Effectiveness of Environmental Policy Integration: Evidence from China's R&D Policy Reform*

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March, 2026

Abstract

This paper examines the environmental policy integration (EPI) that incorporates environmental objectives into the R&D policy, using China's High and New Technology Enterprise (HNTE) policy as an experiment. We find that, after introducing environmental criteria, polluting firms are less likely to obtain HNTE certification, and certified polluting firms reduce R&D investment while enhancing environmental performance. Structural estimates validate these findings, revealing an inverted U-shaped relationship between social welfare and environmental criteria stringency. Policy simulations indicate that EPI outperforms traditional, separate policies, as it promotes greater welfare improvements by encouraging firms to increase abatement intensity without directly distorting their production decisions.

Keywords: Environmental Policy Integration, R&D Investment, Pollution Control

*We thank Joshua Graff Zivin , Daniel Yi Xu, and Kim Ruhl for their constructive discussions and comments, and seminar participants at CUFE, SHUFE, SWUFE, and SUIBE for helpful comments. We acknowledge financial support from the Ministry of Education Project of Key Research Institute of Humanities and Social Sciences at Universities in China (22JJD790014, 2023JZDZ021), the National Natural Science Foundation of China (No.72473029, No.72373030, No. 72433002), Shanghai Institute of International Finance and Economics. We declare no competing interests.

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1 Introduction

Environmental contamination poses a significant threat to human health and long-term development (Graff-Zivin and Neidell, 2012, 2013). Addressing these challenges requires moving beyond isolated policies toward a more integrated framework. In this context, Environmental Policy Integration (EPI) has gained global recognition. EPI emphasizes that environmental challenges are inherently cross-sectoral and cannot be effectively addressed through isolated environmental policies. Thus, it encourages policymakers to embed environmental considerations across diverse sectors, such as agriculture, industry, transportation, and urban planning. It aims to create synergies, mitigate distortions, and align economic and social progress with ecological sustainability. Beyond its concept, EPI has evolved into a practical governance strategy adopted by international organizations, national governments, and local authorities, gradually becoming a widely adopted policy model.[1]

Despite its broad adoption, empirical and quantitative research on EPI remains scarce. This paper examines whether EPI can simultaneously promote both environmental and non-environmental policy goals, particularly when targeting firms. We further investigate whether EPI is socially desirable given potential externalities.

China's High and New Technology Enterprises (HNTE) policy provides an excellent experiment to investigate the effectiveness of EPI. As the most enduring and generous R&D incentive policy in China, it grants a reduced corporate tax rate of 15 percent (versus the base tax rate of 25 percent). This policy strongly stimulates firms' R&D input, although it has faced criticism for resource misallocation toward less innovative projects due to firms' relabeling behaviors (Chen et al., 2021). In 2008, the HNTE program started to take the EPI mode (to make a distinction, henceforth HNTE-env policy). The HNTE-env policy mandates that firms' HNTE certification shall be revoked if they are penalized for environmental violations. Revocation entails the loss of tax benefits, ineligibility to reapply for HNTE status for the next five years, and sunk certification costs. This reform primarily affects polluting firms, as polluting firms are more prone to environmental violations because of looser local regulations. In Section 2, we provide detailed illustrations regarding institutional backgrounds.

We consider a two-period model in which upstream and downstream firms engage in R&D in the first period, which determines their productivity and profitability in the second. In the baseline setting, firms decide whether to apply for HNTE status by weighing certification costs

[1]Examples include extensive efforts on EPI made by the European Union to achieve the emission reduction goals set by the European Commission in 2008 and 2011. It integrates environmental concerns into sectors not fully covered by the European Emission Trading Scheme (EU ETS), such as innovation, energy, transport, and agriculture (Kettner and Kletzan-Slamanig, 2020; Rietig, 2013). In addition, the United Nations' Sustainable Development Goals (SDGs) emphasize the need for integrated approaches to address complex global challenges and underscore the critical role of EPI in advancing the objectives of Agenda 2030.

against the expected increase in firm value due to tax benefits. Under the HNTE-env policy, this decision becomes more complex: since environmental penalties trigger revocation of HNTE status, firms have incentives to adjust both their application decisions and their investment in R&D and pollution abatement. The model yields two testable propositions. First, on the extensive margin, the HNTE-env reform reduces the proportion of downstream firms obtaining HNTE certification; on the intensive margin, it leads to lower R&D and pollution abatement investments. Second, due to the abatement fixed cost, the negative effect of the policy on R&D investment is more pronounced for smaller firms, whereas the positive effect on pollution reduction is stronger for larger firms.

Drawing on a novel database detailing firm-level R&D activities and corporate tax records, this study employs a spatial regression discontinuity design (RDD) to identify the treatment effects of the HNTE-env policy. The RDD strategy exploits a discontinuity of environmental intervention created by China's water quality monitoring stations, as pioneered by (He et al., 2020). Since 2003, water quality readings started to play a pivotal role in evaluating local officials' performance regarding water pollution control. These stations can only detect emissions from upstream, which creates spatially discontinuous incentives for local officials to enforce stricter environmental regulations on firms located upstream of the stations compared to those downstream. As a result, substantial differences emerge in local pollution control and compliance outcomes. We empirically validate this discontinuity by showing that downstream firms are significantly more polluting and thus more likely to be punished than their upstream counterparts.

Our empirical findings indicate that, on the extensive margin, following the implementation of the HNTE-env policy, firms located downstream are less likely to be certified as HNTE and receive fewer tax benefits compared to their upstream counterparts. To further disentangle the effect of environmental compliance from other firm-specific factors, we show that there is no significant difference in the HNTE eligibility between downstream and upstream firms. Despite this, downstream firms are more reluctant to apply for the HNTE certification. We also strengthen the robustness of our findings by examining the non-polluting industries and the impact of the R&D Weighted Deduction policy, which does not incorporate environmental criteria. To examine within-firm responses on the intensive margin, we complement the RDD approach with a difference-in-differences (DID) specification. We find that, after the policy enactment, polluting firms that are already certified as HNTE significantly reduce their R&D investment and perform much better in reducing water pollution. Heterogeneity analysis indicates that, compared with large firms, small firms have less capacity to do pollution abatement and maintain R&D investment.

Furthermore, enlightened by the illustrative model and the empirical findings, we estimate the full-fledged quantitative model via the simulated method of moments approach. Our struc-

tural estimation simultaneously targets upstream and downstream patterns, including firms' R&D distribution, HNTE status, TFP, and pollution emissions. In addition to determining the distributions of fixed and adjustment costs, our model also characterizes the extent of environmental regulation and the pollution penalty for HNTE firms. Our estimated model fits the data moments very well. The estimates are also consistent with the fact that downstream firms suffer a significantly greater probability of environmental penalties. Moreover, the simulation results based on our estimates are consistent with those of reduced-form empirical tests.Based on the structural model, we provide a conceptual framework to gauge whether the HNTE-env policy improves resource allocation and is socially desirable. Our counterfactual analysis indicates an inverted U-shaped relationship between the net benefit and the extent of the environmental penalty. This is attributed to the trade-off between economic costs from TFP loss and health benefits from environmental improvement. Finally, we show that the environmental penalty acts as a desirable companion to the R&D incentives, as it helps mitigate potential misallocation effects and environmental externalities induced by uniform tax credits. [2]

We conclude our quantitative analysis with a policy decomposition that compares the EPI design with separate environmental regulations. Unlike conventional regulations, which apply uniformly to all firms, the EPI scheme specifically targets firms seeking HNTE certification. This saves more monitoring and enforcement costs. Additionally, our simulation results show that conventional regulations cause greater economic losses compared to the EPI scheme. In particular, the EPI scheme causes the TFP losses primarily through reducing R&D investments, and it incentivizes HNTE firms to increase abatement intensity to retain HNTE eligibility without directly distorting their production decisions. By contrast, conventional regulations distort both R&D and production decisions, with production distortions accounting for the majority of the aggregate TFP loss. This is because conventional regulations uniformly increase environmental costs and thereby the marginal cost of production across all firms. Overall, the EPI scheme should be a more advantageous policy to improve social welfare.

Related Literature This paper contributes to three strands of the existing literature. First and foremost, our analysis is related to studies on environmental policy integration. Current studies feature rich dimensions of this notion, for example, scientific consensus on the use of policy integration to address climate change or the transition toward sustainable development (Jordan and Lenschow, 2010; Adelle and Russel, 2013; Candel and Biesbroek, 2016; Runhaar et al., 2014). However, they are primarily conceptual and do not provide comprehensive quantita-

[2]The integration and unification of separate regulative power somewhat assembles other centralization regimes in environmental regulation. Notably, Kong and Liu (2024) show that the centralization of authority in the appointment of civil servants, rather than decentralization, can improve the effectiveness of regulatory enforcement efforts.

tive tests (Trein et al., 2023).[3] Consequently, they do not provide concrete evidence to reveal its full potential in addressing multifaceted development goals. More recently, Nian (2023) documents the advantage of economic incentives over command-and-control tools in reducing rural air pollution. Duan et al. (2021) investigate the interactions between international trade, the environment, and environmental regulations. We take one step further in this literature by empirically and quantitatively investigating the effects, key determinants, and optimal policy formulas of integrating environmental concerns into R&D policies to uncover the frontier of innovation and environmental outcomes.

Second, this paper contributes to the literature concerning the misallocation of innovation resources and the effectiveness of R&D policy incentives. Chu (2009) and Chu and Cozzi (2018) theoretically examine the effects of patent protection policy and R&D subsidies on innovation. Akcigit et al. (2021) find that uniform research subsidies can amplify dynamic misallocations in the economy by over-subsidizing applied research. Closely related, Chen et al. (2021) quantitatively investigate the welfare effects of the HNTE program, and they find that the tax incentives become increasingly expensive as a result of a substantial rise in the reported R&D, which is partly driven by firms' relabeling behaviors.[4] As a departure from the above studies, our work investigates the trade-offs or complementarities between stimulating R&D and curbing pollution. Our theoretical and quantitative frameworks highlight the misallocation of R&D resources between clean and dirty firms, and we also discuss the optimal policy combinations when the environmental effect is considered.

Third, our work relates to the growing research on the environment and technological innovation. A sub-strand of the literature emphasizes the fundamental importance of technological changes in sustainable development. Acemoglu et al. (2012) emphasize the competition between clean and dirty technologies and propose a targeted subsidy to shift R&D from dirty technology to clean technology. [5] Different from these studies, we examine a policy design that does not explicitly target clean or dirty technologies but still phases out R&D that supports dirty production. Another body of literature examines the role of environmental regulations in stimulating firms' R&D investments. A broad range of studies document the effect of environmental regulation on firms' R&D or innovation (Cohen and Tubb, 2018; Ambec et al., 2013) under the Porter's hypothesis. Particularly, Qiu et al. (2018) show that the existence of

[3] Trein et al. (2023) conduct a systematic review of the empirical literature on policy integration. As they point out, among the 413 papers published during the last ten years, no clear pattern of theory or empirical design has been identified in policy integration research, and limited attention has been given to the evaluation of policy integration. See also the literature review by Persson and Runhaar (2018) and Runhaar et al. (2014), which documents that several related empirical papers do not employ an econometric method.

[4] See also the study by König et al. (2022), which develops a model featuring firms' innovation and imitation decisions and quantify the effects of misallocation on TFP growth in China.

[5] Similarly, Aghion et al. (2016) find that a carbon tax can push innovate more in clean (and less in dirty) technologies, and document the path dependence in technology in the type of innovation.

heterogeneous responses in high/low capacity firms' innovation investment. Nevertheless, our findings show that devotion to pollution abatement significantly crowds out firms' R&D investment. Ryan (2012) and Fowlie et al. (2016) suggest that the effects of environmental regulation on firm competitiveness can be driven not only by firm behavior but also by the market structure. We exploit the upstream–downstream setting driven by the decentralized protection system in China, which controls for market, population, and resource conditions. By this setting, our estimate can be interpreted exclusively as firms' direct response to changes in EPI reform.

The remainder of the paper is organized as follows. Section 2 describes the institutional background. Section 3 develops a model to illustrate the theoretical mechanism and testable predictions. Section 4 describes the identification strategy, data, and empirical evidence. Section 5 extends the quantitative model to study the policy impacts on resource allocation efficiency and aggregate welfare. Section 6 concludes the paper.

2 Institutional Background

2.1 HNTE Policy

China's support for HNTE firms can be traced back to the 1980s. The main regulatory bases include the *Interim Rules on Accreditation Criteria of HNTE* (1988), *Standards and Methods on Accreditation of HNTE in High-tech Zone* (1991), *Standards and Methods on Accreditation of HNTE out of High-tech Zone* (1996), and *Uniform Measures on Accreditation of HNTE* (2000). HNTE firms are granted a preferential corporate income tax rate of 15 percent as opposed to the 25 percent or 33 percent statutory rate. They also benefit from R&D weighted deduction from firms' taxable income and tax exemption on technology transfer. [6]

To acquire the HNTE certification, firms operating in high-tech sectors are required to satisfy the following qualifying standards: (**i**) No less than 10 percent of employees work for R&D, and no less than 30 percent of them have associate degrees or above; (**ii**) Sales associated with high-tech innovations account for more than 60 percent of total sales; and (**iii**) R&D intensities (R&D expenses divided by sales) are at least 6 percent, 4 percent, and 3 percent for small (sales smaller than 50 million CNY), medium (sales between 50 and 200 million CNY), and large (sales larger than 200 million CNY) firms, respectively.[7] Firms should also undergo a burden-

[6] In addition to the tax reduction, the accredited HNTE firms might also be preferentially treated by local governments. For example, HNTE firms established in the special economic zones also enjoy a two-year tax exemption followed by a three-year 50 percent tax reduction.

[7] The eight main categories within the high-tech field include electronic information technology, biological and medical technology, aviation and space technology, new materials technology, high-tech services, new energy and energy conservation technology, resources, and environmental technology.

some application procedure. The national science and technology authorities, along with the provincial financial authorities, are responsible for overseeing the review and approval process of HNTE. The HNTE certification is valid for three years and can be renewed once for an additional three years. When the six-year term expires, firms must reapply for HNTE certification. Due to its attractive benefits, the HNTE policy has effectively incentivized firms to actively pursue HNTE certification, thereby significantly affecting firms' R&D investment.

2.2 HNTE-env Policy: A Typical EPI

As the focus of our research, the 2008 HNTE-env policy integrates an environmental criteria into the HNTE certification, which exemplifies a typical EPI mode. In 2008, China's central government amended the *Administrative Measures on Accreditation of High and New Technology Enterprises*, which serves as the primary legal foundation for the accreditation of HNTE. In particular, the amendment introduced an environmental provision stipulating that a firm's HNTE certification shall be revoked if it is penalized for any environmental violations. The consequences of the revocation are not only the return of the tax reductions and other benefits but also the loss of eligibility to apply for HNTE status in the next five years, as well as the ex ante sunk costs incurred to meet the R&D criteria.[8] In our analysis, we refer to this environmental integration as the HNTE-env policy to distinguish it from the traditional HNTE policy without considering firms' environmental behavior. Since January 1, 2008, environmental compliance has been an integral factor in the approval and revocation of HNTE status under the HNTE-env policy.

In practice, it is common for firms to be penalized by environmental agencies. In the realm of water pollution control legislation, firms found in violation of environmental regulations may face a range of penalties, including fines, permit revocations, production restrictions, and even forced shutdowns. For example, firms that discharge water pollutants without a license or exceed the established limits should be subject to rectification measures and fined an amount of two to five times their pollution fees. Even though a firm manages to meet regulatory standards, environmental penalties still pose risks to HNTE status. For instance, accidents involving toxic releases or improper disposal of hazardous waste may result in unintentional fines. Thus, polluting firms inevitably encounter the environmental uncertainties embedded in the HNTE-env program.In practice, environmental violations have indeed led to HNTE revocations. For instance, in 2010, Zijin Mining Group in Fujian Province lost its HNTE certification after its subsidiary illegally discharged a copper-containing acidic solution on July 3 and July

[8]The details can be seen in the policy document, Guo Ke Fa Huo [2008] No. 172, which was issued by Ministry of Science and Technology, Ministry of Finance, and State Taxation Administration and became effective as of January 1st, 2008.

16, 2010, as determined by the Fujian Administration.[9]

This policy design carries significant implications. Even minor instances of environmental noncompliance might lead to the loss of the HNTE certification. Thus, firms are likely to carefully evaluate these risks and adjust their investment decisions in both R&D and pollution abatement. Intuitively, integrating environmental criteria into existing R&D incentives could enhance environmental governance, potentially at lower regulatory costs. However, its effect on firms' R&D investment remains uncertain. These hypotheses warrant rigorous examination, and we provide both theoretical and empirical analyses in the following sections.

2.3 Environmental Variation

The variation of environmental compliance exists in the upstream-downstream dimension of China's water quality monitoring stations. In the 1990s, China started to establish a long-term water quality monitoring network for hydrological data gathering and water disaster forecasting. The monitored indicators can be divided into two categories: one is a comprehensive indicator of water quality, such as temperature, chroma, and pH value; the other relates to toxic substances, such as chromium, cadmium, and organic pesticides. In addition, the monitoring stations can also be used to measure river velocity and discharge to prevent disasters such as floods. In order to consistently receive accessible surface water data, the sampling pipes and pumps for data collection are generally distributed on the trunk stream of rivers, lakes, and reservoirs in China, as shown in Figure B.1. It is noteworthy that the locations of monitoring stations are originally determined by the central government for hydrological purposes, which are independent of local industrial activities. It means that, initially, the central government did not take the regulatory function into account.

Those monitoring stations were not deployed for environmental supervision until 2003, when the central government began setting aggressive targets for water pollution control. During the 10th National Five-Year Plan period, for the first time, China attempted to integrate the accomplishment of environmental protection goals into the performance evaluation framework for provincial, municipal, and county-level governments.[10] Despite the unwavering commitment of the State Council, a comprehensive regime was not established until the amendment of the Surface Water Quality Standard (2002) was finalized.[11] The central govern-

[9] See news report: https://www.chinanews.com.cn/stock/2011/03-18/2915886.shtml.

[10] See the Approval Decision of the State Council on National Five-Year Plan on Environmental Protection, 2001.

[11] The new standard covers 24 parameters for surface water and 85 parameters for drinking water sources. The water quality is classified into five grades from I to V, with grades I, II, or III denoting a benign water quality status and grades IV and V denoting a harmful water quality status. The 2002 standards are fundamental for evaluating the effectiveness of water regulatory frameworks and, more importantly, local governments' achievements in water quality protection. As shown in the Annual National Reports on Ecological and Environmental Conditions, the percentage of surface water monitoring readings above Grade III has gradually increased since

ment set targets for water pollution control, which were then assigned to local governments. Since the reading of water quality can be directly accessed by the central government, it is employed as an evaluation indicator for local officials' efforts on environmental protection. Considering political evaluation and career promotion, local officials set stringent standards on water pollution discharge and implement frequent inspections on water-polluting firms. In particular, they impose tight regulations on upstream firms because pollution discharged upstream flows through the monitoring stations and directly reflects on the real-time readings.

As a result, the environmental intervention targeting upstream firms tends to push them to engage in greater investment in pollution control, advanced environmental management techniques, and regular detections on manufacturing processes to avoid environment-related risks such as waste improper disposal, oil spills, and toxic releases. In Section 4.3, we empirically show that the exposure to stringent environmental regulation contributes to substantially cleaner upstream firms, compared with their downstream counterparts. It creates a discontinuity in environmental compliance between upstream and downstream firms, providing an ideal setting to evaluate the effects of the integration of environmental criteria into the HNTE-env program on firms' application and investment decisions.

