes. If firms use non-green technologies, it need to bear taxes τ. The demand of x_{git} and x_{nit} are:

$$x_{git}=(\frac{\alpha P_{gt}}{\beta})^{\frac{1}{1-\alpha}}A_{git}L_{gt}=(\frac{P_{gt}}{\alpha})^{\frac{1}{1-\alpha}}A_{git}L_{gt}; \tag{16}$$

$$x_{nit}=(\frac{\alpha\left(P_{nt}-\tau\right)}{\beta})^{\frac{1}{1-\alpha}}A_{nit}L_{nt}=(\frac{P_{nt}}{\alpha})^{\frac{1}{1-\alpha}}A_{nit}L_{nt}. \tag{17}$$

Integrating the x_{git} and x_{nit}, relative number of technologies in sector g relative to sector n is:

$$\frac{x_{gt}}{x_{nt}}=(\frac{P_{gt}}{P_{nt}-\tau})^{\frac{1}{1-\alpha}}\frac{L_{gt}}{L_{nt}}\frac{A_{gt}}{A_{nt}}. \tag{18}$$

We define the right hand of Eq. (13) as f0 and the right hand of Eq. (18) as f1. When there is environmental tax, f1 is larger than f0, implying the increase of relative number of technologies in sector g relative to sector n. When environmental tax τ increases, f1 increase, meaning that the relative number of x_{gt} and x_{nt} increases. The ETR has implemented tax reductions and exemptions for enterprises whose emission is below emission standards. For tax exemptions and reductions, the value of $\frac{P_{gt}}{P_{nt}-\tau}$ would increase, resulting in the increase of f1. Because enterprises only use green technology to produce and their emissions are below the emission standards. As the same as the increase of τ, the relative number of x_{gt} and x_{nt} increases. When the technology share α increases, the value of f1 increases. It means that firms would innovate more in GT. We can easily conclude that environmental tax directs firms' innovation from NGT to GT. It is mainly due to the increase in relative market value effect, R&D intensity and productivity effect of GT and NGT under profit maximization.

3. Research design

3.1. Variables

3.1.1. Innovation choices

In this study, we define innovation choice as whether a company chooses GT or NGT when innovating. GT refers to a technological system that follows ecological principles and ecological economic laws, can reduce pollution, lower consumption, and improve ecology (Wang et al., 2024). Although patents are not equivalent to innovation, patent applications and authorizations are important manifestations of innovation (Zhang, 2024). In this study, we divide firms invented patents into green invented patents and non-green invented patents. The relative count of green invented patents and non-green invented patents measures firms innovation choices. The increase of relative count implies that firms are more likely to innovate green technologies. Specifically, we use relative count of patent applications $gipa_{it} / ngipa_{it}$ and relative count of patent granted $gipg_{it} / npipg_{it}$ in empirical tests.

In samples, firms do not innovate green technologies if they have no non-green technologies innovation. Hence, if $ngipa_{it}$ or $ngipg_{it}$ is zero, $gipa_{it}$ and $gipg_{it}$ are zero. There is no situation that $ngipa_{it}$ and $ngipg_{it}$ equal to zero, but $gipa_{it}$ and $gipg_{it}$ don't equal to zero. There are three situations: (1) $ngipa_{it} = 0$, $ngipg_{it} = 0$ and $gipa_{it} = 0$, $gipg_{it} = 0$; (2) $ngipa_{it} \neq 0$, $ngipg_{it} \neq 0$ and $gipa_{it} = 0$, $gipg_{it} = 0$; (3) $ngipa_{it} \neq 0$, $ngipg_{it} \neq 0$ and $gipa_{it} \neq 0$, $gipg_{it} \neq 0$. In situation (1) and (2), we let $gipa_{it} / ngipa_{it}$ and $gipg_{it} / npipg_{it}$ equal to zero. In situation (3), $gipa_{it} / ngipa_{it}$ and $gipg_{it} / npipg_{it}$ equal to their real value.

3.1.2. Environmental tax reform

In 2018, the Chinese government initiated an ETR, discontinuing the previous system of pollutant discharge fees. Based on the pollutant discharge fees, some PRMs increase the taxes but others don't increase. Hence, firms bear higher environment tax in the PRMs which increase the taxes. We introduce $post_t$ as a binary variable, taking the value of 1 for observations from 2018 to 2023 and 0 for those from 2012 to 2017. We introduce $target_i$ as a binary variable, equaling 1 for firms located in PRMs with increased taxes and 0 otherwise. Our focus lies on the interaction term $target_i \times post_t$, representing the joint effect of $target_i$ and $post_t$.

To address potential endogeneity arising from omitted variables and reverse causality, we adopt an IV strategy. Firstly, we utilize the interaction between each Provincial-level Administrative Region's (PRM) water area and the national Industrial Chemical Oxygen Demand (ICOD) as an IV1 for ETR (Chen et al., 2018a). On the one hand, ETR encompasses taxation standards aimed at water pollution, with ICOD serving as a prominent indicator of water pollution levels. On the other hand, governmental initiatives, such as the river chief system, underscore the significance of addressing water pollution issues. Given the time-invariant nature of PRM water area, we interact it with national ICOD to mitigate endogeneity concerns. PRMs with larger water areas during periods of heightened water pollution are more inclined to enact environmental tax increases. Secondly, we employ the proportion of days with temperature inversion throughout the year as IV2 for ETR. Although temperature inversion can occasionally foster crop growth, its adverse effects on air pollution are notable. PRMs experiencing more frequent temperature inversions tend to exhibit more severe air pollution levels. Given the focus of ETR on air pollution standards and governmental efforts to combat air pollution, temperature inversion days serve as a relevant exogenous variable for firms' innovation choices. Consequently, IV1 and IV2 satisfies both correlation and exogeneity conditions.