3 An Illustrative Model

In this section, we propose a simple model of firm decision-making to motivate the empirical and quantitative analysis and to help rationalize how R&D and pollution control, which are two initially separated but later intertwined factors, produce differential outcomes by firms. We consider a two-period setup with firms' endogenous R&D investment and polluting activities. The baseline model combines the theories of Fan et al. (2021) and Chen et al. (2021), where firms decide to engage in R&D during the first period, which determines their productivity and profitability in the subsequent period. In what follows, we start with firms' decisions on R&D and pollution abatement without the HNTE policy. Then, we turn to a situation in which the HNTE policy designed to stimulate high-tech industry and innovation is implemented. Finally, by further integrating the HNTE-env policy, an approach aimed at linking firms' environmental performance to their qualification for obtaining the HNTE certification, we consider how firms strategically decide their expenditures in R&D and pollution control.

3.1 Firms' Decisions without the HNTE Policy

We follow Chen et al. (2021) to consider firms with heterogeneous productivity. There is a continuum of firms located in the neighborhood of water monitoring stations. The individual firm

2003.

is indexed by $i \in [0,2]$. We label the upstream firms by $i \in [0,1]$ and the downstream firms by $i \in (1,2]$. A firm produces output y_{it} with constant-returns-to-scale production technology, $y_{it} = \exp(z_{it})l_{it}$, where l_{it} is a static input bundle with a price of w_{it}, and $\exp(z_{it})$ is the productivity that follows a process of[12]

$$z_{it} = \rho z_{it-1} + \phi \log(d_{it-1}), \tag{1}$$

where d_{it-1} is the R&D investment made in the previous period, parameter $\rho \in (0,1)$ indicates the persistence of the productivity process, and $\phi > 0$ indicates the positive impact of R&D on the firm's productivity. The above specification indicates that the productivity z_{it} is a *state variable* for the individual firm. The implied marginal/average production cost is $\frac{w_{it}}{\exp(z_{it})}$. Each firm faces a demand curve, $y_{it} = p_{it}^{-\sigma} B_t$, where $\sigma > 1$ is the demand elasticity and B_t is the aggregate demand shifter.

Following Annicchiarico and Di Dio (2015), we assume that emissions e_{it} are proportional to the firm's output: $e_{it} = (1 - \xi_{it})\theta y_{it}$, where ξ_{it} denotes the fraction of emissions reduced by the abatement technology, and $\theta > 0$ denotes emissions per unit of output without pollution abatement. The firm must pay a comprehensive cost for pollution induced by environmental regulations, which is linear to the total pollution and is measured by the marginal costs. These costs include but are not limited to firms' pollution tax, compensation payments for damages caused, the installation of online monitoring systems, the employment of environmental staff, etc. For ease of comprehension, we refer costs embedded in the term $f_i e_{it}$ as those induced by environmental regulations hereinafter. Notably, firms' environmental penalties are beyond the scope of $f_i e_{it}$, as we treat them as a separate factor determining whether firms can sustain the HNTE certification provided by the HNTE-env policy. The spending on the pollution fees can be expressed as $\frac{w_{it}}{\exp(z_{it})} f_i e_{it}$, where $f_i = f_u$ if $i \in [0,1]$ and $f_i = f_d$ if $i \in (1,2]$, indicating the tightness of the environmental regulations for the upstream and the downstream firms, respectively. The upstream firms face more stringent regulations than the downstream firms do; thus, we specify that $f_u > f_d$.

When abating pollution, the firm must pay a variable cost that is convex in the abatement ξ_{it} and is proportional to the average production costs, i.e., $v_1 \xi_{it}^{v_2} \frac{w_{it}}{\exp(z_{it})} y_{it}$, where $v_1 > 0$, $v_2 > 1$. The firm also pays a fixed cost $\zeta > 0$ for the abatement in each period.[13] Thus, the firm faces a discrete choice on whether to abate. Let $\mathbb{I}_{it}(\xi_{it} > 0)$ denote the indicator of whether to abate that takes a value of one if the firm chooses to abate pollution, i.e., $\xi_{it} > 0$, and zero otherwise.

[12] For simplicity, we do not introduce any uncertainty in the TFP process in the illustrative model.

[13] This fixed cost represents the investment in purchasing and installing abatement equipment and clean technology, among others, in each period.

The firm's profit function can be defined as:

$$\pi(p_{it}, \xi_{it}|z_{it}) = \left\{ p_{it} - \frac{w_{it}}{\exp(z_{it})} \left[1 + f_i(1-\xi_{it})\theta + v_1 \xi_{it}^{v_2} \right] \right\} y_{it} - \mathbb{I}_{it}(\xi_{it} > 0)\zeta, \tag{2}$$

where the productivity z_{it} is a predetermined state variable. When the firm chooses to abate, the optimal net profit after the pricing and abatement decisions is $\pi^{\mathbf{A}}(z_{it}) \equiv \max_{\{p_{it}, \xi_{it}\}} \pi(p_{it}, \xi_{it}|z_{it}) - \zeta$. Upon choosing to abate pollution, the firms' optimal abatement in each period is to minimize the cost term $1 + f_i(1-\xi_{it})\theta + v_1 \xi_{it}^{v_2}$ and is time invariant, i.e., $\xi_i^* = \left(\frac{\theta f_i}{v_1 v_2} \right)^{\frac{1}{v_2 - 1}}$. It is straightforward that ξ_i is strictly increasing under environmental regulations f_i. Thus, upstream firms adopt greater abatement due to more stringent environmental regulations. Upstream firms also have lower emission intensities $\frac{e_{it}}{y_{it}} = (1-\xi_i)\theta$. When the firm chooses not to abate, the abatement decision is $\xi_{it} = 0$, and the optimal profit after the pricing decision is $\pi^{\mathbf{N}}(z_{it}) \equiv \max_{\{p_{it}\}} \pi(p_{it}, 0|z_{it})$.

The optimal abatement decision in the first period is straightforward and takes a trigger strategy. The Appendix A.1 shows that there exists a unique productivity cutoff z_{i1}^* satisfying $\pi^{\mathbf{A}}(z_{i1}^*) = \pi^{\mathbf{N}}(z_{i1}^*)$. For a firm with sufficiently high productivity such that $z_{i1} > z_{i1}^*$, it opts to abate pollution; otherwise, the firm would not abate. The intuition is that pollution abatement reduces the marginal costs of production due to lower pollution penalties. The abatement-induced reductions in the marginal costs become more prominent as the firm's productivity z_{i1} increases. For optimization, firms with higher productivity tend to pay a fixed cost and choose to abate. There thus exists considerable heterogeneity among abatement decisions by firms of different sizes.

In the first period, the firm needs to conduct R&D investment d_{i1}. As R&D affects the profit in the second period by influencing the productivity state z_{i2}, d_{i1} is an intertemporal decision. Given the initial state of productivity z_{i1}, the firm's R&D decision d_{i1} in period 1, the abatement decision ξ_{i2} and the pricing decision p_{i2} in period 2 jointly solve the following optimization problem:

$$\mathbb{V}_i(z_{i1}) = \max_{\{d_{i1}, p_{i2}, \xi_{i2}\}} (1-\tau_{i1}) \left[\Pi(z_{i1}) - d_{i1} \right] + \beta(1-\tau_{i2}) \pi(p_{i2}, \xi_{i2}|z_{i2}), \tag{3}$$

where $\Pi(z_{i1}) \equiv \max_{\{p_{i1}, \xi_{i1}\}} \pi(p_{i1}, \xi_{i1}|z_{i1}) = \max\{\pi^{\mathbf{A}}(z_{i1}), \pi^{\mathbf{N}}(z_{i1})\}$ is the profit function after the abatement and pricing decisions in period 1; the productivity in period 2, z_{i2}, depends on the R&D activity in the first period, i.e., $z_{i2} = \rho z_{i1} + \phi \log(d_{i1})$.

The marginal effect of R&D on the profit in period 2, $\pi(p_{i2}, \xi_{i2}|z_{i2})$, varies for the abatement strategy in period 2. The existence of fixed abatement costs ζ implies that the optimal R&D decision d_{i1} and the optimal abatement decision ξ_{i2} follow trigger strategies relying on the

initial productivity state z_{i1}.

In particular, there exists a cutoff of the initial productivity z_{i1}^{**} such that (**i**). If $z_{i1} > z_{i1}^{**}$, the firm opts to abate in period 2, that is, $\xi_{i2} = \xi_i^* \equiv \left(\frac{\theta f_i}{v_1 v_2}\right)^{\frac{1}{v_2-1}}$. The optimal R&D decision $d_{i1}(z_{i1}) = d_{i1}^{\mathbf{A}}(z_{i1})$ solves the problem of $\max_{d_{i1}} \mathbb{V}_i^{\mathbf{A}}(d_{i1}, z_{i1}) \equiv (1-\tau_{i1})[\Pi(z_{i1}) - d_{i1}] + \beta(1-\tau_{i2})\pi^{\mathbf{A}}(z_{i2}^{\mathbf{A}})$, where $z_{i2}^{\mathbf{A}} = \rho z_{i1} + \phi d_{i1}^{\mathbf{A}}(z_{i1})$; (**ii**). If $z_{i1} \leq z_{i1}^{**}$, the firm opts not to abate in period 2, that is, $\xi_{i2} = 0$. The optimal R&D decision $d_{i1}(z_{i1}) = d_{i1}^{\mathbf{N}}(z_{i1})$ solves the problem of $\max_{d_{i1}} \mathbb{V}_i^{\mathbf{N}}(d_{i1}, z_{i1}) \equiv (1-\tau_{i1})[\Pi(z_{i1}) - d_{i1}] + \beta(1-\tau_{i2})\pi^{\mathbf{N}}(z_{i2}^{\mathbf{N}})$, where $z_{i2}^{\mathbf{N}} = \rho z_{i1} + \phi d_{i1}^{\mathbf{N}}(z_{i1})$. The productivity cutoff z_{i1}^{**} is determined by the condition $\mathbb{V}_i^{\mathbf{A}}(d_{i1}^{\mathbf{A}}, z_{i1}^{**}) = \mathbb{V}_i^{\mathbf{N}}(d_{i1}^{\mathbf{N}}, z_{i1}^{**})$.

3.2 Firms' Decisions under the HNTE Policy

We now analyze the firm's decisions under the HNTE policy, which aims to support innovation. Any firm certified as an HNTE firm would gain a considerable tax reduction as well as other beneficial treatment during its operation. Notably, this initial policy does not involve the firm's environmental performance. The firm can apply for this certification at the end of the first period. The application incurs a fixed cost of $\psi > 0$.[14] Upon the application, in the second period, the firm can obtain a tax reduction of $\delta > 0$. We label firms applying for the HNTE certification as HNTE firms and those not applying for the HNTE certification as non-HNTE firms.[15] In period 2, the HNTE firms face a tax of $\tau_{i2} - \delta$ instead of τ_{i2}. The non-HNTE firms' tax rate remains at τ_{i2}.

The HNTE firms' optimization problem for the R&D decision in period 1 and abatement and pricing decisions in period 2 are as follows:

$$\mathbb{V}_i^{\mathbf{H}}(z_{i1}) = \max_{\{d_{i1}, p_{i2}, \xi_{i2}\}} (1-\tau_{i1})\left[\Pi(z_{i1}) - d_{i1}\right] + \beta(1-\tau_{i2}+\delta)\pi(p_{i2}, \xi_{i2}|z_{i2}), \tag{4}$$

where the profit functions $\Pi(z_{i1})$ and $\pi(p_{i2}, \xi_{i2}|z_{i2})$ take the same forms as their counterparts in the scenario without HNTE certification. The non-HNTE firms' optimization problem takes the exact form as that in Equation (3). The value function is $\mathbb{V}_i(z_{i1})$.

HNTE firms' optimal R&D and abatement decisions follow similar cutoff strategies as those in the scenario without HNTE certification. In particular, there exists a productivity cutoff $z_{i1}^{\mathbf{H}**}$ above which the firm chooses to abate at the level of ξ_i^* and decide the R&D of $d_{i1}^{\mathbf{H},\mathbf{A}}(z_{i1})$; for those firms with a relatively low initial productivity $z_{i1} < z_{i1}^{\mathbf{H}**}$, they choose not to abate, $\xi_{i1} = 0$ and decide the R&D of $d_{i1}^{\mathbf{H},\mathbf{N}}(z_{i1})$. The Appendix A.2 provides a more detailed analysis of the above optimal decisions. The endogenous HNTE application decision is made by solving the

[14] For simplicity, we ignore the probability of firms' applications being rejected by the authority.

[15] To simplify the exposition, we assume that as long as firms with full eligibility apply for the HNTE certification, they can obtain the certification.

discrete choice problem

$$\max\left\{\mathbb{V}_i^{\mathbf{H}}(z_{i1})-\psi,\mathbb{V}_i(z_{i1})\right\}. \tag{5}$$

The application decision straightforwardly follows a trigger strategy. There exists a productivity cutoff $\hat{z}_{i1}^{\mathbf{H}}$, satisfying $\mathbb{V}_i^{\mathbf{H}}(\hat{z}_{i1}^{\mathbf{H}})-\psi=\mathbb{V}_i(\hat{z}_{i1}^{\mathbf{H}})$, above which the firm chooses to apply for the HNTE certification, pays for the fixed application cost ψ and thus enjoys the tax cut. Under a sufficiently small fixed cost ψ, the cutoff of applying for the HNTE certification $\hat{z}_{i1}^{\mathbf{H}}$ could be lower than the cutoff of abatement $z_{i1}^{\mathbf{H}**}$. Thus, in the second period, the HNTE firms include clean firms with abatement and dirty firms without abatement.

We now analyze the impact of the HNTE policy on firms' abatement decisions. The Appendix A.2 shows that the productivity cutoff for the abatement of HNTE firms is smaller than that of non-HNTE firms, i.e., $z_{i1}^{\mathbf{H}**}<z_{i1}^{**}$. Since the cutoff for applying for the HNTE certification $\hat{z}_{i1}^{\mathbf{H}}$ is below $z_{i1}^{\mathbf{H}**}$, the above condition implies that non-HNTE firms would not conduct abatement due to their low productivity. The condition $z_{i1}^{\mathbf{H}**}<z_{i1}^{**}$ further implies that the HNTE policy induces firms to have stronger incentives to conduct abatement and reduce pollution. This is because the tax credit granted by the HNTE policy enlarges the dispersion of firm values between those abating and not abating. The marginal benefit of abatement increases if the firm applies for the HNTE certification. Therefore, the HNTE policy reduces firms' pollution by encouraging more firms to adopt abatement.

3.3 Firms' Decisions under the HNTE-env Policy

We now extend the analysis by considering the scenario in which environmental factors are integrated into the HNTE certification policy, henceforth the HNTE-env policy. Our model here attempts to account for a firm's probability of losing the HNTE certification due to an environmental violation. We focus on how a firm adjusts alongthe extensive margin (firms' application probability), as well as the intensive margin (R&D and abatement decisions for firms that already have the HNTE certification).

The novelty of the HNTE-env policy is the introduction of a seemingly unrelated factor, i.e., environmental performance, into the industrial policy of innovation. Specifically, firms' HNTE certification will be revoked if they are penalized by the environmental authorities. Once nullified, in addition to returning the tax credits and other benefits received from the government, firms also lose the ability to apply for HNTE certification for 5 years. To model the above policy changes, we consider a penalty probability, $\lambda\left(\xi_{i2}\right)$, with which more polluting downstream firms would be punished by the authorities. Any firm penalized would immediately lose its HNTE certification. The probability monotonically decreases the abatement level in period 2, i.e., $\lambda^{'}\left(\xi_{i2}\right)<0$. According to the provisions in the HNTE-env policy, once the firm in period 2 is punished due to an environmental penalty, it is forced to switch back to a normal

firm without any preferential treatment. Considering that upstream firms are generally much cleaner due to more intensive abatement, we assume these firms to be more compliant and thus impacted less by the HNTE-env policy.[16]

We add the subscript **E** to variables corresponding to the HNTE-env policy. The expected value for a downstream firm that applies for the HNTE certification under the new policy regime becomes

$$\mathbb{V}_i^{\mathbf{E}}(z_{i2}) = [1 - \lambda(\xi_{i2})]\, \mathbb{V}_i^{\mathbf{H}}(z_{i2}) + \lambda(\xi_{i2})\, \mathbb{V}_i(z_{i2}), \tag{6}$$

where $\mathbb{V}_i^{\mathbf{H}}$ and $\mathbb{V}_i$ represent the firm value for those staying in HNTE status and those switching back to non-HNTE status and satisfying Equation (4) and Equation (3), respectively. The expected value for the downstream firms $\mathbb{V}_i^{\mathbf{E}}$ can be further written as

$$\mathbb{V}_i^{\mathbf{E}}(z_{i1}) = \max_{\{d_{i1}, p_{i2}, \xi_{i2}\}} (1 - \tau_{i1})\,[\Pi(z_{i1}) - d_{i1}] + \beta\,\{1 - \tau_{i2} + [1 - \lambda(\xi_{i2})]\delta\}\,\pi(p_{i2}, \xi_{i2}|z_{i2}). \tag{7}$$

Compared with the value of an HNTE firm under the HNTE policy in Equation (4), the HNTE-env policy introduces violation risks that might trigger the revocation of the HNTE certification, implying a lower expected value of the tax credit $[1 - \lambda(\xi_{i2})\delta]$. Since $\lambda'(\xi_{i2}) < 0$, we can show that the optimal abatement for HNTE firms under the HNTE-env policy, $\xi_i^{\mathbf{E}}$, is greater than that under the simple HNTE policy. Compared with those under the HNTE policy, the downstream firms that apply for the HNTE certification under the HNTE-env policy are more incentivized to abate and thus reduce the pollution intensity in period 2. Analogous to the previous analysis, the optimal R&D and abatement decisions follow the cutoff strategies. The firm chooses to abate pollution in period 2 if the productivity is above a cutoff of $z_{i1}^{\mathbf{E}**}$. As discussed in the previous scenarios, the productivity cutoff equates the net value of abating to not abating.

The decision to apply for the certification under the HNTE-env policy also follows the cutoff strategy due to the fixed costs incurred by the application. The firm chooses to apply for the HNTE certification under the HNTE-env policy if and only if its productivity exceeds a cutoff of $\hat{z}_{i1}^{\mathbf{E}}$, which is determined by the condition of $\mathbb{V}_i^{\mathbf{E}}(\hat{z}_{i1}^{\mathbf{E}}) - \psi = \mathbb{V}_i(\hat{z}_{i1}^{\mathbf{E}})$. We consider a sufficiently small fixed cost ψ such that $\hat{z}_{i1}^{\mathbf{E}} < z_{i1}^{\mathbf{E}**}$, which ensures that firms applying for the HNTE certification under the new policy include those with and without abatement. A firm with a sufficiently large productivity $z_{i1} > z_{i1}^{\mathbf{E}**}$ applies for the HNTE certification and conducts

[16] To rationalize this assumption, we test the upstream-downstream discontinuities in environmental penalties levied by the government. Since we have used firm-level environmental penalty data since 2008, to rule out the potential impact of the HNTE-env policy on downstream firms' environmental performance, we split the whole sample into HNTE and non-HNTE subsamples. Arguably, the effect conveyed by firms in the non-HNTE group should be the genuine difference between upstream and downstream firms. As shown in Table 2 in the Section 4, the significantly negative coefficient in Column (1) indicates that downstream firms are far more likely to be punished by environmental agencies.

the optimal abatement of $\xi_i^{\mathbf{E}}$. The level of abatement is higher than that under the traditional HNTE policy, implying a lower pollution intensity under the HNTE-env policy. A firm with a moderate productivity $\hat{z}_{i1}^{\mathbf{E}} < z_{i1} \leq z_{i1}^{\mathbf{E}**}$ applies for the HNTE certification under the HNTE-env policy but refuses to abate. A firm with low productivity $z_{i1} \leq \hat{z}_{i1}^{\mathbf{E}}$ neither applies for the HNTE certification nor abates.

The Appendix A.3 shows that the cutoff of applying for the HNTE certification under the HNTE-env policy $\hat{z}_{i1}^{\mathbf{E}}$ *per se* decreases with the expected tax credit $[1 - \lambda(\xi_{i2})\delta]$. Downstream firms are less likely to apply for the HNTE certification under the HNTE-env policy than upstream firms are. Thus, the HNTE-env policy leads to a negative *extensive margin* effect on downstream firms' R&D activities by reducing their probability of gaining the HNTE certification under the HNTE-env policy. For these firms, their optimal R&D inputs are lower than those under the past HNTE policy for fear of losing the granted benefits due to the apparently higher environmental penalty risks. With inactive R&D activities, they see a further reduction in outputs. Therefore, the HNTE-env policy also has a negative intensive margin effect on the downstream firms' R&D activities. Obviously, the uncertainties inherent in the environmental compliance are economically significant and matter for firms' investment decisions. We hereby specify these effects in the following proposition:

Proposition 1. *The HNTE-env policy lowers the share of downstream firms that gain the HNTE certification (extensive margin effect). For downstream firms already certified as HNTE firms, the HNTE-env policy depresses their R&D investment and reduces their pollution intensity (intensive margin effect).*

Heterogeneity of Policy Impacts Recall that the firm anticipates the future tax credit as well as the possibility of an environmental penalty when making the current decision about investment in R&D and pollution control, and firms with different sizes and productivities should react to the HNTE-env policy differently. Specifically, small firms are more reluctant to afford the fixed abatement costs and face a higher probability of being penalized, resulting in a lower expected tax credit from the HNTE policy. Thus, in contrast to large firms, they would optimally contract their R&D investment. As a result, the pollution reduction effect observed for small firms could be driven solely by reduced output. The Appendix A.3 provides more details about the deductions. The following proposition summarizes the heterogeneous policy impacts on firms of different sizes:

Proposition 2. *(**Heterogeneity of Policy Impacts**) Under fairly loose parameter conditions, the negative impact of the HNTE-env policy on R&D investment is stronger for small firms than for large firms, whereas the pollution reduction effects are stronger for large firms than for small firms.*

In Section 5, our quantitative model introduces higher-dimensional firm heterogeneity by

allowing firms to differ in R&D adjustment costs and abatement technology adoption costs, and shows through numerical simulations that the above propositions remain robust.

4 Empirical Analysis

4.1 Data

We leverage a comprehensive firm-level dataset, which integrates information on firms' R&D as well as various economic activities across an extensive time period. In what follows, we list the data sources and descriptions.

Surveys of Science and Technology Activities of Industrial Firms (SSTA). The SSTA database is based on an annual survey maintained by China's National Bureau of Statistics (NBS). It covers the population of industrial firms that have independent science and technology activities in China. The industrial firms engaged in R&D activities are required to establish an independent R&D accounting system and fill out the *Scientific and Technological Activities and Related Information of Industrial Enterprises Form* each year. It reports comprehensive information on R&D expenditures, R&D employees, innovations, and R&D subsidies, including the firm's HNTE status and HNTE tax credits. The SSTA is a novel database that is currently available for the years between 2008 and 2014. The data are aggregated at the province level to produce the *China Statistical Yearbook on Science and Technology*, an authoritative statistical book in China.

State Administration of Tax (STA). The SAT database is from China's State Administration of Tax. It records detailed information on firms' sales, assets, inputs, tax credits, and R&D activities. On the basis of its sampling strategy, large firms are included each year, and small firms are surveyed in rotation. Unlike the SSTA, the SAT database has a broader coverage of industrial firms' tax information, even though they are not essentially engaged in independent R&D activities. In the SAT, the information relevant to HNTE status is available from 2009 to 2014, and the information relevant to R&D is available from 2006 to 2014. This paper uses the SAT database to complement the SSTA database.

Environmental Survey and Reporting (ESR). The ESR database is maintained by China's Ministry of Ecology and Environment. It covers polluting industrial firms that contribute approximately 80 percent of the total major industrial pollutants in China. The ESR database records detailed information on industrial firm's water pollution (chemical oxygen demand (COD), industrial effluent, ammonia nitrogen (NH_3, NH_{4+}, henceforth NH), etc.), air pollution (sulfur dioxide (SO_2), nitrogen oxide (NO_x), waste gas, etc.), energy use, clean-up facilities, and abatement capacities. We employ the ESR database to test the discontinuities of the environmental outcomes near water quality monitoring stations. The ESR and SSTA databases are matched by each firm's official registration code. For those not matched, we repeat the matching by

their official registration name. Approximately 51 percent of the sample firms in SSTA can be matched with those in the ESR database.

Water Quality Monitoring System. The Ministry of Ecology and Environmental also maintains detailed information on the water quality monitoring stations. Our data cover a population of 970 state-controlled river monitoring stations working in 2010.[17] The data are processed in *ArcGIS*. First, we geo-code the water monitoring stations on the basis of their longitudes and latitudes and place them into China's map, as shown in Figure B.1. Second, we leverage the elevation data that describe the terrain surrounding the monitoring stations to identify the direction of the river flow. Third, after determining the direction of the river, we draw a line perpendicular to the river at the intersection of each monitoring station. With this line as the boundary, firms are categorized into upstream and downstream groups. Finally, we draw a circle centered at the monitoring station with a radius of 20 kilometers to pin down the scope of firms in our regression.

Our study covers the period spanning from 2008 to 2014. The matched data are representative, as they cover firms distributed across 46 two-digit industries and spread nationwide in China. We categorize them into two groups: firms in polluting and nonpolluting industries. Firms in the latter category are unlikely to have been affected by the HNTE-env policy, as there is no significant difference in water pollution law violations between firms located upstream and downstream of the stations.

In Appendix B, Table B.2 describes the means and standard deviations of the key variables. We present the indicators for HNTE-env status and R&D expenditures reported by the SSTA database in Panel A. The information regarding HNTE-env status is also available in the SAT database, and we use it for robustness, and the summary statistics are attached in Panel B.[18] In addition, in Panel C, we present the summary statistics for environmental outcomes, such as COD, industrial effluent, and NH.

4.2 Empirical Specification

Our model predicts that when polluting firms face the risk of certification revocation due to environmental violations, their HNTE application, R&D activities, and pollution abatement investments will adjust in response to the HNTE-env policy. The distinct discontinuity in environmental compliance between upstream and downstream firms enables us to adopt a spatial RDD strategy to investigate the effects of the HNTE-env policy. We therefore use the following

[17] Here, we exclude the monitoring stations built on lakes and reservoirs without concrete upstream and downstream sides. To avoid disturbances from neighboring stations, we also drop the stations that largely overlap within 20 kilometers.

[18] Since the SAT database covers some industrial firms without R&D activities, which enlarge the sample denominator, the mean HNTE-env status is relatively lower than that in Panel A.

specification:

$$Y_{ist} = \alpha_1 Upstream_i + \alpha_2 Dist_i + \alpha_3 Upstream_i \times Dist_i + \boldsymbol{\theta}' X_{ist} + \epsilon_{ist}, \tag{8}$$

subject to $-h \leq Dist_i \leq h$. In Equation (8), Y_{ist} denotes the outcome variable of firm i at monitoring station s in year t. $Upstream_i$ is an indicator that equals one if a firm is located upstream of the monitoring station, and zero if located downstream. α_1 represents the discontinuous change in the corresponding outcomes caused by the local asymmetric environmental intervention at the monitoring stations. $Dist_i$ measures the distance between firm i and its adjacent monitoring station. The parameter h in the constraint denotes the MSE-optimal bandwidth suggested by Calonico et al. (2018). X_{ist} denotes a vector of time-variant firm-level control variables, such as firm age and sales. ϵ_{ist} denotes the error term.

Discussion on Local Randomization A credible RDD estimate can be interpreted as an average treatment effect (ATE) at the cutoff, provided that two crucial assumptions are satisfied: local randomization and no sorting around the cutoff. In our setting, the assumption of local randomization implies that firms should be randomly assigned around the water quality monitoring stations. Lee (2008) and Lee and Lemieux (2010) suggest a testable approach that the assignment of running variable can be viewed as good as randomized if the upstream-downstream continuities in the pre-determined covariates at the water quality monitoring stations can be verified. In this paper, we construct a neighborhood of a 20km-radius circle for each monitoring station, as illustrated in Figure B.1(b). It is arguably easy to examine that the baseline covariates, such as geographic, meteorologic, and socioeconomic factors, that are all determined prior to the realization of the running variable, vary smoothly just upstream and just downstream the monitoring stations.

Discussion on Spatial Sorting The second assumption implies that entrepreneurs do not precisely cluster in the upstream or downstream direction. For instance, a pollution-intensive firm may prefer loose environmental regulation and thus choose to locate itself downstream of the monitoring station. In this case, a large scale of this upstream-downstream sorting might bias our estimates. In this study, the main sample firms are distributed around approximately 720 river monitoring stations nationwide, covering 17 water-polluting industries.[19] To alleviate the concern regarding spatial sorting, we conduct the following tests:

First, we check firms' locations between 1998 and 2014, and find that a small proportion of our sample firms ever changed their locations in the upstream-downstream direction. We

[19]The classification of water-polluting industries is outlined in Table B.1, which is established by the National Ministry of Environmental Protection.

exclude those samples for robustness. As the two critical assumptions pin down the validity of the spatial RD design, our underlying assumption is that firms right downstream the monitoring stations represent a good counterfactual for the firms right upstream of the monitoring stations.

Second, according to Lee (2008) and Lee and Lemieux (2010), we can verify this assumption by examining whether the density of the firms locally distributed at the monitoring stations is continuous. Bugni and Canay (2021) develop an approximate sign test that can statistically conduct this test. We adopt this auxiliary procedure and find that, for each monitoring station in our sample, there are no statistically significant discontinuities in the distribution of firms within the 20km-radius neighborhood of the monitoring stations.

Third, we include the interaction of station and year fixed effects to absorb the potential confounding factors specific to monitoring stations and other potential omitted variables at the station level that vary over time. Additionally, the finest industry fixed effects (four-digit industry code) are included to account for the systematic differences in managerial and production techniques across the sample firms. By controlling for the set of fixed effects, our comparison comes from upstream and downstream observations that belong to the same industry, are located near the same monitoring station, and are in the same year.

4.3 Discontinuity in Environmental Compliance

Before proceeding to the investigation on model predictions, we first provide a formal empirical analysis on the discontinuity in environmental compliance between upstream and downstream firms in the neighborhood of monitoring stations. By doing so, we can provide a robust explanation for firms' varying responses, if any, to the HNTE-env policy.

4.3.1 Water Pollution

Table 1 reports the discontinuities in the emissions levels of water pollutants between upstream and downstream firms from 2003 to 2007. This period spans from the establishment of a government water quality evaluation system to the year before the HNTE-env policy implementation. The estimates present the ex-ante discrepancy in pollution emissions between upstream and downstream firms. In each column, we control for firm-level characteristics, two-digit industry fixed effects, and the interaction of station- and year-fixed effects. Columns (1)-(3) of Panel A show that, upstream firms in water-polluting industries discharge significantly less COD, industrial effluent, and NH compared to the downstream counterparts. This finding aligns with the findings in He et al. (2020). In Columns (1)-(3) of Panel B, we do not observe any discontinuities in the water pollutants discharge for the subsample of non-water-polluting firms. This is because, although these firms report water pollution data, they are not officially

classified as water-pollution-intensive and therefore are not targeted by local water pollution regulations. This comparison confirms that downstream firms have been more polluting than upstream ones due to looser environmental supervision since 2003.

In addition, we conduct a placebo test by exploiting the data on firms' air emissions. Air pollutants, such as SO_2, NOx, industrial soot, and waste gas, fall outside the scope of water quality monitoring stations. Thus, no significant discontinuity in air pollutant emissions along the upstream-downstream dimension. This conjecture is confirmed by Table B.5 of the Appendix B. The robustness checks reinforce the validity of our RD design by showing that predetermined covariates evolve continuously at the monitoring stations, while the discontinuity exists exclusively in environmental compliance.

4.3.2 Environmental Penalty

The above test verifies that, closely located around the monitoring stations, downstream firms are significantly more polluting than upstream firms. In this subsection, we aim to examine whether the pollution discontinuity leads to environmental penalties, which directly relate to the environmental compliance criteria in the HNTE-env policy. Ideally, we should use penalty information prior to the implementation of the HNTE-env policy to test the above argument. However, we are not able to do so due to a lack of reliable environmental penalty data during that period.[20] Alternatively, we use the penalty data that covers the period immediately after the enforcement of the HNTE-env policy (2008-2014). In particular, we split the sample into firms that are accredited as HNTE and those that are not. Presumably, non-HNTEs would not strategically adapt to the HNTE-env policy by investing more in pollution abatement to reduce the probability of penalties. Therefore, we can observe a significant discontinuity in environmental penalties between non-HNTE firms, and then infer their initial conditions.

As reported in Column (1) of Table 2, the estimated coefficients are significantly negative, indicating that upstream non-HNTE firms incur fewer penalties from the environmental agency than their downstream counterparts. In contrast, as shown in Column (2), no comparable discontinuity is observed between upstream and downstream HNTE firms. Our estimates confirm that downstream firms are penalized more frequently for violations of environmental regulations. In subsequent analysis, we show that this discontinuity is an important factor affecting their HNTE applications and investment decisions.

[20]The mandatory disclosure of environmental penalty information by government agencies began in 2008, which is required by the *Measures for the Disclosure of Environmental Information (Trial)*.

Table 1: Upstream-Downstream Discontinuity: Water Pollutant Discharge (2003-2007)

	log(**COD**)	log(**Effluent**)	log(**NH**)
	(1)	**(2)**	**(3)**
Panel A: Firms in polluting industries			
RDD Estimate	-0.560***	-0.796***	-0.302***
	(0.120)	(0.201)	(0.052)
Bandwidth	7.176	4.827	9.540
Firm Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year-station FE	Yes	Yes	Yes
Kernel Type	Triangular	Triangular	Triangular
Observations	19,204	19,620	16,687
Panel B: Firms in nonpolluting industries			
RDD Estimate	0.013	-0.152	0.164
	(0.150)	(0.211)	(0.108)
Bandwidth	6.413	4.696	4.048
Firm Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year-station FE	Yes	Yes	Yes
Kernel Type	Triangular	Triangular	Triangular
Observations	18,564	18,981	16,213

Notes: Columns (1)-(3) report estimates on a range of water pollutants: chemical oxygen demand (COD), industrial effluent, ammonia nitrogen (NH_3, NH_{4+}), respectively. The MSE-optimal bandwidth is based on the default kernel type suggested by Calonico et al. (2018). Firm controls include the firm's age and total assets. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

4.4 Extensive Effects of HNTE-env Policy

The above exercises strengthen the validity of our RDD strategy by showing that the discontinuity merely exists in water-related environmental compliance. This could account for the difference in the probability of HNTE certification between upstream and downstream firms in water-polluting industries. In this section, we provide a formal analysis.

Table 2: Upstream-Downstream Discontinuity: Environmental Penalty (2008-2014)

	(1) log(**penalty**) **(non-HNTE)**	(2) log(**penalty**) **(HNTE)**
RDD Estimate	-0.132**	0.095
	(0.061)	(0.063)
Bandwidth	3.904	4.959
Firm Controls	Yes	Yes
Industry FE	Yes	Yes
Year-station FE	Yes	Yes
Kernel Type	Triangular	Triangular
Observations	25,121	4,136

Notes: Columns (1)–(2) report the estimates for the number of environmental penalties incurred by non-HNTE firms and HNTE firms, respectively, for a range of water pollutants: chemical oxygen demand (COD), ammonia nitrogen (NH_3, NH_{4+}), and industrial effluent. The MSE-optimal bandwidth is based on the default kernel type suggested by Calonico et al. (2018). Firm controls include the firm's age and total assets. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

4.4.1 Discontinuity in HNTE Status

To test our Proposition 1 in the theoretical model, we begin by graphically presenting the effects of the HNTE-env policy on the HNTE status between clean and dirty firms. In Figure 1, the horizontal axis presents the running variable ($Dist_i$), which denotes the distance between firms and water quality monitoring stations. The dashed vertical line at $Dist_i = 0$ denotes the location of the monitoring stations. The right-hand side of the vertical line displays the upstream firms, and the left-hand side displays the downstream firms. The dots represent the local means of the outcomes within a bin size of 2 kilometers, and the corresponding shaded area represents the 95 percent confidence interval. "*HNTE-env probability*" denotes the probability that firms are accredited as HNTE. For each outcome, we report two sets of fitted curves. The curves in Panels A and C plot the estimations fit with a local linear approach, and the fitted curves in Panels B and D further include a polynomial function of the running variable as control. In Panels A and B, the estimation of the HNTE-env probability absorbs firm-level characteristics; In Panels C and D, the estimation of the HNTE-env probability is based on a residualized outcome with the interaction of station and year fixed effects and industry fixed effects absorbed. There is a prominent discontinuous jump precisely at the cutoff point, which is the geographic location of the water quality monitoring station. The figure suggests that compared with upstream firms, firms downstream are much less likely to be accredited as

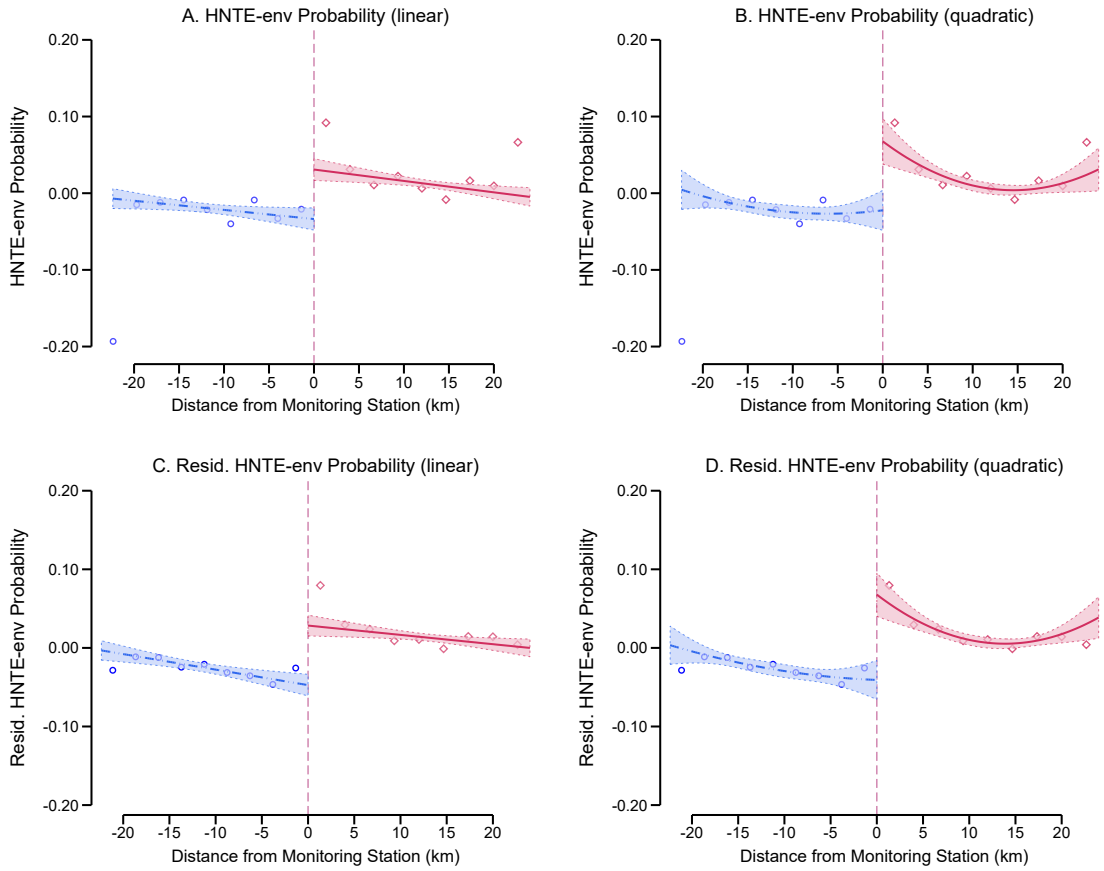


Figure 1: Upstream-Downstream Discontinuity: Obtaining HNTE Status

Notes: Figure 1 plots the discontinuities in the probability of being accredited as HNTEs between upstream and downstream firms. In Panels A-D, the y axis presents "*HNTE probability*", which denotes the probability that firms are accredited as HNTE. In Panels A and B, the estimation of the HNTE-env probability absorbs firm-level characteristics; In Panels C and D, the estimation of the HNTE-env probability is based on a residualized outcome with the interaction of station and year fixed effects and industry fixed effects absorbed. It is noteworthy that, due to the inclusion of control variables in each estimate, the outcome variable could potentially take on negative values. The horizontal axis denotes the distance between industrial firms and the water quality monitoring stations. The middle vertical line at $Dist_i = 0$ denotes the location of the water quality monitoring stations. The right-hand side of the vertical line displays the upstream firms, and the left-hand side displays the downstream firms. The curves in Panels *A* and *C* plot the estimations fit with a local linear approach, and the fitted curves in Panels *B* and *D* further include a polynomial function of the running variable as control. The dot represents the local means of the corresponding outcomes within a bin size of 2 kilometers, and the corresponding shaded area represents the 95 percent confidence interval.