3.1.3. Control variables

We control following variables in our empirical models by referring to the study of Huang et al. (2022), Ribau et al. (2017) and Liu et al. (2023b): firms total assets ($lntotalasset_{i,0} \times t$), firms total debts ($lntotaldebt_{i,0} \times t$), firms intangible assets ($lnintangibleasset_{i,0} \times t$), firms Research and Development (R&D) workers ($lnrdworker_{i,0} \times t$), firms age ($lnfirmage_{i,t}$), firms ownership ($ownership_{i,t}$), firms' revenue ($\ln revenue_{i,t}$). In order to address the impact of outliers, we employ a winsorization technique on all continuous control variables, limiting extreme values to the top and bottom 1% (Lasrado & Zakaria, 2020; Shao & Xu, 2024).

We conduct robustness check to exclude other factors' effect. (1) $er_{c,t}$. We use cities' environmental regulation intensity to exclude the effect of governmental C&C environmental regulations. (2) $subsidy_{i,t}$. We use subsidies received by enterprises to exclude the effect of subsidies, which could induce firms' "greenwashing".

Polluting level and market competition are important factor influencing firms' innovation choice. We use $pl_{i,t}$ and $HHI_{i,t}$ to conduct heterogeneity analysis. $pl_{i,t} = 1$ means that firms are in heavy-polluting industries and $pl_{i,t} = 0$ represents that firms are in low-polluting industries. $HHI_{i,t}$ is the Herfindahl-Hirschman index, representing market competition.

3.1.4. Mechanism variables

We use firms' operating profit ($opearatingprofit_{i,t}$) and net profit ($netprofit_{i,t}$) to test the effect of firms' innovation choice on firms' profit. (2) We use TFP ($tfp\_op_{i,t}$ and $tfp\_lp_{i,t}$) to test the productivity effect. (3) We use firms' number of being cited of patents ($cited_{i,t}$) to test market value effect. (4) We use firms' R&D spend ($R\&Dspend_{i,t}$) to test R&D intensity effect.

3.2. Model specification

To examine the impact of ETR on firms' innovation choices, we consider the reform as a quasi-natural experiment. Consequently, we employ a DID model (Shahzad et al., 2022; Huang et al., 2022; Liu et al., 2022), specified as follows:

$$\frac{gipa_{i,t}}{ngipa_{i,t}} = \alpha + \beta \times target_i \times post_t + \gamma \times CV_{i,0} \times t + \delta_j + \delta_p + \delta_t + \epsilon_{i,t}, \tag{19}$$

where i, j, p, t denote firm, industry, PRM and year, respectively. $gipa_{it} / ngipa_{it}$ denotes the relative count of two patent applications, which is replaced by $gipg_{it} / npipg_{it}$ representing the relative count of two patents granted. $CV_{i,0} \times t$ encompasses control variables, defined as the interaction of initial values with time trends. δ_j, δ_p, and δ_t are fixed effects for industry, PRM, year, and firm, respectively. $\epsilon_{i,t}$ is error term.

To analyze the mechanisms underlying this effect, we include interactions between $target_i \times post_t$ and both innovations (GT and NGT) within the same model.

$$y_{i,t} = \alpha + \beta_1 \times target_i \times post_t \times GT + \beta_1 \times target_i \times post_t \times NGT + \gamma \times CV_{i,0} \times t + \delta_j + \delta_p + \delta_t + \in_{i,t}, \quad (20)$$

where $y_{i,t}$ denotes firms' revenue, R&D intensity, and productivity, respectively. It is important to mention that we use changes in firms' revenue to reflect market value shifts due to data availability constraints. Our primary interest lies in the coefficients β_1 and β_2, which measure the differential impact of innovation in GT and NGT on $y_{i,t}$ before and after the ETR. A finding of $\beta_1 > \beta_2$ would indicate that innovation in GT exerts a greater influence on $y_{i,t}$ compared to innovation in NGT in the context of the ETR.

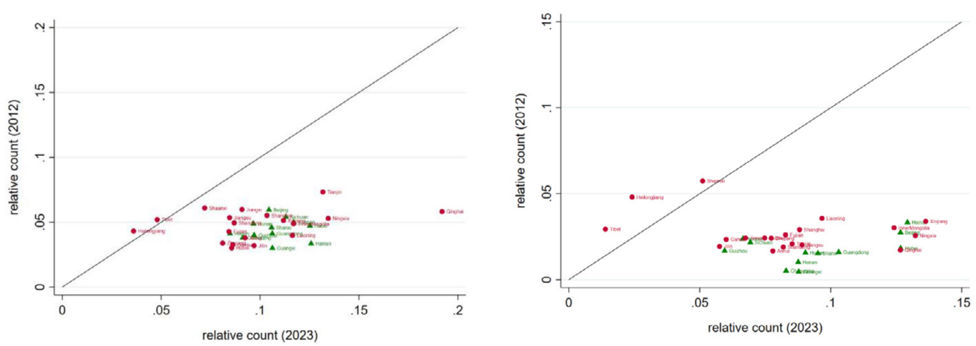
Furthermore, to enhance the robustness of causal identification in mechanism analysis, we construct the following model to analyze the mechanism.

$$y_{i,t} = \alpha + \beta \times \frac{GT}{NGT} + \gamma \times CV_{i,0} \times t + \delta_j + \delta_p + \delta_t + \in_{i,t}, \quad (21)$$

$y_{i,t}$ denotes firms' revenue, R&D intensity, and productivity, respectively. The coefficient β estimates the effect of the relative number of GT and NGT on firms' revenue, R&D intensity, and productivity. If $\beta > 0$, it means that the increase of the relative number of GT and NGT is beneficial for firms' revenue, R&D intensity, and productivity. Compared to NGT, firms have more willing to innovate in GT.