HNTEs.

Table 3 quantifies the graphical findings in Figure 1. The dependent variables in Columns (1) and (2) refer to firms' HNTE status, whereas those in Columns (3) and (4) denote the log value of tax credits claimed by HNTE firms. The baseline estimates in Columns (1) and (3) control for firm-specific variables: firm's age and sales. Our preferred estimates in Columns (2)

Table 3: Upstream-Downstream Discontinuity: Obtaining HNTE Status

	HNTE status	HNTE status	log(HNTE subsidy)	log(HNTE subsidy)
	(1)	(2)	(3)	(4)
Panel A: Firms in polluting industries				
RDD Estimate	0.354***	0.161***	2.781***	1.692***
	(0.074)	(0.045)	(0.606)	(0.409)
Bandwidth	3.099	4.447	2.984	3.853
Firm Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Year-station FE	No	Yes	No	Yes
Kernel Type	Triangular	Triangular	Triangular	Triangular
Observations	32,772	32,540	32,772	32,540
Panel B: Firms in nonpolluting industries				
RDD Estimate	0.086**	-0.020	0.731**	0.103
	(0.041)	(0.019)	(0.319)	(0.173)
Bandwidth	3.541	7.042	3.596	6.090
Firm Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Year-station FE	No	Yes	No	Yes
Kernel Type	Triangular	Triangular	Triangular	Triangular
Observations	97,301	97,027	97,301	97,027

Notes: "HNTE status" refers to a firm that possesses the HNTE certification after the HNTE-env reform. "HNTE subsidy" refers to the tax credits that a firm can claim from the HNTE-env program. The MSE-optimal bandwidth is based on the default kernel type suggested by Calonico et al. (2014). Firm controls include the firm's age and total assets. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

and (4) further control for industry fixed effects and station-year pair fixed effects. The RDD estimates and bandwidths are obtained by implementing the "robust bias-corrected" confidence intervals with the default triangular kernel type (Calonico et al., 2014). As such, our estimates represent the discontinuities between upstream and downstream firms that are in the same industry, observed in the same year, and geographically adjacent to the same monitoring station.

In Panel A, we apply the RDD estimations to sample firms in water-polluting industries, as the discontinuity in environmental intervention exists only among the water-polluting firms near the monitoring stations. Column (2) shows that, closely adjacent to the monitoring stations, downstream firms are 16.1 percent less likely to obtain the HNTE certification than upstream firms under the HNTE-env policy. Column (4) consistently shows that downstream

firms claim substantially fewer tax credits than their upstream counterparts. In Panel B, we repeat the RDD estimations using the sample firms from non-water-polluting industries. In addition to environmental intervention, we aimed to examine whether there are any other factors that can explain the upstream–downstream discontinuities in shaping the outcomes of HNTE-env certification. If this phenomenon is true, we should also see an asymmetric pattern among the non-water-polluting firms in the counterfactual state of not receiving environmental treatment. Nevertheless, we do not see any results comparable with those in Panel A, neither in significance nor in magnitude. This result suggests that the discontinuity in environmental intervention is the primary factor responsible for the treatment effects on the differences in firms' HNTE status. Moreover, we carry out three additional robustness checks: (1) comparing firms within four-digit industry; (2) excluding firms that migrate in the upstream-downstream direction, which merely represents a small proportion of the sample; (3) utilizing data from a different survey, and present the results in Table B.3 in Appendix B. These results alleviate certain concerns on sample selection and suggest the robustness of our main findings.

Within the optimal bandwidth, the mean logarithmic value of COD is 2.157 for firms immediately upstream of the monitoring station.[21] The RDD estimate in Column (1) of Table 1 represents an approximate 25.96 percent increase in COD emissions. Combining the estimates in Column (1) of Panel A in Table 3 together, we can infer that the 16.1 percent lower probability of obtaining HNTE is associated with a 26 percent increase in COD emissions of downstream firms. It ascertains that after the enforcement of HNTE-env policy since 2008, downstream firms take into account of penalty risks due to environmental violations and become disadvantageous when applying for the HNTE certification.

4.4.2 HNTE Eligibility, Application, and Revocation

Based on the above results, one might suspect that the observed discontinuity in firms' likelihood of obtaining HNTE certification at the monitoring station under the HNTE-env policy could be driven not only by other inherent differences between downstream and upstream firms. We therefore examine whether the observed differences persist in firms' HNTE eligibility, application, and revocation. Specifically, these three dimensions respectively reflect whether firms meet the R&D requirements, their willingness to apply for HNTE certification, and whether their certification is subsequently revoked. This exercise helps address concerns that the discontinuity might be driven not only by environmental factors but also by other firm-level characteristics relevant to HNTE eligibility.

In Table 4, Panel A reports the estimates restricting samples to firms in water-polluting in-

[21] COD is a water quality indicator, which represents the amount of dissolved oxygen needed to oxidize chemical organic matter in water. It is one of the most commonly targeted pollutants by the environmental agencies in China.

Table 4: Upstream-Downstream Discontinuity:
Eligibility, Application, and Revocation of the HNTE Certification

	HNTE eligibility	**HNTE application**	**HNTE revocation**
	(1)	**(2)**	**(3)**
Panel A: Firms in polluting industries			
RDD Estimate	0.091	0.034**	-0.040
	(0.060)	(0.017)	(0.073)
Bandwidth	4.474	8.632	7.611
Firm Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year-station FE	Yes	Yes	Yes
Kernel Type	Triangular	Triangular	Triangular
Observations	32,540	28,188	4,348
Panel B: Firms in nonpolluting industries			
RDD Estimate	-0.004	-0.016	0.024
	(0.030)	(0.014)	(0.039)
Bandwidth	5.643	6.799	9.497
Firm Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year-station FE	Yes	Yes	Yes
Kernel Type	Triangular	Triangular	Triangular
Observations	97,027	79,820	17,205

Notes: "HNTE eligibility" refers to a firm is eligible for the acquisition of HNTE certification in terms of the key HNTE-env R&D criteria: firm size, R&D intensity, and R&D staff proportion. "HNTE application" refers to a firm that successfully gains the HNTE certification during the sample period. "HNTE revocation" refers to a firm's HNTE-env status is revoked during the sample period. The MSE-optimal bandwidth is based on the default kernel type suggested by Calonico et al. (2014). Firm controls include the firm's age and total assets. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

dustries. In Column (1), the dependent variable "*HNTE eligibility*" is an indicator that refers to a firm holds the R&D eligibility for the application of HNTE certification. It equals one if a firm satisfies the key HNTE criteria: firm size, R&D intensity, and R&D staff proportion, and zero otherwise. The coefficient is close to zero and statistically insignificant, suggesting that upstream and downstream firms show little differences in eligibility for acquiring the HNTE certification in terms of their R&D investment. This finding also suggests that, absent the environmental criteria, HNTE application eligibility would be continuous at the monitoring stations. In Column (2), the indicator "*HNTE application*" equals one if a firm applies for the HNTE certification during the sample period 2008-2014, and zero otherwise. The estimate indicates

a 0.03 points lower probability of initiating the application process for downstream firms than upstream firms. It verifies that downstream firms are more reluctant to apply for the HNTE certification, even though they are also eligible for it. In Column (3), the indicator "*HNTE revocation*" equals one if a firm's HNTE status is revoked, and zero if it maintains the status during the sample period 2008-2014. The estimate is quite consistent and comparable to that in Column (2), indicating that downstream firms are more likely to lose their HNTE certification. In Panel B, we do not observe any significant discontinuities in those outcomes for firms in nonpolluting industries.

Table 4 shows that the inclusion of environmental criteria becomes a key factor influencing downstream firms' incentives to apply for HNTE certification, even though there is no significant difference in eligibility between downstream and upstream firms.

4.4.3 Placebo Test: Alternative R&D Policy Without Environmental Criteria

Consider a scenario in which environmental criteria were not incorporated into the R&D policy. Would upstream and downstream firms demonstrate the same motivation to apply for policy benefits? In principle, the answer should be yes. While we cannot carry out such an experiment in reality, another China's core R&D subsidy policy, the *R&D Weighted Deduction* (henceforth RDWD) policy, can be a good counterfactual for the HNTE-env policy.

The key feature of RDWD is that it is in a counterfactual state of not involving environmental terms. The qualification for the RDWD is much simple. It merely requires firms to establish an independent R&D accounting sheet for the audition by a third party. As generous as HNTE-env program, it allows eligible firms to deduct 50 percent of R&D expenses from taxable income, and the deduction can be at the rate of 150 percent for the R&D expenses incurred by the development of intangible assets, such as inventions. In 2020, subsidies from the HNTE-env and RDWD programs represented approximately 21 percent and 24 percent of the total government spending on science and technology development, respectively.

In Table 5, all specifications are restricted to sample firms in water-polluting industries and control for firm-level covariates, two-digit industry indicators, and the interaction of station and year indicators. In Columns (1)-(4), all the coefficients are close to zero, and none of them are statistically significant. In particular, Columns (3) and (4) show that discontinuities exist neither in the application nor in the revocation process of the RDWD policy. It indicates that, had the environmental criteria not been integrated into the HNTE-env policy, the upstream and downstream firms should have remained the same in the application and revocation process of the HNTE-env policy. Moreover, it reassures us that, in addition to environmental compliance, no other factors specific to the monitoring stations can account for the differences in firms' motivation or ability to obtain R&D subsidies. The counterfactual analysis also favors knowl-

Table 5: Upstream-Downstream Discontinuity: Placebo Test on RDWD Program

	RDWD status	log(RDWD subsidy)	RDWD application	RDWD revocation
	(1)	(2)	(3)	(4)
RDD Estimate	0.025	-0.082	0.007	0.007
	(0.031)	(0.274)	(0.010)	(0.065)
Bandwidth	4.589	3.300	9.860	4.713
Firm Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year-station FE	Yes	Yes	Yes	Yes
Kernel Type	Triangular	Triangular	Triangular	Triangular
Observations	27,942	27,942	27,276	5,172

Notes: RDWD is another China's core R&D subsidy policy that does not involve environmental criteria in its certification process. "RDWD status" refers to a firm that is entitled to claim R&D tax exemptions from the RDWD program. "RDWD subsidy" refers to the amount of R&D subsidies that a firm can claim from the RDWD program. "RDWD application" refers to a firm that successfully obtains RDWD entitlement during the sample period. "RDWD revocation" refers to a firm that is revoked from the RDWD status during the sample period. The MSE-optimal bandwidth is based on the default kernel type suggested by Calonico et al. (2014). Firm controls include firm's age and total assets. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

edge that the integrated environmental criteria play a crucial role in the HNTE-env program. It does work for creating a disadvantageous situation for dirty firms to get access to the HNTE certification.

4.5 Intensive Effects of the HNTE-env Policy

In this section, we further empirically verify our proposition 1 by studying whether the HNTE-env policy can stimulate within-firm R&D investment and emission reduction. Here, we utilize a Difference-in-Differences (DID) specification:

$$Y_{ist} = \beta Year2008_t \times HNTEenv_i + \boldsymbol{\theta}' X_{ist} + \delta_i + s_i \times \gamma_t + u_{ist}, \tag{9}$$

where Y_{ist} represents the outcome variables: R&D investment and water pollutants discharge of firm i at station s in year t. $Year2008_t$ is an indicator, which equals 1 for the period during 2008-2014, and 0 for the period during 2005-2007. $HNTEenv_i$ equals 1 if a firm is certified as an HNTE both before and after 2008, and 0 if it has never been granted HNTE status during the sample period. The treatment group includes the firms that maintained a stable HNTE status before and after 2008. The only relevant shock affecting them is the introduction of environ-

mental criteria into the HNTE certification. Notably, firms that switched their HNTE status at any point during the sample period are excluded from this regression sample. X_{ist} denotes a vector of time-variant firm-level covariates, including firm age and sales. Firm fixed effects (δ_i) are used to control for time-invariant characteristics that could confound the treatment effects at the firm level, such as ownership, industry, and geographical features. The interaction of station and year fixed effects ($s_i \times \gamma_t$) controls for shocks specific to monitoring stations varying across years at the macro level. u_{ist} denotes the error term.

Compared to the RDD approach above, the DID approach allows us to control for firm fixed effects, which enables the identification of the intensive within-firm changes in R&D and pollution abatement investment decisions. The coefficient of our interest, β, represents the treatment effects of the HNTE-env policy on firms' R&D investment or pollutant discharge.

Table 6 reports the within-firm effects of the HNTE-env policy on firms' R&D investment. In Columns (1) and (2), we separately apply the DID specification to subsamples located upstream and downstream of the water quality monitoring stations, respectively. The estimate in each column in Table 6 represents a separate regression, which controls for firm-level covariates, firm fixed effects, and station-year pair fixed effects. The estimate in Column (1) is positive and statistically insignificant, suggesting that the HNTE-env policy has no effect on upstream HNTE firms' R&D investment. Recall that upstream firms have been exposed to stringent environmental intervention and actively engaged in environmental compliance since 2003. Thus, the estimate assures that environmental integration into R&D policies does not constrain R&D activities in clean and environmentally compliant firms. In contrast, the estimate in Column (2) is negative, indicating that the HNTE-env policy tends to decrease downstream HNTE firms' R&D investment. Nevertheless, the estimate is statistically insignificant.

In Column (3), the coefficient of the triple interaction term $Year2008_t \times HNTEenv_i \times Down_i$ estimates the within-firm changes in R&D investment in downstream HNTE firms compared with their upstream counterparts after the enforcement of the HNTE-env policy.[22] The coefficient shows that the downstream HNTE firms significantly cut approximately 18 percent [$(e^{0.17}$-1)%] of their R&D investment in response to the HNTE-env policy compared with upstream HNTE firms. Furthermore, we examine the within-firm effects of the HNTE-env policy

[22]Based on our model predictions, downstream firms face a greater risk of losing their HNTE status due to environmental noncompliance, and therefore are more likely to meet the environmental requirements after the implementation of the HNTE-env policy. This leads to more pronounced changes in their R&D and environmental abatement decisions. We thus use the following specification:

$$Y_{ist} = \beta_1 Year2008_t \times HNTEenv_i \times Down_i + \beta_2 Year2008_t \times HNTEenv_i$$
$$+\beta_3 Year2008_t \times Down_i + \beta_4 HNTEenv_i \times Down_i + \boldsymbol{\theta}' X_{ist} + \delta_i + s_i \times \gamma_t + u_{ist},$$

where $Down_i$ is a dummy variable equal to one when a firm i is located downstream and zero otherwise. The other settings resemble those in Equation (9).

Table 6: Intensive Effects of the HNTE-env Policy on Firms' R&D Investment

	Upstream	**Downstream**		
	log(**R&D**)	log(**R&D**)		log(**R&D**)
	(1)	**(2)**		**(3)**
$Year2008_t \times HNTEenv_i$	0.017	-0.036	$Year2008_t$	-0.153***
	(0.026)	(0.046)	$\times HNTEenv_i$	(0.049)
			$\times Down_i$	
Firm Controls	Yes	Yes	Firm Controls	Yes
Firm FE	Yes	Yes	Firm FE	Yes
Industry FE	Yes	Yes	Industry FE	Yes
Year-Station FE	Yes	Yes	Year-Station FE	Yes
$\mathbf{R}^2$	0.875	0.923	$\mathbf{R}^2$	0.896
Observations	39,877	22,247	Observations	63,133

Notes: $Year2008_t$ is an indicator, which equals 1 for the period during 2008-2014, and 0 for the period during 2005-2007. $HNTEenv_i$ equals 1 if a firm is certified as an HNTE both before and after 2008, and 0 if it has never been granted HNTE status during the sample period. The treatment group includes the firms that maintained a stable HNTE status before and after 2008. The only relevant shock affecting them was the introduction of environmental criteria into the HNTE policy. $Down_i$ is a dummy variable equal to one when a firm i is located downstream and zero otherwise. Firm controls include the firm's age and total assets. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

on firms' R&D outcomes—patents. We find that the results consistently reinforce the findings regarding firms' R&D investment; See Table B.6 in Appendix B.

Table 7 reports the intensive margin effects of the HNTE-env policy on firms' environmental performance. Columns (1) and (2) present the estimates based on the subsample restricted to upstream and downstream firms, respectively. Column (3) presents the coefficient of the triple term $Year2008_t \times HNTEenv_i \times Down_i$. In each column, the panels from top to bottom present the estimates for COD, industrial effluent, and NH discharge. Column (1) shows that the HNTE-env policy does not induce any pollution abatement within the upstream HNTE firms. In contrast, Column (2) shows that the integration of the environmental criteria leads to a substantial reduction in COD, effluent, and NH within the downstream HNTE-env firms. The estimates in Column (3) are consistent with the fact that downstream HNTE-env firms significantly reduce their amount of water pollutants compared to upstream HNTE firms after the HNTE-env policy is enforced. In addition, parallel trend tests in Figure B.3 suggest that, in the absence of the HNTE-env program, both groups could have followed a similar trend

regarding the discharge of water pollutants. However, for downstream firms, when the HNTE-env policy is implemented, we observe a sudden divergence: downstream treatment firms significantly reduce the discharge of water pollutants, which reinforces the plausibility of the DID identification.