3.3. Data source and description

Our sample consists of Chinas listed manufacturing firms from 2012 to 2023. Out of the 5,300 listed firms, we exclude non-manufacturing firms and those designated as ST and ST* firms. This leaves us with 3,400 manufacturing firms, totaling 26,966 firm-year observations. Within this sample, 10,257 observations fall into the treated group, while 16,709 belong to the control group. Our data are sourced from the China Stock Market Accounting Research (CSMAR) dataset, the China National Intellectual Property Administration, the Resource Discipline Innovation Platform, and the National Bureau of Statistics. These observations distribute in 29 sub-industry of manufacturing industry, mainly in manufacture of computer, communication and other electronic equipment. In region level, there samples distribute in 31 PRMs in China mainland, the samples in Guangdong, Jiangsu and Zhejiang are most.



a) Patent application b) Patent authorization

Figure 1. The ratio between green and non-green patent over PRM in 2014 and 2022

Figure 1 illustrates the ratio of innovation in GT to NGT across various PRMs[4]. Red circles represent PRMs with unchanged tax rates, while green triangles represent PRMs with increased tax rates. The x-axis denotes the ratio of two innovations in 2023, and the y-axis denotes the ratio in 2014. Figure 1a and 1b measure innovation by patent applications and authorizations, respectively. Scatter points indicate the ratio in 2012 and 2023. Points lying to the left of the 45-degree line indicate that the ratio was higher in 2014 than in 2022, whereas points to the right indicate the opposite. The distance from these points to the 45-degree line represents the magnitude of the change between 2012 and 2023. In most PRMs, the innovation in GT has outpaced innovation in NGT. PRMs with increased tax rates have experienced a larger increase in the ratio from 2012 to 2023, with exceptions such as Ningxia, Qinghai, and Tianjin. Tianjin benefits from knowledge spillovers from its proximity to Beijing. Ningxia and Qinghai had relatively few innovations in GT in 2012[5], leading to a high innovation growth rate in GT.

Table 1 presents a statistical summary of key variables for the treated and control groups. The relative count of two patents is higher in the treatment group than in the control group. Specifically, the mean of $gipa_{i,t} / ngipa_{i,t}$ in the treatment group is 1.5 times that of the control group. The mean of $gipg_{i,t} / ngipg_{i,t}$ is 0.067 in the treatment group and 0.047 in the control group. Descriptive statistics of control variables indicate that our sample maintains covariate balance, ensuring the effectiveness of randomization across treatment and control groups.

Table 1. The statistical description of key variables

	Treatment group			Control group		
	Max	Mean	Min	Max	Mean	Min
Dependent variables						
$ngipa_{i,t}$	8,767	34.33	0	7,268	15.07	0
$ngipg_{i,t}$	3,899	16.29	0	2,826	6.54	0
$gipa_{i,t}$	677	2.55	0	265	1.13	0
$gipg_{i,t}$	248	0.93	0	127	0.44	0
$gipa_{i,t} / ngipa_{i,t}$	20.15	0.104	0	14.25	0.07	0
$gipg_{i,t} / ngipg_{i,t}$	8.648	0.067	0	16.39	0.047	0
Mechanisms variables						
$opearatingprofit_{i,t}$	878.795	5.616	–168.176	541.099	4.490	–448.574
$netprofit_{i,t}$	653.751	4.784	–170.494	484.047	3.848	–466.623
$tfp\_lp_{i,t}$	12.99	10.96	3.5	13.26	10.92	1.92
$tfp\_op_{i,t}$	14.59	11.52	3.69	16.59	11.54	2.79

[4] The counts of green and non-green patents were obtained from the 2012 and 2023 Annual Reports on Intellectual Property Statistics.

[5] In 2012, Qinghai and Ningxia had 5 and 42 green patent authorizations, respectively, the lowest among PRMs.

End of Table 1

	Treatment group			Control group		
	Max	Mean	Min	Max	Mean	Min
$cited_{i,t}$	1200	19.957	0	1706	9.033	0
$R\,\&\,Dspend_{i,t}$	188.04	2.569	0	205.952	1.723	0
Control vairbles						
$lntotalasset_{i,0}$	20.02	15.12	9.73	20.71	15.05	9.51
$lndebt_{i,0}$	19.74	14	7.87	20.3	13.92	8.39
$lnintangleasset_{i,0}$	16.96	11.68	2.37	17.48	11.61	0.23
$lnrdworker_{i,0}$	3.72	0.36	0	8.27	0.29	0
$lnfirmage_{i,0}$	4.01	2.87	1.1	4.16	2.87	1.1
$ownership_i$	1	0.268	0	1	0.22	0
$lnrevenue_{i,0}$	26.961	21.431	14.317	27.528	21.381	13.818
$er_{c,t}$	0.01	0.003	0	0.012	0.003	0
$subsidy_{i,t}$	549×10^7	697×10^5	0	546×10^7	509×10^5	0
$pl_{i,t}$	1	0.341	0	1	0.368	0
$HHI_{i,t}$	1	0.066	0	0.595	0.069	0.014
Instrumental variables						
$IV1$	14.7	3.11	0.13	36.05	6.13	0.06
$IV2$	0.54	0.26	0.05	0.63	0.33	0
Observation	10,257			16,709		

Notes: This table presents the description results before winsorization.

4. Results

4.1. Baseline results

Table 2 presents the baseline results regarding the effect of ETR on the relative count of green versus non-green invented patents. The dependent variables are $gipa_{i,t} / ngipa_{i,t}$ and $gipg_{i,t} / ngipg_{i,t}$, respectively. In column (2), the coefficient of $target_i \times post_t$ is 0.029, with 1% significant level, suggesting that ETR encourages firms to apply for more patents in GT compared to NGT. In column (4), the coefficient of $target_i \times post_t$ is 0.025, indicating that the reform boosts the number of granted green invented patents. Notably, the coefficient in column (2) is larger than that in column (4), which has two implications. Firstly, there is significant competition for patent authorization in green innovation. Secondly, governments might aim to prevent excessive green patent applications to avoid over-subsidization through patent authorizations.