As complementary tests, we graphically present the dynamic changes in discontinuities in R&D investment and environmental performance between upstream and downstream firms during different policy stages.[23] As shown in Figure B.2 in the Appendix B, we observe that the upstream–downstream discontinuities in firms' R&D investment did not occur until 2003, when upstream firms were exposed to stringent environmental enforcement. This finding indicates that the environmental intervention substantially crowded out upstream firms' R&D expenditures. When our sample is restricted to non-HNTE firms, the crowding-out effects persist for the subsequent sample years. In contrast, the pattern is reversed if we restrict our sample to HNTE firms after 2008. With the HNTE-env policy in place, we find that upstream HNTE firms gradually outperform their downstream counterparts in R&D investment. The results for pollution emissions also provide further evidence for the role of environmental integration in increasing HNTE firms' pollution abatement.

Overall, the evidence above has two important implications. First, the HNTE-env policy compels polluting firms to cut emissions but also reduces their R&D investment. Second, the policy is more effective for downstream firms, since upstream firms have largely cleaned up under prior strict enforcement and are less impacted by the HNTE-env criteria.

4.6 Heterogeneous Effects

According to Proposition 2, large and small firms have distinct responses to the HNTE-env policy. That is, the negative impact of the HNTE-env policy on R&D investment is stronger for small firms than large ones, while the pollution reduction effects are stronger for large firms than small ones. To test this hypothesis, we adopt the following specification:

$$\begin{aligned} Y_{ist} = \beta_1 Year2008_t \times HNTEenv_i \times Large_i + \beta_2 Year2008_t \times HNTEenv_i \\ + \beta_3 Year2008_t \times Large_i + X_{ist} + \delta_i + s_i \times \gamma_t + u_{ist}, \end{aligned} \tag{10}$$

where $Large_i$ equals one for large firms with sales above 20 million Chinese yuan (CNY), and equals zero for small firms with sales below 20 million CNY. The division aligns with the def-

[23] We split the whole period into two stages: 2003, the starting year of the stringent water quality regulations for upstream firms, and 2008, the effective year of the HNTE-env policy. For each year, we separately plot an RDD estimate and 95 percent confidence interval, with firm-level covariates, two-digit industry indicators, and monitoring station indicators absorbed. The estimation of the solid lines restricts samples to water-polluting firms without HNTE certification; the estimation of the dashed lines restricts samples to HNTE firms in polluting industries.

Table 7: Intensive Effects of the HNTE-env Policy on Firms' Environmental Performance

	Upstream	**Downstream**		
	log(COD)	**log(COD)**		**log(COD)**
	(1)	**(2)**		**(3)**
$Year2008_t \times HNTEenv_i$	0.226	-1.532***	$Year2008_t \times HNTEenv_i$	-1.770***
	(0.168)	(0.348)	$\times Down_i$	(0.358)
$\mathbf{R}^2$	0.905	0.912	$\mathbf{R}^2$	0.891
Observations	8,500	5,222	Observations	14,700
	log(Effluent)	**log(Effluent)**		**log(Effluent)**
	(4)	**(5)**		**(6)**
$Year2008_t \times HNTEenv_i$	0.168	-1.695***	$Year2008_t \times HNTEenv_i$	-2.022***
	(0.188)	(0.360)	$\times Down_i$	(0.366)
$\mathbf{R}^2$	0.927	0.920	$\mathbf{R}^2$	0.917
Observations	8,789	5,351	Observations	15,108
	log(NH)	**log(NH)**		**log(NH)**
	(4)	**(5)**		**(6)**
$Year2008_t \times HNTEenv_i$	0.036	-1.306***	$Year2008_t \times HNTEenv_i$	-1.263***
	(0.029)	(0.276)	$\times Down_i$	(0.193)
$\mathbf{R}^2$	0.792	0.863	$\mathbf{R}^2$	0.881
Observations	6,345	3,890	Observations	11,021

Notes: $Year2008_t$ is an indicator, which equals 1 for the period during 2008-2014, and 0 for the period during 2005-2007. $HNTEenv_i$ equals 1 if a firm is certified as an HNTE both before and after 2008, and 0 if it has never been granted HNTE status during the sample period. The treatment group includes the firms that maintained a stable HNTE status before and after 2008. The only relevant shock affecting them was the introduction of environmental criteria into the HNTE policy. $Down_i$ is a dummy variable equal to one when a firm i is located downstream and zero otherwise. Firm controls include the firm's age and total assets. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

inition in the HNTE-env policy. Other denotations remain the same as the specification in Equation (9). The coefficient of the triple interaction term, β_1, captures how the large HNTE-env firms distinctly respond to the integration of the environmental criteria from their small

counterparts.

Table 8 reports the heterogeneous effects of the HNTE-env policy on the R&D investment of firms of different sizes. We separately apply the DDD specification to subsample firms located upstream and downstream of the water quality monitoring stations and present the estimates in Columns (1) and (2), respectively. In Column (1), the coefficient of the triple term is small in magnitude and statistically insignificant. This suggests that neither the large nor the small upstream HNTE firms heterogeneously adjust R&D investment in response to the 2008 HNTE-env policy. Nevertheless, the coefficient of the triple term in Column (2) shows that large HNTE firms spend approximately 27 percent [($e^{0.24}$-1)%] more on R&D investment than do small HNTE firms after the enforcement of the HNTE-env policy. The coefficient of the interaction $Year2008_t \times HNTEenv_i$ suggests that this is caused mainly by a significant reduction in R&D investment undertaken by small HNTE-env firms.

Furthermore, Table 9 reports the heterogeneous effects on firms' environmental performance. All columns control for firm-level characteristics, firm fixed effects, and station-by-year fixed effects. For firms located upstream of the water quality monitoring stations, Columns (1)-(3) consistently demonstrate that the heterogeneous effects on water pollutant discharge do not exist. This finding indicates that neither the large nor the small HNTE firms distinctly place efforts on pollution abatement in response to the HNTE-env policy. For firms located downstream of the water quality monitoring station, the coefficients of the triple terms in Columns (4)-(6) show that large HNTE firms substantially reduce their COD, industrial effluent, and NH discharge, respectively, more than their small counterparts do after the enforcement of the HNTE-env policy. The coefficients of the interaction $Year2008_t \times HNTEenv_i$ in Columns (4)-(6) are all negative but statistically insignificant, which indicates that we can attribute the heterogeneity mainly to large firms' efforts in pollution abatement.

To test how the observed emission reduction from large HNTE firms is realized, we examine the impact of the HNTE-env policy on firms' emission intensity. We re-estimate Equation (10) using firms' pollution intensity, which is calculated as the total pollution derived from the output.Table B.7 in the Appendix B presents the estimation results. The table indicates that large downstream HNTE firms significantly lower their emissions intensity because of the HNTE-env policy compared to the small counterparts.

Overall, the above evidence indicates a trade-off between pollution abatement and R&D investment, which hinges on firm size. These results align closely with the predictions of Proposition 2 and provide strong evidence that, compared to large firms, small firms have a reduced capacity to both implement pollution abatement and maintain R&D investment simultaneously.

Table 8: Policy Intensive Effects on Firms' R&D Investment: Large vs. Small Firms

	Upstream	**Downstream**
	log(**R&D**)	log(**R&D**)
	(1)	**(2)**
$Year2008_t \times Large_i \times HNTEenv_i$	-0.044	0.227***
	(0.052)	(0.084)
$Year2008_t \times HNTEenv_i$	0.036	-0.261***
	(0.030)	(0.060)
$Year2008_t \times Large_i$	0.587***	0.647***
	(0.012)	(0.017)
Firm Controls	Yes	Yes
Firm FE	Yes	Yes
Industry FE	Yes	Yes
Year-Station FE	Yes	Yes
$\mathbf{R}^2$	0.880	0.927
Observations	35,898	19,968

Notes: $Year2008_t$ is an indicator, which equals 1 for the period during 2008-2014, and 0 for the period during 2005-2007. $HNTEenv_i$ equals 1 if a firm is certified as an HNTE both before and after 2008, and 0 if it has never been granted HNTE status during the sample period. The treatment group includes the firms that maintained a stable HNTE status before and after 2008. The only relevant shock affecting them was the introduction of environmental criteria into the HNTE policy. $Large_i$ equals one for large firms with sales above 20 million Chinese yuan (CNY), and equals zero for small firms with sales below 20 million CNY. All columns control for firm-level characteristics, firm fixed effects, and station-by-year fixed effects. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 9: Policy Intensive Effects on Firms' Environmental performance: Large vs. Small Firms

	Upstream			**Downstream**		
	log(**COD**)	log(**Effluent**)	log(**NH**)	log(**COD**)	log(**Effluent**)	log(**NH**)
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Year2008_t \times Large_i \times HNTEenv_i$						
	-0.173	-0.243	-0.014	-1.631*	-1.655*	-1.081*
	(0.337)	(0.373)	(0.057)	(0.835)	(0.903)	(0.640)
$Year2008_t \times HNTEenv_i$						
	0.310	0.306	0.039	-0.195	-0.277	-0.380
	(0.253)	(0.280)	(0.044)	(0.769)	(0.837)	(0.578)
$Year2008_t \times Large_i$						
	0.042	-0.158*	0.043***	-0.057	-0.079	-0.017
	(0.085)	(0.095)	(0.015)	(0.116)	(0.104)	(0.119)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Station FE	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{R}^2$	0.904	0.927	0.791	0.911	0.919	0.859
Observations	7,489	7,744	5,520	4,618	4,753	3,393

Notes: $Year2008_t$ is an indicator, which equals 1 for the period during 2008-2014, and 0 for the period during 2005-2007. $HNTEenv_i$ equals 1 if a firm is certified as an HNTE both before and after 2008, and 0 if it has never been granted HNTE status during the sample period. The treatment group includes the firms that maintained a stable HNTE status before and after 2008. The only relevant shock affecting them was the introduction of environmental criteria into the HNTE policy. $Large_i$ equals one for large firms with sales above 20 million Chinese yuan (CNY), and equals zero for small firms with sales below 20 million CNY. Firm controls include the firm's age and total assets. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

5 Quantitative Analysis

The above empirical findings identify the set of firms' possible adjustments to the HNTE-env policy. The causal connections in support of our illustrative model alone provide an incomplete picture of economy-wide responses, as economists and policy-makers also want to know the impact of the HNTE-env policy on welfare, productivity, and other aggregate economic factors. This is because both ends, i.e., innovation and the environment, are crucial for countries such as China that are undergoing transformational development. More importantly, counterfactual analyses are needed to exploit optimal policy options to maximize social welfare. Therefore, the quantitative analyses in this section, paired with the preceding empirical parts, allow us to reconcile micro-level and macro-level channels in driving the effectiveness of the HNTE-env policy.

To do that, we extend the simple illustrative model in Section 3 by incorporating more realistic factors, including the productivity shock, R&D adjustment cost, higher-dimensional firm-level heterogeneity in R&D efficiency and abatement cost, and the minimum requirement of R&D intensity set by the HNTE policy. The last element introduces firms' endogenous notching behaviors around the thresholds studied in Chen et al. (2021), allowing our model to fit the rich pattern observed in the empirical distribution of R&D activities. The details of the full quantitative model are in the Appendix C. We employ the simulated method of moments to estimate the structural parameter. Based on a conceptual framework elucidating market externalities, we quantify the economic consequences of the HNTE-env policy and compare it with separate environmental regulations.

5.1 Parameterizations

We begin with the calibration of the model parameters. We first discuss those that can be externally calibrated, directly inferred, or drawn from the literature. Following Head and Mayer (2014), we specify the demand elasticity $\sigma = 5$. We estimate the AR(1) process of TFP evolution for non-R&D firms. The estimation yields calibrated values for the persistence of the productivity process $\rho = 0.827$ and the standard deviation of shocks $\sigma_u = 0.280$. On the basis of the estimate of Chen et al. (2021), we set the elasticity of productivity to R&D investment ϕ to be 0.09,[24] and the discount factor β to be 0.925. For the parameters in the abatement cost function, we follow Annicchiarico and Di Dio (2015) and set $v_1 = 0.185$ and $v_2 = 2.8$. The HNTE legal document indicates that the average tax rates for non-HNTE and HNTE firms are 25% and

[24]The range of previous estimation results is between 2% and 17% (Hall et al., 2010). In the Appendix E, we alternatively allow TFP elasticity to be jointly estimated with other parameters based on our model and data moments. The estimation yields a value of TFP elasticity fairly close to that in our baseline setting.

15%, respectively, implying a tax credit rate of $\delta = 10\%$.

The parameters specific to our model are jointly estimated by matching the model simulated moments with their data counterparts. To better match the R&D distribution in the data, we follow Chen et al. (2021) and introduce a heterogeneous and quadratic adjustment cost in the form of $g(d_{it}, \pi_{it}) = \frac{b\pi_{it}}{2}\left[\frac{d_{it}}{\pi_{it}}\right]^2$, where d_{it} and π_{it} are the firm's R&D investments and profits, respectively. The parameter of the adjustment cost function b is assumed to follow a log-normal distribution with a mean μ_b and a standard deviation σ_b. We further specify that the fixed costs for applying for the HNTE certification and pollution abatement follow an exponential distribution with means of μ_ψ and μ_ζ, respectively. The above shocks are assumed to be independently and identically distributed across firms. Without loss of generality, we normalize the environmental regulation parameter for the upstream firms f_u to be 1, so the estimate for f_d measures the relative environmental regulations for downstream firms. In our benchmark estimation, we consider a linear form of the penalty probability levied by the environmental agencies that could trigger HNTE firms to lose their certification under the HNTE-env program, i.e., $\lambda_i(\xi) = \lambda_i(1-\xi)$.[25] A larger λ_i indicates a greater probability of the HNTE certification being revoked due to the pollution penalty for a given level of abatement. Furthermore, we normalize the penalty parameter λ_u for upstream firms to zero, as these firms are cleaner after being more tightly regulated. The estimate for λ_d then measures the relative risk of being punished for downstream firms.[26]

Estimation Procedure. We employ the simulated method of moments to jointly estimate the parameters $\Omega = \{\mu_b, \sigma_b, \mu_\psi, \theta, f_d, \mu_\zeta, \lambda_d\}$. For a set of parameter values, we simulate the distribution of firms' productivity, R&D adjustment costs, the fixed cost for the HNTE application, and the fixed cost for pollution abatement. We then solve firms' optimal R&D application, investment, and abatement decisions under different tax credits and environmental criteria. The simulated moments are constructed by aggregating the firm-level decisions. We repeat the above procedure ten times and average over these simulations. We estimate the parameter set, Ω, by minimizing the difference between the data moments and those generated by the distribution of the simulated firms. The criterion function takes the form of

$$Q(\Omega) = \begin{bmatrix} \mathbf{m}^D(\Omega) - \mathbf{m}_0^D \\ \mathbf{m}^E(\Omega) - \mathbf{m}_0^E \end{bmatrix}' \mathbf{W} \begin{bmatrix} \mathbf{m}^D(\Omega) - \mathbf{m}_0^D \\ \mathbf{m}^E(\Omega) - \mathbf{m}_0^E \end{bmatrix}, \tag{11}$$

[25] In the Appendix E, we also consider a flexible form of the environmental penalty probability and find that our baseline estimates remain robust.

[26] In the Appendix E, we relax this assumption and alternatively allow the penalty parameter λ_u for upstream firms to be jointly estimated with the other parameters. The estimation results suggest that the value of λ_u is quite small and is not significantly different from zero.

where $\mathbf{W}$ is a bootstrapped covariance weighting matrix, $\mathbf{m}^D(\Omega)$ represents the simulated moments regarding firms' R&D and TFP distributions, and $\mathbf{m}^E(\Omega)$ represents those regarding firms' polluting activities. $\mathbf{m}_0^D$ and $\mathbf{m}_0^E$ represent the corresponding data moments. The first set in $\mathbf{m}^D(\Omega)$ includes the histogram of R&D intensity, specifically, the fraction of firms falling in three equally spaced intervals below the notch threshold (3%) and between 5% and 9%. We also include the average R&D intensity for firms over the interval between 3% and 5%, in which firms are more likely to be affected by the HNTE-env reform in the extensive margin. The second set in $\mathbf{m}^D(\Omega)$ incorporates the fraction of HNTE firms, as well as the average TFP (normalized by the location-industry mean) for non-HNTE and HNTE firms. Regarding the moment vector $\mathbf{m}^E(\Omega)$, we include the average pollution emission intensity measured by the average COD emissions per output. Here, we separately compute the pollution moments for non-HNTE and HNTE firms. Notably, we incorporate related moments from both upstream and downstream firms, as the distinctions in pollution cost induced by the environmental regulations and the probability of an environmental penalty for HNTE firms play crucial roles in identifying key parameters in the quantitative model. See the Appendix D for more details on the solution and estimation procedures.

Identification. While the simulated moments jointly determine the parameter values, we provide a heuristic description of how we use the upstream and downstream patterns to identify each parameter. We begin with the R&D and TFP moments $\mathbf{m}^D(\Omega)$. The histogram of R&D intensity in both areas helps to identify the distribution of R&D adjustment costs, b. Given the R&D distribution, firms are more willing to apply for the HNTE certification under the HNTE-env policy when the penalty parameter λ_i is smaller, the application fixed cost ψ is lower, or the benefit of R&D investment is greater (intuitively, when firms have higher productivity z). The pollution costs induced by the environmental regulation f_i and the abatement fixed costs μ_ζ also affect the R&D distribution and application decisions because higher costs due to the environmental regulations reduce the marginal benefits from R&D.

We further discuss the role of pollution moments $\mathbf{m}^E(\Omega)$. The distribution of pollution emissions for upstream and downstream firms are jointly determined by the emissions intensity parameter θ, the environmental regulation parameter f_d, and the mean abatement fixed costs μ_ζ. Pollution emissions increase with the emissions intensity parameter θ and the average abatement fixed costs μ_ζ but decrease with the extent of environmental regulations, f_d. Moreover, the pollution emissions for HNTE firms is also affected by the probability of being penalized by the environmental agencies, λ_i, as it directly leads to a higher probability of HNTE revocation. This also induces firms to reduce their emissions intensity.

The upstream and downstream firms face differential environmental regulations, f_i, and an environmental penalty probability parameter λ_i under the HNTE-env policy. From the dis-

cussion above, a higher f_i and λ_i not only reduce firms' pollution emissions but also decrease their R&D intensity and likelihood of applying for the HNTE certification. The disparities in patterns of data moments, $\mathbf{m}^D(\Omega)$ and $\mathbf{m}^E(\Omega)$, between the two areas help us to identify these two parameters. Another benefit of using the additional moments from both areas is that they provide additional overidentifying restrictions for our estimation.