Table 2. The ETR and firms innovation choices

	$gipa_{i,t}$ / $ngipa_{i,t}$		$gipg_{i,t}$ / $ngipg_{i,t}$	
	(1)	(2)	(3)	(4)
$target_i \times post_t$	0.029***	0.029***	0.024***	0.025***
	(0.009)	(0.009)	(0.007)	(0.007)
$lntotalasset_{i,0} \times t$		0.000		0.009
		(0.009)		(0.007)
$lndebt_{i,0} \times t$		0.012*		0.014***
		(0.006)		(0.005)
$lnintangleasset_{i,0} \times t$		–0.001		–0.007**
		(0.004)		(0.003)
$lnrdworker_{i,0} \times t$		0.004		-0.018
		(0.019)		(0.014)
$lnfirmage_{i,t}$		–0.037**		–0.041***
		(0.017)		(0.012)
$ownership_i$		0.009		0.013
		(0.012)		(0.009)
$lnrevenue_{i,0} \times t$		–0.002		–0.003
		(0.005)		(0.004)
constant	0.068**	0.068**	0.05**	–0.009
	(0.029)	(0.098)	-0.021	(0.074)
Industry fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
R2	0.42	0.46	0.33	0.44
Observation	26,966	26,966	26,966	26,966

Notes: Standard errors are reported in parentheses; *** p < .01, ** p < .05, * p < .1. (Hereinafter the same).

4.2. Justification of identification

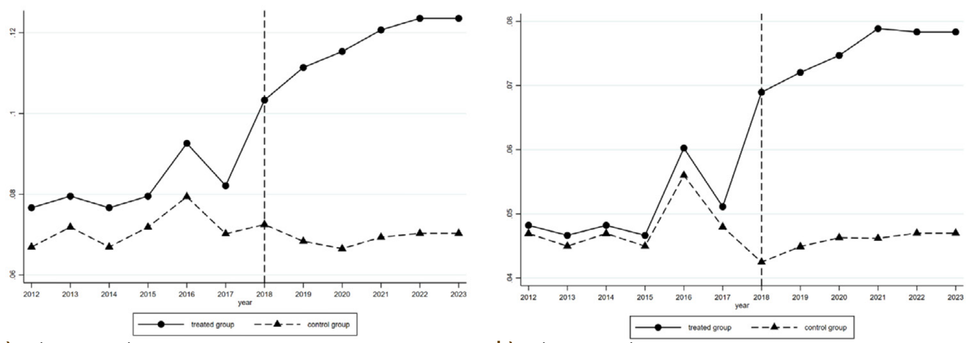
Table 3 presents the findings regarding the dynamic effect of ETR on firms innovation choices between GT and NGT. The coefficients of $target_i \times year2012$, $target_i \times year2013$, $target_i \times year2014$, $target_i \times year2015$, $target_i \times year2016$, and $target_i \times year2017$ are statistically insignificant across all columns, suggesting no discernible impact on firms innovation choices prior to ETR. This confirms the validity of the parallel trend assumption, as depicted in Figure 2. The treatment and control groups exhibit a fluctuating upward trend before 2018. Post-2018, the treatment group demonstrates a rapid increase, while the control group displays a fluctuating trend. Moreover, the coefficients of $target_i \times year2018$, $target_i \times year2019$, $target_i \times year2020$, $target_i \times year2021$, $target_i \times year2022$, and $target_i \times year2023$ are positive and statistically significant, indicating that ETR indeed stimulates firms to innovate in GT rather than NGT.

Table 3. The dynamic effect of the ETR

	$gipa_{i,t}$ / $ngipa_{i,t}$		$gipg_{i,t}$ / $ngipg_{i,t}$	
	(1)	(2)	(3)	(4)
$target_i \times year2012$	0.008	0.01	–0.001	–0.004
	(0.018)	(0.019)	(0.014)	(0.015)
$target_i \times year2013$	0.014	0.011	0.001	–0.005
	(0.018)	(0.019)	(0.014)	(0.014)
$target_i \times year2014$	0.006	0.007	–0.001	–0.005
	(0.018)	(0.018)	(0.014)	(0.014)
$target_i \times year2015$	0.008	0.008	–0.002	–0.005
	(0.017)	(0.017)	(0.013)	(0.013)
$target_i \times year2016$	0.024	0.024	0.014	0.012
	(0.017)	(0.017)	(0.013)	(0.013)
$target_i \times year2017$	0.016	0.016	0.005	0.004
	(0.016)	(0.016)	(0.012)	(0.012)
$target_i \times year2018$	0.036**	0.034**	0.02*	0.02*
	(0.016)	(0.016)	(0.012)	(0.012)
$target_i \times year2019$	0.036**	0.035**	0.022*	0.023*
	(0.016)	(0.016)	(0.012)	(0.012)
$target_i \times year2020$	0.04***	0.039**	0.023**	0.025**
	(0.015)	(0.016)	(0.011)	(0.012)
$target_i \times year2021$	0.048***	0.044***	0.029***	0.031**
	(0.015)	(0.015)	(0.011)	(0.011)
$target_i \times year2022$	0.048***	0.051***	0.028***	0.031***
	(0.015)	(0.015)	(0.011)	(0.011)
$target_i \times year2023$	0.053***	0.05	0.031***	0.027**
	(0.015)	(0.015)	(0.011)	(0.011)

End of Table 3

	$gipa_{i,t}$ / $ngipa_{i,t}$		$gipg_{i,t}$ / $ngipg_{i,t}$	
	(1)	(2)	(3)	(4)
control variables	No	Yes	No	Yes
industry fixed effect	Yes	Yes	Yes	Yes
province fixed effect	Yes	Yes	Yes	Yes
year fixed effect	Yes	Yes	Yes	Yes
firm fixed effect	Yes	Yes	Yes	Yes
R2	0.42	0.46	0.33	0.44
Observation	26,966	26,966	26,966	26,966



a) $gipa_{i,t}$ / $ngipa_{i,t}$ b) $gipg_{i,t}$ / $ngipg_{i,t}$

Figure 2. Parallel trend

Table 4 illustrates the findings obtained through the PSM-DID method. Figure 3 shows the match results of covariates. The coefficient of $target_i \times post_t$ emerges as significant across all columns, suggesting that ETR consistently stimulates firms to innovate in GT rather than NGT, irrespective of the sample used. This reinforces the baseline results and underscores the robustness of the estimated effect.