5.2 Estimates of Structural Parameters

Table 10 reports the estimated value of the parameter set $\{\mu_b, \sigma_b, \mu_\psi, \theta, f_d, \mu_\zeta, \lambda_d\}$ and the corresponding standard errors. The table shows that all the estimates are statistically significant. The estimates of the R&D adjustment cost distribution parameters, $\mu_b = 7.410$ and $\sigma_b = 1.827$, are comparable with the results in Chen et al. (2021).[27] The estimate of the emissions intensity parameter θ is 0.358, which measures the average emissions without any pollution abatement. As expected, the estimate of the environmental regulation parameter for the downstream area is 0.848, significantly lower than that of the upstream area, which is normalized to 1. This result is consistent with the fact that downstream firms face looser environmental regulation than upstream firms do. From the estimate of the mean fixed abatement cost, $\mu_\zeta = 0.483$, our calculation indicates that the fixed abatement cost is burdensome. For downstream firms that decide to adopt abatement, the fixed abatement cost is, on average, 19.25% of their expected profit. This fairly high fixed cost prevents small firms from conducting abatement within the extensive margin, resulting in heterogeneous policy effects on firms of different sizes. Finally, the estimate of the punishment probability parameter λ_d is significantly greater than zero, with a magnitude of approximately 0.4. This result suggests that, given the same emissions intensity, compared with upstream firms, downstream firms face a greater probability of having their HNTE certification revoked and losing the benefits already gained due to the environmental penalty by the authorities.

Table 11 compares the model-simulated moments with the data moments. While we consider various sets of data patterns for both upstream and downstream firms, the table suggests that our model does a satisfactory job of matching the targeted moments.[28] In particular, our model replicates the distribution of R&D intensity for both areas quite well. Our model closely fits the fraction of HNTE status firms in the data and the positive correlation between TFP and the application decision. Moreover, our simulated moments of pollution emissions in different

[27] The estimates of μ_b and σ_b in Chen et al. (2021) are approximately 8.0 and 2.0, respectively. Our estimated value for the mean fixed application cost μ_ψ is 1.313. Under this parameter value, our numerical simulation suggests that for downstream firms applying for the HNTE program, the fixed application cost accounts for, on average, 5.70% of their expected profit. In Chen et al. (2021), the estimated ratio of the fixed application cost to the expected profit is, on average, 4.4%, which is slightly lower than our estimate. The deviation could be attributed to our estimation targeting additional data regarding firms' HNTE status and pollution emissions.

[28] The average distance between the simulated and data moments is approximately 11.99%.

areas are close to those in the data. In Appendix E, we estimate an extended model incorporating firms' potential misreporting R&D (relabeling) behaviors for the HNTE applications studied in Chen et al. (2021). The results indicate that the estimates of key parameters are close to the baseline estimation and that introducing firms' relabeling behaviors does not significantly improve the model fit for the targeted moments. In Appendix E, we also conduct a series of robustness checks to assess the sensitivity of our results to alternative model specifications and parameter assumptions. Given the estimated parameter values, we can simulate the model to understand how firms respond to the HNTE-env policy and its aggregate implications.

Table 10: Result of the Structural Estimates

Parameters	R&D adjust. cost		Avg. appl. fixed cost	Emission intensity	Env. regu. cost	Avg. abate. fixed cost	Penalty prob. para.
	μ_b	σ_b	μ_ψ	θ	f_d	μ_ζ	λ_d
Estimates	7.410	1.827	1.313	0.358	0.848	0.483	0.400
Standard Errors	0.028	0.031	0.037	0.016	0.032	0.029	0.094

Notes: The estimates of other structural parameters are based on calibrated values discussed in Section 5.1. We use moment conditions based on the information on firms' R&D intensity, HNTE status, TFP distributions, and emission intensity.

5.3 Simulating Counterfactual Policies

We now quantify the effects of combinations of environmental penalties and R&D tax incentives and their aggregate implications for R&D investment, productivity growth, and pollution emissions. We further consider the optimal environmental penalty for HNTE firms under various preferential tax rates by comparing the policy's economic costs and health benefits. Through these exercises, we attempt to determine whether the environmental policy integration (EPI) scheme could improve allocation efficiency and is socially desirable.

Alternative tax credit and environment penalty. We first simulate alternative versions of the HNTE-env policy that combine different levels of environmental penalties and R&D tax credits. Without the loss of generality, we simulate the policies for downstream firms that face a higher probability of being punished and having the R&D tax credit retracted. Figure 2 presents the policy effects of introducing different extents of environmental penalties to the R&D tax credit. The benchmark model corresponds to the policy regime with a tax credit of $\delta = 10\%$ and zero probability of a pollution penalty ($\lambda_d = 0$). The x-axis denotes the parameter of the penalty function, λ_d. A larger λ_d indicates a greater environmental punishment risk for HNTE applicants. The y-axis denotes the differences in the percentage of corresponding

Table 11: Simulated versus Targeted Data Moments

	Upstream Firms		Downstream Firms	
Variable	Model	Data	Model	Data
R&D Distribution Moments				
Below the notch (%)				
$[0.3, 1.2]$	0.247	0.266	0.247	0.242
$[1.2, 2.1]$	0.203	0.154	0.207	0.175
$[2.1, 3.0]$	0.123	0.131	0.128	0.129
Above the notch (%)				
$[5.0, 6.3]$	0.085	0.092	0.085	0.095
$[6.3, 7.6]$	0.062	0.051	0.060	0.049
$[7.6, 9.0]$	0.045	0.030	0.045	0.030
Mean of R&D intensity [3.0, 5.0]	0.038	0.039	0.038	0.039
HNTE-Status Related Moments				
Fraction of HNTE Firms (%)	0.153	0.155	0.131	0.140
Average TFP (HNTE Firms)	0.091	0.115	0.107	0.117
Average TFP (non-HNTE Firms)	-0.023	-0.021	-0.023	-0.019
Emission Related Moments				
COD Emission (HNTE Firms)	0.087	0.087	0.099	0.093
COD Emission (non-HNTE Firms)	0.142	0.131	0.165	0.172

Notes: This table compares the model-simulated moments with those from the data. The details of targeted moments are discussed in Section 5.1. The table shows that our quantitative model fits the upstream and downstream data moments quite well based on seven parameter values shown in Table 10.

variables for downstream firms compared with those in the benchmark model. The red, blue, and green lines correspond to the cases with tax credits of 8%, 10%, and 12%, respectively.

Panels A and B of Figure 2 show the extensive and intensive effects of the R&D policies. From Panel A, we find that the increase in penalty probability, captured by the model parameter, λ_d, reduces the fraction of firms that decide to apply for the HNTE certification and the relevant tax credits. In contrast, a higher tax credit attracts more firms to apply for HNTE status, reflected by the fact that a larger δ shifts the curve upward.[29] Under our baseline estimates, the fraction of HNTE firms in the downstream area declines by 14.33% relative to the benchmark. Panel B presents the intensive margin effects on the average R&D investment for incumbent HNTE firms. The panel indicates that an increase in λ_d reduces the average R&D investment for incumbent HNTE firms in the downstream area, whereas a larger tax credit δ increases R&D inputs. Compared with the benchmark without any environmental penalties, the baseline estimate of the penalty probability, $\lambda_d = 0.4$, reduces, on average, R&D investment by 1.52% and revocation risk for HNTE firms.

Panel C of Figure 2 displays the aggregate policy implications for productivity growth.[30] As discussed above, a higher punishment parameter, λ_d, has extensive and intensive effects on firms' decisions, contributing to depressed productivity. Given our baseline estimates, the TFP loss is approximately 0.063%. This result implies that introducing the environmental criteria raises the fiscal cost of stimulating R&D, with the elasticity of the tax-to-R&D ratio increasing from 4.65 to 4.84 according to our calculations. The increase in tax credits, in contrast, results in a positive effect on TFP, as larger R&D tax credits, regardless of firms' emissions behaviors, encourages their R&D investment.

Panel D of Figure 2 indicates that introducing the HNTE-env policy decreases aggregate water pollution emissions. The more intensive abatement input of HNTE firms plays a critical role in this result. Under our baseline estimates, the overall pollution reduction is approximately 3.50% compared with the benchmark. In addition, the effect of the R&D tax credit on pollution is contingent on the penalty probability parameter λ_d. When λ_d is relatively small, a higher tax credit results in greater aggregate pollution emissions, as firms are motivated to expand their R&D investment, thereby emitting more due to an enlarged production scale. However, when the penalty parameter is sufficiently high, the pattern changes. A higher tax credit now leads to a larger reduction in emissions, as HNTE firms allocate more investment to abatement to

[29] In the Appendix F, we present the selection effect of the environment criteria. We show that a higher parameter of the probability of an environmental penalty could mitigate the resource misallocation caused by the tax credit. This is because introducing the environmental criteria depresses the incentive for firms with lower productivity and higher adjustment costs to apply for the tax subsidy.

[30] Here, we follow Chen et al. (2021) to define the aggregate measure of firms' log-productivity as Z_t, which satisfies $Z_t^{\sigma-1} = (\sum_i \exp\{(\sigma-1)z_{i,t}/(1+\mu_i)\})$, where σ denotes the elasticity of demand and μ_i indicates the marginal cost due to environmental regulation. See Appendix G.1 for detailed technical details.

avoid losing their certification due to environmental penalties.[31]

Firm-size effect. Since the firm's sales level is strictly increasing in productivity, we define firms whose productivity z_{i1} is greater than the median as large firms and the rest as small firms. We simulate the policy effect on firms' R&D investments and emissions for each size group. Figure 3 shows the heterogeneous effects of the increase in the penalty probability parameter, λ_d, on incumbent HNTE firms of different sizes in the downstream area. Panels A and B present the changes in R&D investments and pollution emissions for incumbent HNTE firms, respectively. Comparing the red and blue lines in each panel, we find that with the increase in λ_d, small firms reduce R&D investments to a greater extent but abate less pollution emissions. In terms of magnitude, the model-based calculation indicates that small firms reduce R&D investments by 0.30% but abate less pollution by 0.50% compared with large firms. These results are consistent with our theoretical predictions and empirical findings. The reason is that pollution abatement is costly, and thus, small firms are less willing to afford the fixed cost. Therefore, they face a greater probability of being penalized after the environmental criteria are integrated into the HNTE policy, which depresses their incentives to expand R&D expenditures.

5.4 Welfare implications

In Appendix G, we provide a full characterization of the externalities at play in our framework. We embed both consumption and environmental quality in a household utility function to capture the *environmental externality*, which arises because production firms do not account for the negative effects of their pollution emissions on households. Moreover, from a social perspective, the optimal level of aggregate R&D investment may deviate from the choices made by individual firms. This is because firms make their R&D decisions based on their own initial productivity and expected returns, without considering their collective impact on the aggregate economy. Through theoretical analysis and above numerical simulation, we show that while the HNTE policy stimulates R&D activities and enhances aggregate productivity, it also incentivizes firms to expand their production scale, irrespective of their abatement decisions. Consequently, the HNTE policy helps address the potential issue of insufficient R&D investment but exacerbates environmental externalities. In comparison, the EPI scheme can serve as a complementary tool for the R&D tax credit by inducing HNTE firms to adopt a higher intensity of pollution abatement. While this policy intervention mitigates the negative environmental externalities associated with industrial pollution emissions, it simultaneously introduces a

[31] In the Appendix F, we perform the above policy simulations again in the extended framework with firms' relabeling behaviors. The results suggest that our baseline simulated outcomes remain robust. Moreover, we find that introducing the environmental criteria into the HNTE policy could dampen firms' incentive to misreport R&D expenditures.

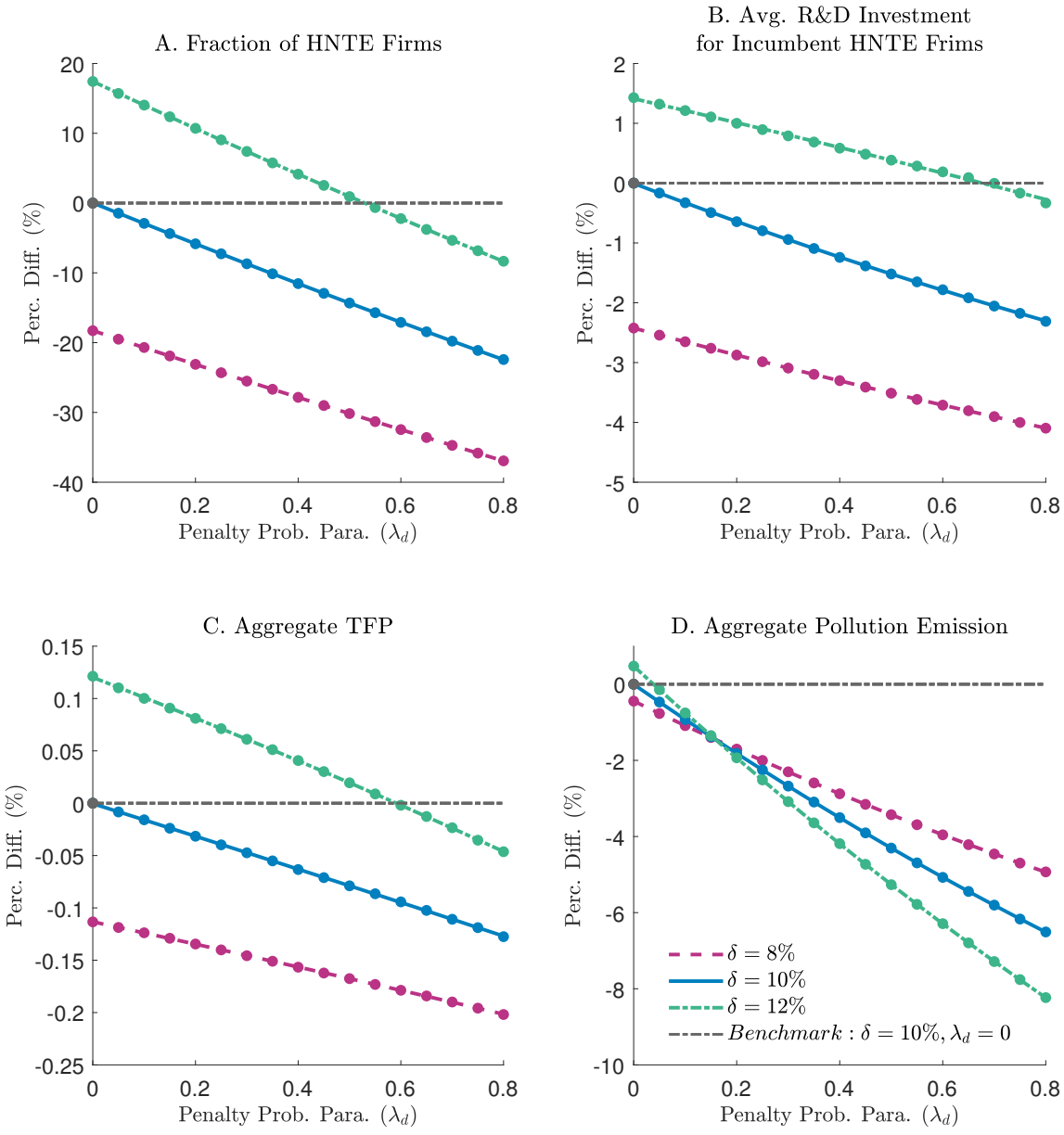


Figure 2: Simulated counterfactual policies: Alternative tax credit and environment penalties

Notes: These panels present the policy effects of alternative tax credits and environmental penalties on aggregate outcomes of interest. The x-axis represents the parameter of the penalty probability function, λ_d, and the y-axis denotes the percentage deviation of corresponding variables from those in the benchmark case with the penalty probability parameter $\lambda_d = 0$ and the tax credit $\delta = 10\%$. Incumbent HNTE firms refer to those applying for HNTE status in the benchmark case. The dots in each panel represent the average change in corresponding statistics, and the polynomial curves are the fitted trends. The red, blue, and green color corresponds to the case with tax credits, 8%, 10%, and 12%, respectively.

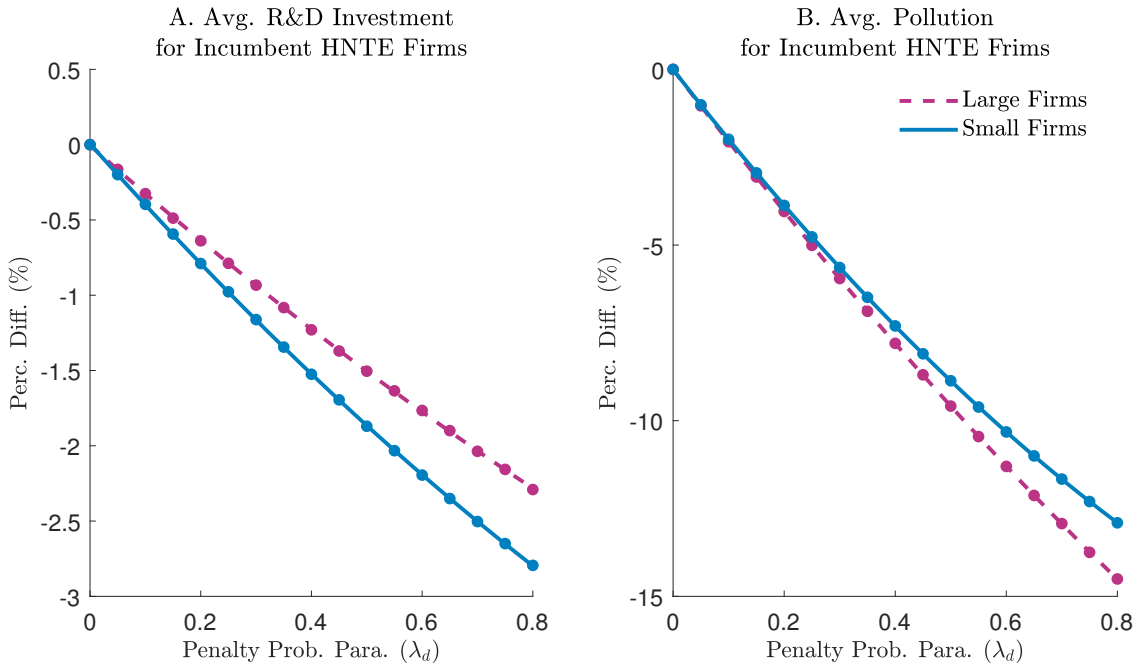


Figure 3: Simulating counterfactual policies: Firm-size effects

Notes: The panels in this figure present the heterogeneous effects of policy on R&D investment and pollution. The x-axis represents the parameter of the penalty probability function, λ_d, and the y-axis denotes the percentage deviation of corresponding variables from those in the benchmark case with the penalty probability parameter $\lambda_d = 0$ and the tax credit $\delta = 10\%$. Incumbent HNTE firms refer to those applying for HNTE status in the benchmark case. We define firms with productivity, z_{i1} larger than the median as large firms (the red line in each panel) and others as small ones (the red line in each panel). The dots in each panel represent the average change in corresponding statistics, and the polynomial curves are the fitted trends.

trade-off by attenuating the fiscal stimulus for R&D activities.

To examine the optimal level of environmental penalty integrated into R&D tax credit, we then quantify the welfare implications of the HNTE-env policy. We compare the overall economic costs due to productivity losses and the environmental benefits from water quality improvement.[32] Our evaluation strategy is that we first simulate the welfare impacts for the downstream area of 20 km around the water quality monitoring stations and then extrapolate the value for the aggregate welfare effects using the share of the economic activities of the downstream area relative to the whole country.

From 2011 to 2014, the annual average manufacturing value added by downstream polluting firms with R&D activities located 20 kilometers around the water monitoring stations was approximately 143.13 billion CNY. From our calculations based on the baseline estimate, the TFP losses caused by the HNTE-env policy are approximately 0.063%. Thus, the industrial losses are approximately 0.091 (-0.063 % $\times$ 143.13) billion yuan per year.[33]

On the basis of the Environmental Quality Standard for Surface Water, a decrease in the COD concentration of approximately 16% corresponds to one degree of water quality improvement. In our sample, the share of water pollution abatement of polluting firms with R&D investment accounts for 22.19% of the overall abatement. According to the model's simulation, the total emissions reduction for firms performing R&D is 3.50%. This implies that the degree of aggregate water pollution reduction will be 0.78% (22.19% $\times$ 3.50%), which is equivalent to a 0.049 degree of water quality improvement. As water quality improvement by a single grade decreases the digestive cancer death rate by 9.7% (Ebenstein, 2012), the HNTE-env policy leads to an approximately 0.47% decrease in digestive cancer deaths.

Using the share of aggregate value added for downstream firms located 20 kilometers around the water monitoring stations, we can estimate that the total population of the downstream region is approximately 39.68 million. Moreover, the morbidity rate of digestive cancer (gastric cancer, esophageal cancer, and intestinal cancer) was approximately 4.1 per ten thousand individuals in 2010. Given that the mean value of a statistical life is approximately 1.4 million yuan (World Bank, 2007), the benefits of saving lives from clean water becomes 0.107 billion per year, which is slightly greater than that of the industrial losses (0.091 billion) resulting from a decrease in TFP.

Analogous to the above calculation, we simulate the economic costs and health benefits given different levels of the penalty probability parameter, λ_d. The results are shown in Appendix F. Next, we compute the net benefits by subtracting the economic costs from the health

[32] Despite these two factors being the most fundamental determinants for evaluating policy effectiveness, we admit that it is difficult to quantify other elements, such as the enforcement costs of pollution monitoring, the spillover of R&D and pollution emissions, the tax transfer to firms, and others.

[33] Due to constant-return-to-scale production technology, we can show that the growth in aggregate output is linear to that in aggregate productivity, Z_t; See Appendix G.1 for morel details.

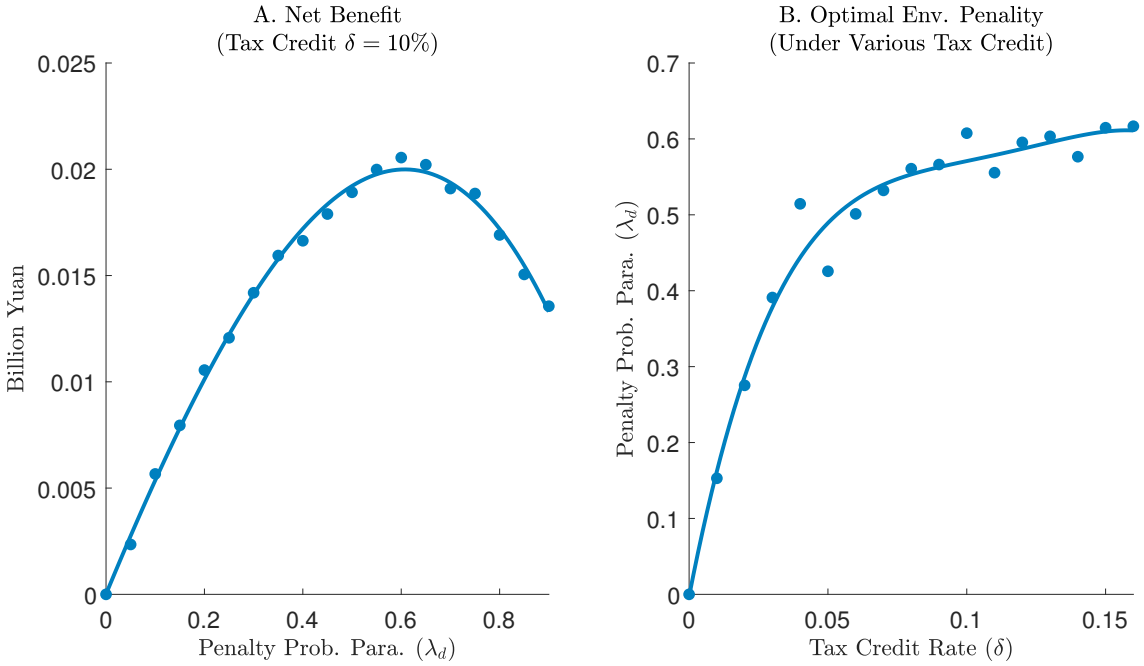


Figure 4: Simulating counterfactual policies: Optimal pollution penalty

Notes: Panel A presents the net benefit (health benefit - economic loss) of the environmental penalty. The x-axis represents the coefficient of the penalty probability function, λ_d, and the y-axis denotes the net benefit in the billion yuan compared to those in the benchmark case with $\lambda_d = 0$, and tax credit $\delta = 10\%$. Panel B presents optimal environmental penalties under different levels of an R&D tax credit. The x-axis represents the tax credit rate, and the y-axis denotes the optimal coefficients of the penalty probability function, λ_d, that maximize the net benefit of the policy combination. The dots in each panel represent the level of corresponding statistics, and the polynomial curves are the fitted trends.

benefits. Panel A of Figure 4 graphically displays the net benefits under different punishment parameter values, λ_d, while holding the tax credit rate constant at $\delta = 10\%$. The panel indicates an inverted-U relationship between the net benefits and the punishment parameter λ_d, with the maximum point at approximately 0.56. The inverted U-shaped curve here clearly shows that we should precisely calculate the peak (largest welfare gain) to determine the best level of environmental regulation stringency. If the environmental agencies cannot partially determine the probability of an environmental penalty due to incomplete information on a firm's compliance status, the policy-maker could consider changing the sufficient condition of the current HNTE-env policy by, for example, narrowing down the types or severity of the environmental penalties that could trigger the revocation of a firm's HNTE status.

Furthermore, we repeat the revenue-cost analysis for different R&D tax credit rates and numerically find the optimal environmental policy parameter, λ_d, that maximizes the net benefits under each scenario. Panel B of Figure 4 presents the quantitative results. As shown at the point corresponding to $\lambda_d = 0$, the policy-maker does not need an environmental tool without the R&D tax subsidy. When the tax credit increases, the policy stimulates polluting firms to expand their R&D investment, thereby releasing more pollution due to higher output. As highlighted in the above analysis, due to the potential risk of having their HNTE certification revoked, polluting firms have stronger incentives to abate more pollution. Therefore, as an effective complement, an intensive environmental criterion (a larger λ_d) is needed to mitigate the adverse effect on the environment and then enhance social welfare. Thus, the optimal extent of integrating the environmental criteria into an R&D policy, captured by the penalty probability parameter λ_d, exhibits a positive trend in relation to the R&D tax credit. This suggests a complementary relationship between the R&D tax credit policy and environmental criteria in promoting aggregate social welfare.[34]

Overall, the above quantitative analysis suggests that as a form of EPI, the HNTE-env policy could be beneficial, as it helps to effectively mitigate the expansion of dirty firms (environmental externalities) caused by a uniform tax incentive.

5.5 Is EPI a Better Choice than Separate Regulations?

Analogous to the previous analysis, we simulate the alternative levels of environmental regulations on downstream firms, as captured by the parameter f_d in our model. Figure F.2 in Appendix F presents the simulated policy effects of implementing varying levels of environmental regulations. The figure shows that similar to the EPI scheme, separate environmental

[34]The estimated points in panel B are not strictly increasing due to the simulation error. When λ_d becomes sufficiently large, a more intensive R&D tax credit policy will cause little or even less pollution emissions, as shown in Figure 2; see Section 5.3 for a detailed discussion. Thus, the optimal policy parameter λ_d is concave with respect to the R&D tax credit.

regulations also mitigate firms' pollution emissions, albeit at the cost of diminishing R&D investment. Despite the above results, to determine more precisely whether the EPI is more effective and socially desirable, we should compare it directly with the scenario where R&D stimulus and environmental regulation policies are implemented separately.

To examine the source of policy effects, we decompose the aggregate effect on emission reductions into two components: contributions from HNTE and non-HNTE firms. Panels A and B of Figure 5 present the constitution of policy effects. The blue, red, and green lines represent the aggregate effects, and contributions from HNTE firms, and those from non-HNTE firms. The panels indicate that the EPI scheme specifically targets firms that apply for the HNTE certification, while separate regulations apply equally to all firms. In Appendix G.2, we provide detailed analytical illustrations for the policy decomposition. Further, we compute the corresponding TFP loss given the same level of emission reduction induced by different policies, as shown by the blue lines in Panels C and D of Figure 5. Comparing Panels C and D, we find that the EPI scheme causes a lower TFP loss for achieving the same level of emission reduction. Specifically, to achieve a 3.50% reduction in pollution abatement (the case with $\lambda_d = 0.40$ in the baseline estimates), the stringency of environmental regulations should increase from 0.848 to 0.864. Given this increase in f_d, the TFP losses are approximately 0.149%, which is more than double the losses caused by the EPI scheme (0.063%). In Figure F.4 of the Appendix F, we further simulate the economic losses and health benefits for different levels of environmental regulation parameters, f_d, in the separate regulation setup. The simulation shows that the economic losses caused by more stringent environmental regulations dominate the health benefits, leading to a monotonically negative effect on social welfare.

Since aggregate productivity is the sum of productivity (adjusted by marginal pollution costs) across all individual firms, intervention policies may influence aggregate TFP through two channels.[35] First, both the EPI scheme and tighter separate environmental regulations will reduce firms' expected returns in the second period, which diminishes their incentive to expand R&D inputs in the first period. This leads to lower growth in the aggregate productivity. Second, these policies may distort production decisions by altering firms' marginal pollution costs per unit of output. Specifically, the EPI scheme increases pollution costs for HNTE firms by incentivizing them to enhance abatement intensity to retain eligibility for the tax credit. In contrast, tighter separate environmental regulations raise pollution fees per unit of emissions, which increases the marginal pollution cost for producing each unit of output. As a result, separate regulations more intensively distort production decisions for all firms, compelling them to set higher prices and reduce output levels. Panels C and D of Figure 5 present the simulation results by decomposing TFP losses into these two key channels. The red and green lines

[35] See Appendix G.2 for more technical details.

represent TFP losses attributed to the R&D reduction effect and the production distortion effect, respectively. The results reveal that under the EPI scheme, the majority of TFP loss (over 90% of the total impact) stems from the reduction in firms' R&D inputs. In contrast, separate environmental regulations impact TFP through both reducing R&D investments and distorting production decisions, with the latter accounting for over 80% of the total impact.

Overall, the above analysis indicates that the EPI scheme, at least the HNTE-env policy in our research, has advantages in improving social welfare. Compared with conventional environmental regulations, the EPI scheme only targets firms choosing to apply for the HNTE certification rather than the dispersed mass, which reduces the monitoring and enforcement costs. Moreover, the EPI scheme result in fewer economic losses by causing a smaller negative effect on aggregate productivity. This is because tighter environmental regulations uniformly raise the marginal costs of production for all enterprises. In contrast, the EPI scheme encourages firms to become cleaner to avoid losing the tax credit while not directly distorting their production decisions.

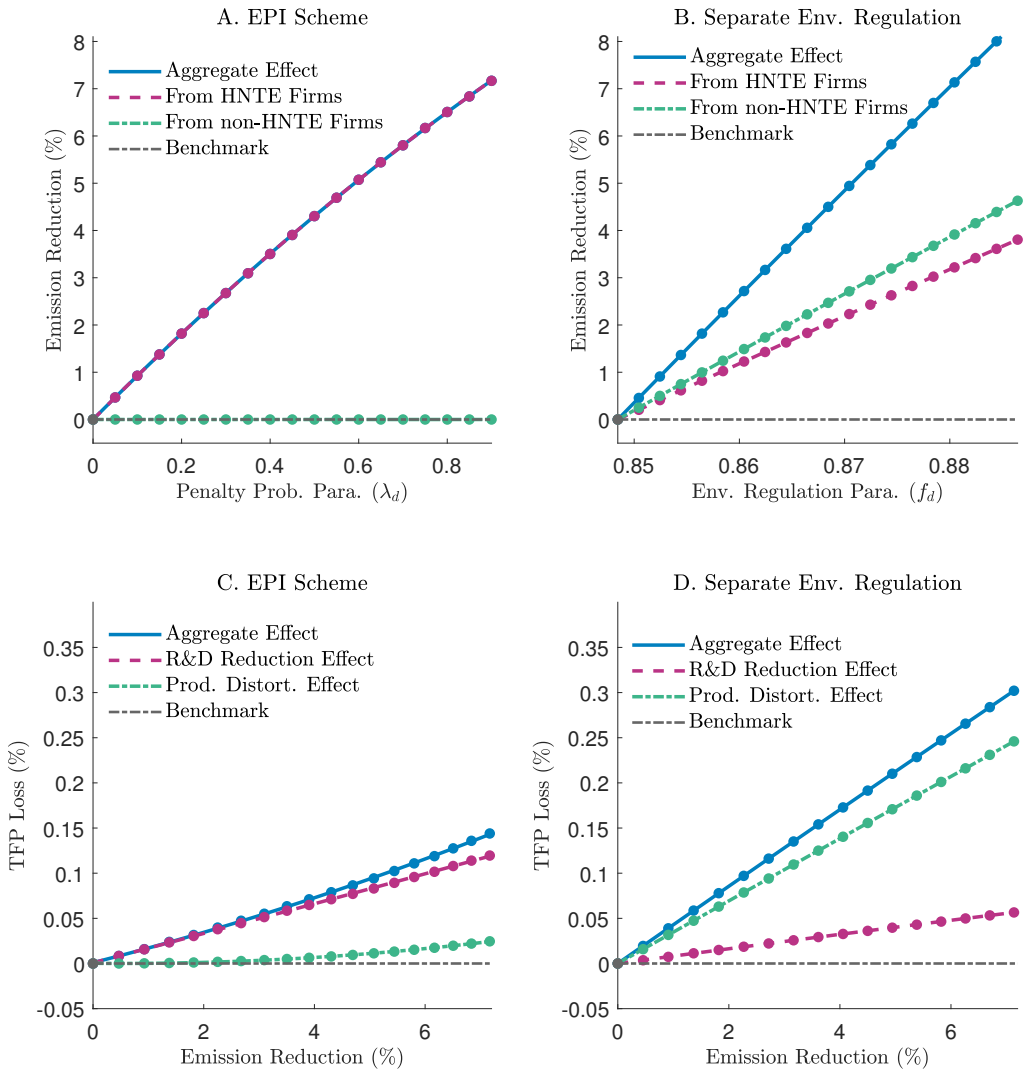


Figure 5: Decomposing policy effects: Different types of policies

Notes: These panels present the decomposition of the policy effects of alternative environment penalties integrated into the R&D tax credit and separate environmental regulations. In Panel A and B, the x-axis represents the parameter of corresponding policy parameters, and the y-axis denotes the percentage of emission reductions compared to those in the benchmark case with the tax credit $\delta = 10\%$, zero probability of being eliminated from the tax credit ($\lambda_d = 0$), and the baseline level of environment regulations ($f_d = 0.848$). The blue, red, and green lines represent the aggregate effects, and contributions from HNTE firms, and those from non-HNTE firms. In Panel C and D, the x-axis represents the level of emission reductions induced by different policies, and the y-axis denotes the TFP loss to achieve the corresponding emission reductions. Both variables are measured relative to the benchmark case with the tax credit $\delta = 10\%$, zero probability of being eliminated from the tax credit ($\lambda_d = 0$), and the baseline level of environment regulations ($f_d = 0.848$). The blue, red, and green lines represent the aggregate effects, and contributions from the R&D reduction effect, and those from the production distortion effect. The dots in each panel represent the average change in corresponding statistics, and the polynomial curves are the fitted trends.

6 Concluding Remarks

Over the past decade, various policy instruments have been employed to target a transition to sustainable development. For a multitasking government, finding the most cost-effective regulatory tools to address environmental problems is always at the core. Enlightened by the EPI notion, we empirically and quantitatively examine the prominent HNTE-env policy, which integrates environmental criteria into an R&D policy domain. Our findings show that the HNTE-env policy reduces the proportion of downstream polluting firms gaining the HNTE certification, given that they do not statistically differ from upstream firms in R&D eligibility. The reason is that the downstream firms are more polluting and are more likely to be environmentally punished. The intensive margin analysis further shows that HNTE firms accordingly reduce their R&D investment and pollution abatement, with smaller firms seeing greater reductions in R&D investment but fewer efforts in pollution abatement.

The quantitative analyses verify these empirical findings and explicate that conventional separate regulations in both domains alone uniformly distort the production decisions of both HNTE and non-HNTE firms by increasing their marginal costs, resulting in larger aggregate TFP losses than the EPI scheme alone. However, the EPI can be remarkably successful by spurring HNTE firms to reduce pollution emissions without uniformly distorting the production decisions of all types of firms. So, the EPI scheme does improve social welfare. This success, however, hinges on the rationally decided extent of environmental integration, or more specifically, on the HNTE-env policy setup and the environmental penalty probability that may trigger the HNTE certification to be revoked.

Our research provides the very first rigorous examination of the broadly adopted EPI notion. The policy implications are beyond the scope of the HNTE-env policy specifically studied in this paper. First, we quantify the impact of integrating environmental criteria into the R&D tax credit. The EPI scheme induces HNTE firms to reduce emissions more but dampens their incentive to apply for the tax credit (in the extensive margin) and prompts them to conduct less R&D (in the intensive margin). Therefore, policy-makers face a trade-off between environmental improvement and productivity growth when social welfare is considered. Second, under a greater R&D subsidy, polluting firms tend to expand their size but do little to reduce their pollution emissions. Thus, it is optimal to impose tighter environmental criteria for HNTE firms if the government plans to implement a more intensive R&D subsidy. As highlighted by Hsiang et al. (2019), understanding the determinants of heterogeneity in environmental benefits and damages is crucial for welfare analysis and policy design. The findings in our paper indicate that when adopting integrated policies targeting individual firms, a more delicate policy regime should be designed to take into account interactions across different policy lines.

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Appendices

A Details on Illustrative Model

A.1 Firms' Decision without HNTE Policy

When choosing to abate the pollution, the firms' optimal abatement ξ_{it}^* is to maximize the current profit π_{it} or to minimize the cost term $1 + f_i(1-\xi_{it})\theta + v_1\xi_{it}^{v_2}$. The first-order condition implies a time-invariant optimal abatement, ξ_i^*,

$$\xi_i^* \equiv \left(\frac{\theta f_i}{v_1 v_2}\right)^{\frac{1}{v_2-1}}. \tag{A.1}$$

The implied marginal cost for firm's adopting abatement technology, c_{it}, is

$$c_{it}^{\mathbf{A}}(z_{i1}) = \frac{w_{it}}{\exp(z_{it})}\left[1 + f_i(1-\xi_i^*)\theta + v_1\left(\xi_i^*\right)^{v_2}\right] = \frac{w_{it}}{\exp(z_{it})}\left(1+\mu_i^*\right), \tag{A.2}$$

where $\mu_i^* = f_i\theta\left[1 - \frac{v_2-1}{v_2}\left(\frac{f_i\theta}{v_1 v_2}\right)^{\frac{1}{v_2-1}}\right]$. Under the condition that $\xi_i^* \in (0,1)$, μ_i is strictly increasing in f_i. The upstream firms, given other things equal, face a higher marginal cost because of stricter regulation from the government.