Table 4. PSM-DID estimation

	$gipa_{i,t}$ / $ngipa_{i,t}$		$gipg_{i,t}$ / $ngipg_{i,t}$	
	(1)	(2)	(3)	(4)
$target_i \times post_t$	0.029***	0.029***	0.024***	0.025***
	(0.009)	(0.009)	(0.007)	(0.007)
constant	0.068**	0.061	0.05**	–0.007
	(0.029)	(0.098)	(0.021)	(0.074)
control variables	No	Yes	No	Yes

End of Table 4

	$gipa_{i,t}$ / $ngipa_{i,t}$		$gipg_{i,t}$ / $ngipg_{i,t}$	
	(1)	(2)	(3)	(4)
industry fixed effect	Yes	Yes	Yes	Yes
province fixed effect	Yes	Yes	Yes	Yes
year fixed effect	Yes	Yes	Yes	Yes
firm fixed effect	Yes	Yes	Yes	Yes
R2	0.42	0.46	0.33	0.44
Observation	26,966	26,966	26,966	26,966

To further validate the robustness of the baseline findings, we conduct a bootstrapping placebo test by introducing a placebo treatment. Among the 3,400 unique firms observed during the sample period, 1,253 firms are situated in PRM that increased environmental taxes based on pollutant discharge fees. To perform the bootstrapping placebo test, we randomly select 1,253 firms from the total sample as the pseudo treatment group and repeat this process 1000 times. Figure 4 illustrates the distribution of estimated coefficients derived from the placebo test. The coefficients obtained from the placebo test are consistently lower than those estimated in the baseline regression, suggesting that the baseline results are not merely the result of random chance.

Apart from creating a pseudo-treated group, we manipulate the timing of ETR implementation. The ETR officially commenced on January 1, 2018, coinciding with the abolition of pollutant discharge fees. Some PRM increased environmental taxes based on pollutant discharge fees, while others adhered to the existing standards. By advancing ETR by one year, we examine the impact on firms innovation choices, as presented in Table 5. The coefficient of $target_i \times post_t$ is found to be statistically insignificant, indicating that altering the timing of

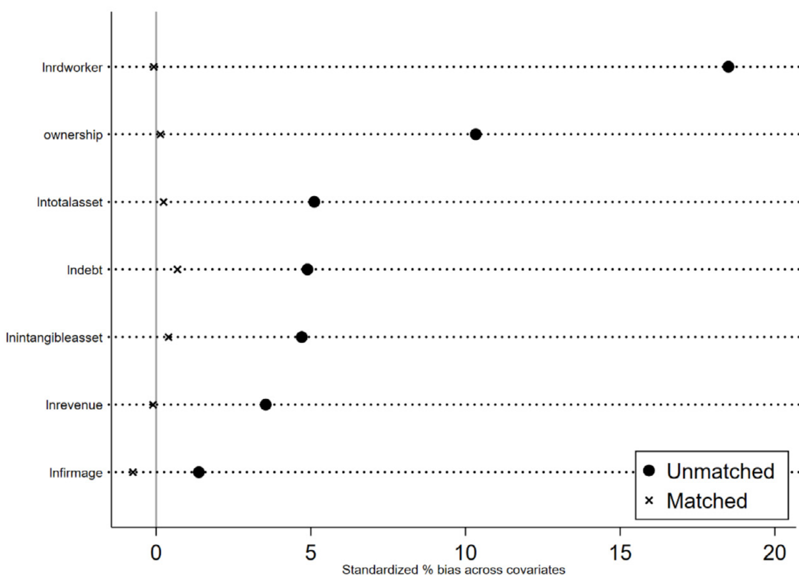
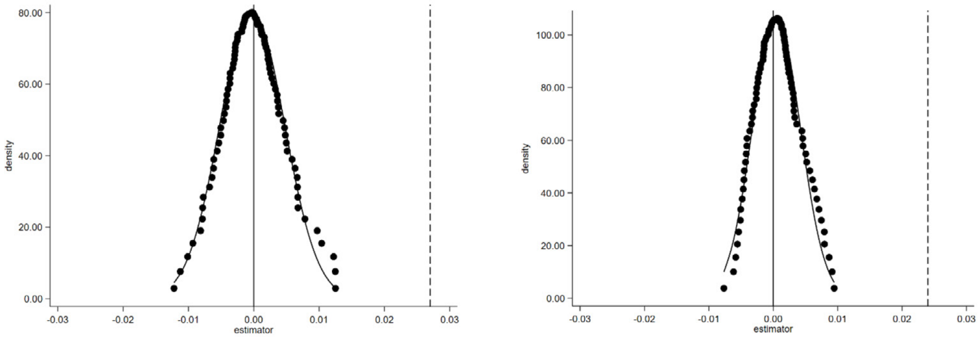


Figure 3. PSMDID standardized mean difference



a) $gipa_{i,t}$ / $ngipa_{i,t}$ **b)** $gipg_{i,t}$ / $ngipg_{i,t}$

Figure 4. Placebo test by creating a pseudo treatment

ETR does not affect firms innovation choices. This further corroborates the baseline findings: ETR encourages firms to innovate in GT rather than NGT.

Table 5. Change the time of implementing ETR

	$gipa_{i,t}$ / $ngipa_{i,t}$		$gipg_{i,t}$ / $ngipg_{i,t}$	
	(1)	(2)	(3)	(4)
$target_i \times post_t$	–0.001	–0.001	0.005	0.006
	(0.01)	(0.01)	(0.008)	(0.008)
constant	0.07**	–0.032	0.049**	–0.031
	(0.028)	(0.097)	(0.022)	(0.080)
control variables	No	Yes	No	Yes
industry fixed effect	Yes	Yes	Yes	Yes
province fixed effect	Yes	Yes	Yes	Yes
year fixed effect	Yes	Yes	Yes	Yes
firm fixed effect	Yes	Yes	Yes	Yes
R2	0.39	0.44	0.31	0.42
Observation	26,966	26,966	26,966	26,966

4.3. Additional robustness check

In addition to the aforementioned endogeneity tests, this study employs further robustness checks to validate our primary findings. First, firms' innovation decisions may be influenced by governmental C&C environmental regulations (Kemp & Pontoglio, 2011; Zhao et al., 2023). To investigate this, we extract environment-related terminology from government work reports and compute the pro- portion of such terms in the overall vocabulary (Chen et al., 2018b). Subsequently, we categorize the samples into two groups based on the stringency of C&C environmental regulations: strict and weak. The outcomes, depicted in Table 6, utilize the *suest* and *bdiff* methods to assess inter-group disparities. Notably, the difference test results between strict and weak C&C environmental regulations are not statistically significant, suggesting that ETR, rather than C&C environmental regulations, drives firms to innovate more in GT compared to NGT.

Second, firms' innovation choices are influenced by subsidies. Some firms pursue green technologies for increased subsidy, which is termed as "greenwashing" (Hu et al., 2023d; Guo et al., 2016). "Greenwashing" refers to the practice of presenting a product, policy, or activity as more environmentally friendly than it truly is. We segment the samples into two categories based on the level of subsidies received by firms. The findings, presented in Table 7. The coefficient of $target_i \times post_t$ is higher in the high subsidy group compared to the low subsidy group at a significance level of 5%. However, this distinction is not significant regarding patent authorizations. These results suggest that firms are inclined to innovate more in GT relative to NGT in pursuit of higher subsidies, although governmental mechanisms, such as patent authorization, serve as a corrective measure.

Table 6. Excluding the effect of C&C environmental regulations

	$gipa_{i,t}$ / $ngipa_{i,t}$				$gipg_{i,t}$ / $ngipg_{i,t}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$target_i \times post_t$	0.041***	0.036***	0.037***	0.019**	0.02***	0.011	0.021***	–0.002
	(0.008)	(0.01)	(0.007)	(0.008)	(0.006)	(0.007)	(0.005)	(0.006)
constant	–0.07	0.030	–0.313***	–0.205*	–0.094***	0.014	–0.139*	–0.163*
	(0.046)	(0.054)	(0.097)	(0.111)	(0.033)	(0.038)	(0.075)	(0.084)
control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.53	0.73	0.8	0.6	0.51	0.61	0.8	0.8
Observation	13,987	12,979	13,987	12,979	13,987	12,979	13,987	12,979
Different test	0.16		0.018		1.07		0.022	
	(0.687)		(0.21)		(0.300)		(0.150)	

Third, the emergence of COVID-19 spurred significant market demand for medical and pharmaceutical products, thereby fostering advancements in the manufacturing of medicines (Tsiotas & Tselios, 2022). We identify 337 firms engaged in the manufacture of medicines or bearing names indicative of biological, medical, or pharmaceutical sectors. Among them, 100 firms were listed between 2020 and 2022. To mitigate the potential impact of COVID-19 on firms' innovation activities, we exclude firms associated with medicine manufacturing or related vocabulary from our sample. The results, outlined in Table 8, reaffirm that ETR prompts firms to innovate more in GT than NGT.

Table 7. Excluding the effect of gain for more subsidy

	$gipa_{i,t}$ / $ngipa_{i,t}$				$gipg_{i,t}$ / $ngipg_{i,t}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$target_i \times post_t$	0.050***	0.016**	0.051***	0.016***	0.013**	0.011	0.016***	0.008
	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
constant	0.068	0.044	–0.280**	–0.222**	0.054	–0.064**	–0.219***	0.149*
	(0.056)	(0.046)	(0.116)	(0.010)	(0.040)	(0.032)	(0.075)	(0.001)
control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.79	0.38	0.94	0.55	0.76	0.28	0.52	0.35
Different test	8.67		0.035		0.13		0.009	
	0.003		0.060		0.722		0.27	
observation	13,628	13,338	13,628	13,338	13,628	13,338	13,628	13,338

Table 8. Excluding pharmaceutical industry or pharmaceutical firms

	$gipa_{i,t}$ / $ngipa_{i,t}$	$gipg_{i,t}$ / $ngipg_{i,t}$
	(1)	(2)
$target_i \times post_t$	0.035***	0.014***
	(0.005)	(0.004)
constant	–0.209**	–0.034
	(0.076)	(0.058)
control variables	Yes	Yes
industry fixed effect	Yes	Yes
province fixed effect	Yes	Yes
year fixed effect	Yes	Yes
firm fixed effect	Yes	Yes
R2	0.33	0.35
Observation	24,280	24,280

Table 9. IV-estimation

	$gipa_{i,t}$ / $ngipa_{i,t}$		$gipg_{i,t}$ / $ngipg_{i,t}$	
	First stage	Second stage	First stage	Second stage
IV1	0.023***		0.023***	
	(0.000)		(0.000)	
IV2	0.592***		0.592***	
	(0.062)		(0.062)	
$target_i \times post_t$		0.110***		0.074***
		(0.035)		(0.026)
constant	–0.650***	0.067	–0.650***	–0.038
	(0.038)	(0.072)	(0.038)	(0.054)
Control variables	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
province fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
R2	0.73	0.25	0.73	0.23
Observation	26,966	26,966	26,966	26,966
Test of endogeneity				
Durbin chi2(1)	4.806(p = 0.167)		3.589(p = 0.135)	
Wu-Hausman F (1, 26887) Weak instrumental test	4.793(p = 0.168)		3.579(p = 0.136)	
Minimum eigenvalue statistic Test of overidentifying	1658.71		1658.71	
Sargan chi2(1)	0.532(p = 0.465)		0.274(p = 0.601)	
Basmann	0.466(p = 0.466)		0.273(p = 0.601)	

4.4. Endogeneity of environmental tax reform

To address the endogeneity, we employ an IV approach. The results are presented in Table 9. The dependent variables include the relative counts and granted counts of green and non-green patented inventions. The first-stage results indicate a positive and statistically significant relationship between IV1 and IV2 and ETR at a 1% significance level. Subsequently, the coefficient associated with $target_i \times post_t$ demonstrates that ETR stimulates firms to innovate more in GT compared to NGT. Endogeneity tests indicate that ETR is exogenous to firms' innovation choices, while weak instruments tests and overidentifying tests confirm that both IV1 and IV2 meet exogeneity and correlation conditions.

4.5. Heterogeneity analysis

Besides the governmental C&C environmental regulations, subsidies and COVID-19, we analyze the effect of polluting level and market competition on firms' innovation choice under the ETR. We use triple-difference method and incorporate polluting level and market competition in triple interaction term, respectively. Table 10 shows that comparing to firms in low-polluting industries, firms in heavy-polluting industry innovate more in GT. We use the Herfindahl-Hirschman index to measure market competition. AS market competition intensifies, firms innovate more in GT under the ETR.

Table 10. Heterogeneity analysis

	$gipa_{i,t}$ / $ngipa_{i,t}$		$gipg_{i,t}$ / $ngipg_{i,t}$	
	(1)	(2)	(3)	(4)
	Polluting level	Market competition	Polluting level	Market competition
DDD	0.159***	–0.029***	0.098***	–0.010**
	(0.053)	(0.007)	(0.037)	(0.005)
constant	–0.049***	–0.097***	–0.106*	–0.104*
	(0.016)	(0.027)	(0.011)	(0.019)
control variables	Yes	Yes	Yes	Yes
industry fixed effect	Yes	Yes	Yes	Yes
province fixed effect	Yes	Yes	Yes	Yes
year fixed effect	Yes	Yes	Yes	Yes
firm fixed effect	Yes	Yes	Yes	Yes
R2	0.559	0.576	0.504	0.508
Observation	26,966	26,966	26,966	26,966

4.6. Influencing mechanisms analysis

The theoretical model finds that the relative count of GT and NGT is influenced by relative market value, R&D intensity and productivity based on the principle of maximizing profits. First, we empirically test the effect of firms' innovation choice on firms' profit. Table 11 shows the effect of the relative count of GT and NGT on firms' profits. The increase of the relative count of GT and NGT can increase firms' profit, which means that innovating more in GT can bring more profit for firms.

We test the specific influencing mechanisms. The initial mechanism through which ETR shapes firms' innovation decisions is via the productivity effect. Table 12 provides an overview of the impact of innovation on firms' TFP amid ETR. In columns 1 and 3, these coefficients indicate that, under ETR, GT exert a larger and positive influence on TFP compared to NGT. In columns 2 and 4, these coefficients reveal the similar results. These findings validate the notion that ETR tends to bolster firms' productivity more significantly through GT than NGT, thereby contributing to the preference for GT adoption.

Table 11. The effect of relative number of GT and NGT on firms' profit

	$operatingprofit_{i,t}$		$netprofit_{i,t}$	
	(1)	(2)	(3)	(4)
$gipa_{i,t}$ / $ngipa_{i,t}$	2.527***		2.152***	
	(0.658)		(0.552)	
$gipg_{i,t}$ / $ngipg_{i,t}$		3.904***		3.414***
		(0.933)		(0.781)
constant	3.207***	3.232***	3.290***	3.309***
	(0.943)	(0.943)	(0.790)	(0.790)
control variables	Yes	Yes	Yes	Yes
industry fixed effect	Yes	Yes	Yes	Yes
province fixed effect	Yes	Yes	Yes	Yes
year fixed effect	Yes	Yes	Yes	Yes
firm fixed effect	Yes	Yes	Yes	Yes
R2	0.418	0.419	0.359	0.361
Observation	26,966	26,966	26,966	26,966

Table 12. Influence mechanism estimation

	Productivity				Market Value		R&D Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$target_i \times post_t \times ngipa_{it}$	0.003**		0.001***		0.039		0.012***	
	(0.000)		(0.000)		(0.060)		(0.004)	
$target_i \times post_t \times gipa_{it}$	0.03***		0.052***		3.425***		0.423***	
	(0.001)		(0.002)		(0.581)		(0.043)	
$target_i \times post_t \times ngipg_{it}$		0.007***		0.004***		0.144		0.037***
		(0.000)		(0.001)		(0.115)		(0.008)
$target_i \times post_t \times gipg_{it}$		0.027***		0.043***		9.902***		1.045***
		(0.002)		(0.005)		(1.250)		(0.094)
constant	8.967***	8.959***	2.439***	2.448***	–85.593***	–84.263***	–8.890***	–8.855***
	(0.048)	(0.052)	(0.117)	(0.115)	(13.456)	(13.409)	(0.686)	(0.685)
control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.852	0.83	0.733	0.74	0.174	0.179	0.396	0.398
Observation	26,966	26,966	26,966	26,966	26,966	26,966	26,966	26,966

The second mechanism elucidating the impact of ETR on firms' innovation choices pertains to the market value effect. Columns (5) and (6) show the effects of innovation choices on firms' number of being cited of patent following ETR. The coefficients indicate that, compared to innovations in NGT, the impact of innovations in GT is greater under ETR. The third mechanism concerns R&D intensity. In this analysis, we utilize the R&D spend within a firm as a proxy for R&D intensity. However, disentangling the expansion of R&D intensity than NGT. Table 13 reports the effects of the relative number of GT and NGT on productivity, market value and R&D intensity. The relative number of GT and NGT has positive effects on firms' productivity, market value and R&D intensity. The results increase the robustness of influencing mechanisms.

Table 13. The effect of relative number of GT and NGT on productivity, market value and R&D intensity

	Productivity				Market Value		R&D Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$gipa_{i,t}$ / $ngipa_{i,t}$	0.013***		0.015***		21.864***		1.040***	
	(0.002)		(0.004)		(1.999)		(0.193)	
$gipg_{i,t}$ / $ngipg_{i,t}$		0.009***		0.004		30.668***		1.590***
		(0.003)		(0.005)		(2.772)		(0.273)
constant	8.945***	8.943***	2.431***	2.430***	−93.715***	−94.368***	2.075***	2.085***
	(0.055)	(0.055)	(0.118)	(0.118)	(13.407)	(13.406)	(0.276)	(0.276)
control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.809	0.808	0.728	0.728	0.177	0.177	0.680	0.681
Observation	26,966	26,966	26,966	26,966	26,966	26,966	26,966	26,966

5. Discussions

Our findings contribute to the growing body of literature on environmental taxation, innovation, and GT development. Several studies from the past decade have explored similar themes, examining how regulatory frameworks and tax policies can incentivize firms to develop GT. For instance, Karmaker et al. (2021) argue that environmental taxes, if well-structured, can not only reduce environmental harm but stimulate innovation by altering firms' cost-benefit calculations. Our study extends this literature by empirically testing the effects of ETR on the innovation decisions of firms in the manufacturing sector, with a focus on green technology development.

Moreover, Gillingham et al. (2009) discuss how market-based instruments, such as taxes and subsidies, influence firms' R&D investment decisions. They note that environmental taxes can stimulate innovation in GT when firms perceive a sufficiently large financial benefit. Our results align with this, as we find that ETR increases the likelihood of firms innovating in GT, particularly when there is a market advantage associated with these technologies. Another relevant strand of literature is Romer's (1990) theory on endogenous technological change, which posits that innovations are driven by economic incentives that shape the direction of technological progress. Our study supports this framework by demonstrating that ETR can create strong economic incentives for firms to shift their innovation focus toward GT. However, the potential for "greenwashing" presents a challenge to the effectiveness of ETR. Hu et al. (2023c) explore how firms engage in deceptive environmental practices to gain regulatory advantages. Our studies' findings echo this concern, emphasizing the need for stringent regulatory oversight and the implementation of more precise definitions of what constitutes legitimate green innovation. Hedegaard et al. (2024) suggest that environmental taxes can lead to a perverse outcome if not carefully designed. While our study generally finds positive impacts of ETR on green innovation, it highlights the importance of ensuring that these policies are carefully calibrated to avoid such unintended consequences.

6. Conclusions

This study explores the empirical impact of ETR on the innovation choices of firms, specifically in terms of shifting their focus from NGT to GT. Our findings suggest that ETR can serve as a strategic instrument to redirect firms' innovation efforts toward GT, which are essential for promoting sustainable economic growth. This conclusion is supported by various robustness checks.

The key findings of this study are: (1) ETR shifts innovation towards GT under profit maximization. A well-structured environmental tax, shift firms' innovation focus, presumably because of increased cost-effectiveness, market signals, and productivity advantages associated with green innovations. Innovating more in GT can increase firms' profit. (2) Substitution between GT and NGT. When GT and NGT are sufficiently close substitutes, firms are more likely to pivot toward GT, facilitating long-term sustainable growth. This finding underscores the need for carefully designed policy interventions that provide a strong price signal to firms without imposing excessive burdens. (3) R&D intensity, market value, and productivity effects. Our investigation into the relative R&D intensity effect, market value effect, and productivity effect reveals that firms decisions are influenced not only by tax incentives but by the broader market and productivity dynamics. (4) The risks of "greenwashing". While environmental taxes can intensify competition in green innovation, they incentivize firms to claim greenness without meaningful technological advancements. This reinforces the need for stringent approval processes for green technologies, ensuring that genuine innovations are distinguished from low-value technological advancements. (5) Impact of external factors: The study carefully controls for the potential confounding effects of C&C environmental regulations, subsidies, and the COVID-19 pandemic. These external factors could otherwise distort the relationship between ETR and firm-level innovation outcomes.

Given these findings, several key policy recommendations can be drawn: (1) Tailored environmental taxation policies. Policymakers should design environmental taxes in such a way that they create clear economic incentives for firms to innovate in GT. (2) Stronger regulatory oversight to combat "greenwashing". As firms are motivated by regulatory benefits rather than genuine technological advancement, policymakers should establish stringent standards and certification processes for GT. (3) Support for R&D in GT. Governments could complement ETR with subsidies or direct funding for R&D in GT, particularly in sectors where firms face significant upfront costs in developing new innovations. (4) Addressing market failures and promoting substitution. Given the importance of substitutability between GT and NGT, policymakers should consider how to remove barriers to the adoption of GT, such as market access, information asymmetries, or coordination failures between firms and consumers.

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Author contributions

Hu Hui and Yuqi Zhu conceived the study and were responsible for the design and development of the data analysis. Yuqi Zhu and Yulong Wang was responsible for data collection and analysis. Hu Hui and Lin Ye wrote the first draft of the article and did the revision.

Disclosure statement

The authors declare that they have no conflict of interest.

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