If the firm decides not to abate ($\xi_{it} = 0$), the emission intensity is simply $\frac{e_{it}}{y_{it}} = \theta$ and thereby the pollution cost due to environmental regulation becomes $\frac{w_{it}}{\exp(z_{it})}f_i\theta$. The implied marginal cost for firms without abatement, c_{it}, is given by

$$c_{it}^{\mathbf{N}}(z_{i1}) = \frac{w_{it}}{\exp(z_{it})}\left(1 + f_i\theta\right) > c_{it}^{\mathbf{A}}(z_{i1}), \tag{A.3}$$

Given the abatement decision, the optimal pricing is given by $p_{it}^* = \frac{\sigma}{\sigma-1}c_{it}$. Thus, the profits for firms with different abatement decisions satisfy

$$\pi_{it}^{\mathbf{N}}(z_{i1}) = \frac{Y_t}{\sigma}\left(\frac{\sigma}{\sigma-1}c_{it}^{\mathbf{N}}\right)^{1-\sigma} = \gamma_{it}\cdot\left[\frac{\exp(z_{it})}{1+f_i\theta}\right]^{(\sigma-1)}, \tag{A.4}$$

$$\pi_{it}^{\mathbf{A}}(z_{i1}) = \frac{Y_t}{\sigma}\left(\frac{\sigma}{\sigma-1}c_{it}^{\mathbf{A}}\right)^{1-\sigma} - \zeta = \gamma_{it}\cdot\left[\frac{\exp(z_{it})}{1+\mu_i^*}\right]^{(\sigma-1)} - \zeta, \tag{A.5}$$

where $\gamma_{it} = \frac{1}{\sigma}\left(\frac{\sigma-1}{\sigma}\frac{1}{w_{it}}\right)^{\sigma-1}Y_t$ is a constant irrelevant to firm size and abatement decision. We now discuss the firms' decision on adopting abatement technology in the first period. Consider a marginal firm that is indifferent with abatement or not, i.e., $\pi_{i1}^{\mathbf{N}}(z_{i1}) = \pi_{i1}^{\mathbf{A}}(z_{i1})$. We have the

condition for the productivity threshold z_{i1}^*,

$$\gamma_{i1} \cdot \left[\frac{\exp(z_{i1}^*)}{1+f_i\theta}\right]^{(\sigma-1)} = \gamma_{i1} \cdot \left[\frac{\exp(z_{i1}^*)}{1+\mu_i^*}\right]^{(\sigma-1)} - \zeta, \tag{A.6}$$

which further implies

$$z_{i1}^* = \left(\frac{\zeta}{\gamma_{i1}}\right)^{\frac{1}{\sigma-1}} \left[(1+\mu_i^*)^{1-\sigma} - (1+f_i\theta)^{1-\sigma}\right]^{\frac{1}{\sigma-1}}, \tag{A.7}$$

For any firm with $z_{it} > z_{i1}^*$, it opts to abate pollution; otherwise, the firm would not abate. Therefore, we can write the optimal abatement decision as

$$\xi_{i1} = \begin{cases} \xi_i^*, & \text{if } z_{i1} > z_{i1}^* \\ 0, & \text{otherwise} \end{cases}. \tag{A.8}$$

Note that the profit in period 2, π_{i2}, depends on the productivity z_{i2}, which is affected by the productivity in period 1, z_{i1}, and the R&D investment in period 1, d_{i1}. Therefore, the abatement decision is much more complex as it is jointly determined with the R&D choice in period 1.

From Equation (3), the optimal conditions for the firm's R&D investment decision for firms without/with abatement in the second period imply that

$$d_{i1}^{\mathbf{N}}(z_{i1}) = \omega_i \left[\frac{\exp(\rho z_{i1})}{1+f_i\theta}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, \tag{A.9}$$

$$d_{i1}^{\mathbf{A}}(z_{i1}) = \omega_i \left[\frac{\exp(\rho z_{i1})}{1+\mu_i^*}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, \tag{A.10}$$

where $\omega_i = \left[\phi(\sigma-1)\gamma_{i2}\frac{\beta(1-\tau_{i2})}{1-\tau_{i1}}\right]^{\frac{1}{1-\phi(\sigma-1)}}$ is a constant unrelated to firms' productivity and pollution cost. Here, we assume that $\phi(\sigma-1) < 1$, ensuring the existence of the optimal R&D investment. Otherwise, firms might opt for infinite R&D investment. Under this condition, the optimal R&D increases with TFP z_{i1}. It declines with the environmental regulation f_i and consequently with μ_i^*. The optimal firm values for those without and with abatement in the second period can be expressed as

$$\mathbb{V}_i^{\mathbf{N}}\left(d_{i1}^{\mathbf{N}}, z_{i1}\right) = (1-\tau_{i1})\left\{\pi_{i1} + \left[\frac{1}{\phi(\sigma-1)} - 1\right] d_{i1}^{\mathbf{N}}\right\}, \tag{A.11}$$

$$\mathbb{V}_i^{\mathbf{A}}\left(d_{i1}^{\mathbf{A}}, z_{i1}\right) = (1-\tau_{i1})\left\{\pi_{i1} + \left[\frac{1}{\phi(\sigma-1)} - 1\right] d_{i1}^{\mathbf{A}}\right\} - \beta(1-\tau_{i2})\zeta. \tag{A.12}$$

Note that π_{i1} satisfies equation (2) and is predetermined when the firm makes its R&D decision. Consequently, it is unrelated to the R&D decision and abatement choice in the second period. Consider a marginal firm that is indifferent with abatement or not in the second period, i.e., $\mathbb{V}_i^{\mathbf{A}}(d_{i1}^{\mathbf{A}}, z_{i1}^{**}) = \mathbb{V}_i^{\mathbf{N}}(d_{i1}^{\mathbf{N}}, z_{i1}^{**})$. We have the condition for the productivity threshold z_{i1}^{**},

$$\left[\frac{1}{\phi(\sigma-1)} - 1\right]\left[d_{i1}^{\mathbf{A}}(z_{i1}^{**}) - d_{i1}^{\mathbf{N}}(z_{i1}^{**})\right] = \frac{\beta(1-\tau_{i2})}{1-\tau_{i1}}\zeta, \tag{A.13}$$

where $d_{i1}^{\mathbf{A}}(z_{i1}^{**})$ and $d_{i1}^{\mathbf{N}}(z_{i1}^{**})$ are determined by Equations (A.9) and (A.10), respectively. Due to the fact that $f_i\theta > \mu_i^*$, we can show that the left-hand side of the cutoff condition (A.13) increases with the productivity z_{i1}, which ensures the existence and uniqueness of the solution. Thus, the firms' optimal R&D and abatement decision is characterized as follows

$$\xi_{i2} = \begin{cases} \xi_i^*, & \text{if } z_{i1} > z_{i1}^{**} \\ 0, & \text{otherwise} \end{cases}, \tag{A.14}$$

$$d_{i1} = \begin{cases} \omega_i\left[\frac{\exp(\rho z_{i1})}{1+\mu_i^*}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, & \text{if } z_{i1} > z_{i1}^{**} \\ \omega_i\left[\frac{\exp(\rho z_{i1})}{1+f_i\theta}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, & \text{otherwise} \end{cases}, \tag{A.15}$$

where $\omega_i = \left[\phi(\sigma-1)\gamma_{i2}\frac{\beta(1-\tau_{i2})}{1-\tau_{i1}}\right]^{\frac{1}{1-\phi(\sigma-1)}}$ negatively related with the tax rate, τ_{i2}.

A.2 Firms' Decision under HNTE policy

Analogous to the case without the HNTE policy, the optimal conditions for firms applying for the HNTE certification without and with abatement are respectively

$$d_{i1}^{\mathbf{H,N}}(z_{i1}) = \omega_i^{\mathbf{H}}\left[\frac{\exp(\rho z_{i1})}{1+f_i\theta}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, \tag{A.16}$$

$$d_{i1}^{\mathbf{H,A}}(z_{i1}) = \omega_i^{\mathbf{H}}\left[\frac{\exp(\rho z_{i1})}{1+\mu_i^*}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, \tag{A.17}$$

where $\omega_i^{\mathbf{H}} = \left[\phi(\sigma-1)\gamma_{i2}\frac{\beta(1-\tau_{i2}+\delta)}{1-\tau_{i1}}\right]^{\frac{1}{1-\phi(\sigma-1)}} > \omega_i$. Substituting the above two equations into firms' value function (4), the optimal firm values for those applying for the HNTE certification

without and with abatement in the second period can be expressed as

$$\mathbb{V}_i^{\mathbf{H,N}}\left(d_{i1}^{\mathbf{H,N}}, z_{i1}\right) = (1-\tau_{i1})\left\{\pi_{i1} + \left[\frac{1}{\phi(\sigma-1)} - 1\right] d_{i1}^{\mathbf{H,N}}\right\}, \tag{A.18}$$

$$\mathbb{V}_i^{\mathbf{H,A}}\left(d_{i1}^{\mathbf{H,N}}, z_{i1}\right) = (1-\tau_{i1})\left\{\pi_{i1} + \left[\frac{1}{\phi(\sigma-1)} - 1\right] d_{i1}^{\mathbf{H,A}}\right\} - \beta(1-\tau_{i2}+\delta)\zeta. \tag{A.19}$$

From the value function for the marginal firm that are indifferent about the abatement, i.e., $\mathbb{V}_i^{\mathbf{H,N}}\left(d_{i1}^{\mathbf{H,N}}, z_{i1}^{\mathbf{H}**}\right) = \mathbb{V}_i^{\mathbf{H,A}}\left(d_{i1}^{\mathbf{H,N}}, z_{i1}^{\mathbf{H}**}\right)$, we can derive the condition for the productivity threshold $z_{i1}^{\mathbf{H}**}$,

$$\left[\frac{1}{\phi(\sigma-1)} - 1\right]\left[d_{i1}^{\mathbf{H,A}}\left(z_{i1}^{\mathbf{H}**}\right) - d_{i1}^{\mathbf{H,N}}\left(z_{i1}^{\mathbf{H}**}\right)\right] = \frac{\beta(1-\tau_{i2}+\delta)}{1-\tau_{i1}}\zeta, \tag{A.20}$$

where $d_{i1}^{\mathbf{H,A}}\left(z_{i1}^{\mathbf{H}**}\right)$ and $d_{i1}^{\mathbf{H,N}}\left(z_{i1}^{\mathbf{H}**}\right)$ are determined in Equations (A.16) and (A.17), respectively. Under the condition $f_i\theta > \mu_i^*$, we can show that the left-hand side of the cutoff condition (A.20) increases with the productivity z_{i1}, which ensures the existence and uniqueness of the solution.

Since the application for the HNTE certification requires the payment of a fixed cost denoted as $\psi > 0$, the application decision solves a discrete choice problem, $\max\left\{\mathbb{V}_i^{\mathbf{H}}(z_{i1}) - \psi, \mathbb{V}_i(z_{i1})\right\}$. From the value function for the marginal firms, that are indifferent between two options, we can solve the condition for the application threshold, $\hat{z}_{i1}^{\mathbf{H}}$,

$$(1-\tau_{i1})\left[\frac{1}{\phi(\sigma-1)} - 1\right]\left(\omega_i^{\mathbf{H}} - \omega_i\right)\cdot\left[\frac{\exp\left(\rho\hat{z}_{i1}^{\mathbf{H}}\right)}{1+f_i\theta}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}} = \psi. \tag{A.21}$$

where $\omega_i^{\mathbf{H}} = \left[\phi(\sigma-1)\gamma_{i2}\frac{\beta(1-\tau_{i2}+\delta)}{1-\tau_{i1}}\right]^{\frac{1}{1-\phi(\sigma-1)}} > \omega_i$. From the above equation, it is straightforward to show that the cutoff $z_{i1}^{\mathbf{H}}$ decreases with δ and increases with the environmental regulation f_i. Consequently, once a monitoring station is set up, upstream firms are less likely to opt for the HNTE certification because they are subject to higher pollution cost due to stricter regulations. To summarize, the firms' optimal R&D and abatement decision is characterized in

as follows,

$$\xi_{i2}^{\mathbf{H}} = \begin{cases} \xi_i^*, & \text{if } z_{i1} > z_{i1}^{\mathbf{H}**} \\ 0, & \text{otherwise} \end{cases}, \tag{A.22}$$

$$d_{i1}^{\mathbf{H}} = \begin{cases} \omega_i^{\mathbf{H}} \left[\frac{\exp(\rho z_{i1})}{1+\mu_i^*}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, & \text{if } z_{i1} > z_{i1}^{\mathbf{H}**} \\ \omega_i^{\mathbf{H}} \left[\frac{\exp(\rho z_{i1})}{1+f_i\theta}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, & \text{if } \hat{z}_{i1}^{\mathbf{H}} < z_{i1} < z_{i1}^{\mathbf{H}**} \\ \omega_i \left[\frac{\exp(\rho z_{i1})}{1+f_i\theta}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, & \text{if } z_{i1} < \hat{z}_{i1}^{\mathbf{H}} \end{cases}, \tag{A.23}$$

Due to the fact that $\frac{\omega_i^{\mathbf{H}}}{1-\tau_{i2}+\delta} > \frac{\omega}{1-\tau_{i2}}$, we can demonstrate that $z^{\mathbf{H}**} < z^{**}$ from the cutoff condition (A.20). This implies that more firms are incentivized to abate pollution after the enactment of the HNTE policy. This is because the tax credit brought by the HNTE certification widens the gap in firm values for abating and non-abating firms. Moreover, under a sufficiently large abatement cost parameter v_2, we could show that a stricter environment control f_i widens the gap in firm values between abating and non-abating firms, i.e., $\frac{\partial\left[\mathbb{V}^{\mathbf{H,A}}(z_{i1})-\mathbb{V}^{\mathbf{H,N}}(z_{i1})\right]}{\partial f_i} > 0$. Due to the monotonicity of $\mathbb{V}^{\mathbf{H,A}}(z_{i1}) - \mathbb{V}^{\mathbf{H,N}}(z_{i1})$, we have that $z_{u1}^{\mathbf{H}**} < z_{d1}^{\mathbf{H}**}$. This suggests that the fraction of abating firms in the downstream area is lower compared to that of the upstream one. Combining with the fact that $\xi_d < \xi_u$, we can verify that downstream firms (on average) abate more pollution compared to upstream ones.

A.3 Firms' Decision under HNTE-env Policy

From the value function (7) under the HNTE-env policy, the optimal condition for the abatement in period 2, $\xi_i^{\mathbf{E}}$, is given by

$$v_1 v_2 \xi_{i2}^{v_2-1} - f_i\theta = -\frac{\delta\lambda'(\xi_{i2})}{\beta(\sigma-1)\{1-\tau_{i2}+[1-\lambda(\xi_{i2})]\cdot\delta\}}\left[1+f_i(1-\xi_{i2})\theta+v_1\xi_{i2}^{v_2}\right]. \tag{A.24}$$

Since $\lambda'(\xi_{i2}) < 0$, it is easy to demonstrate that $\xi_i^{\mathbf{E}} > \xi_i^*$. Furthermore, a downstream firm under the HNTE-env policy has a higher marginal cost, $\mu_i^{\mathbf{E}} > \mu_i^* = f_i\theta\left[1-\frac{v_2-1}{v_2}\left(\frac{f_i\theta}{v_1 v_2}\right)^{\frac{1}{v_2-1}}\right]$. Analog to analysis for the case with the simple HNTE policy, the optimal conditions for firms applying for the HNTE certification under HNTE-env policy without and with abatement are

respectively

$$d_{i1}^{\mathbf{E,N}}\left(z_{i1}\right) = \omega_i^{\mathbf{E,A}}\left[\frac{\exp\left(\rho z_{i1}\right)}{1+f_i\theta}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, \tag{A.25}$$

$$d_{i1}^{\mathbf{E,A}}\left(z_{i1}\right) = \omega_i^{\mathbf{E,A}}\left[\frac{\exp\left(\rho z_{i1}\right)}{1+\mu_i^{\mathbf{E}}}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, \tag{A.26}$$

where $\omega_i^{\mathbf{E,N}} = \left[\phi\left(\sigma-1\right)\gamma_{i2}\frac{\beta(1-\tau_{i2}+[1-\lambda(0)]\delta)}{1-\tau_{i1}}\right]^{\frac{1}{1-\phi(\sigma-1)}}$, $\omega_i^{\mathbf{E,A}} = \left[\phi\left(\sigma-1\right)\gamma_{i2}\frac{\beta\left(1-\tau_{i2}+\left[1-\lambda\left(\xi_i^{\mathbf{E}}\right)\right]\delta\right)}{1-\tau_{i1}}\right]^{\frac{1}{1-\phi(\sigma-1)}}$. Since $\lambda\left(0\right) > \lambda\left(\xi_i^{\mathbf{E}}\right)$, it can be shown that $\omega_i^{\mathbf{E,N}} < \omega_i^{\mathbf{E,A}} < \omega^{\mathbf{H}}$. Therefore, we have $d_{i1}^{\mathbf{E,N}} < d_{i1}^{\mathbf{H,N}}$ and $d_{i1}^{\mathbf{E,A}} < d_{i1}^{\mathbf{H,A}}$, suggesting that the HNTE-env policy reduces the optimal R&D intensity for firms applying for the tax credit regardless of their abatement decisions.

Next, we analyze the extensive margin of applying the HNTE certification under the HNTE-env policy. Substituting the Equations (A.25) and (A.26) into firms' value function (7), the optimal firm values for those applying the HNTE certification with and without abatement in the second period can be further expressed as

$$\mathbb{V}_i^{\mathbf{E,N}}\left(d_{i1}^{\mathbf{E,N}}, z_{i1}\right) = \left(1-\tau_{i1}\right)\left\{\pi_{i1} + \left[\frac{1}{\phi\left(\sigma-1\right)}-1\right]d_{i1}^{\mathbf{E,N}}\right\}, \tag{A.27}$$

$$\mathbb{V}_i^{\mathbf{E,A}}\left(d_{i1}^{\mathbf{E,N}}, z_{i1}\right) = \left(1-\tau_{i1}\right)\left\{\pi_{i1} + \left[\frac{1}{\phi\left(\sigma-1\right)}-1\right]d_{i1}^{\mathbf{E,A}}\right\} - \beta\left(1-\tau_{i2}+\left[1-\lambda\left(\xi_i^{\mathbf{E}}\right)\right]\delta\right)\zeta. \tag{A.28}$$

From the value function for the marginal firm, that are indifferent between abating or not, i.e., $\mathbb{V}_i^{\mathbf{E,N}}\left(d_{i1}^{\mathbf{E,N}}, z_{i1}^{\mathbf{E}**}\right) = \mathbb{V}_i^{\mathbf{E,A}}\left(d_{i1}^{\mathbf{E,A}}, z_{i1}^{\mathbf{E}**}\right)$, we have the condition for the productivity threshold z_{i1}^{E**},

$$\left[\frac{1}{\phi\left(\sigma-1\right)}-1\right]\left[d_{i1}^{\mathbf{E,A}}\left(z_{i1}^{\mathbf{E}**}\right) - d_{i1}^{\mathbf{E,N}}\left(z_{i1}^{\mathbf{E}**}\right)\right] = \frac{\beta\left(1-\tau_{i2}+\left[1-\lambda\left(\xi_i^{E}\right)\right]\delta\right)}{1-\tau_{i1}}\zeta, \tag{A.29}$$

where $d_{i1}^{\mathbf{E,N}}\left(z_{i1}^{\mathbf{E}**}\right)$ and $d_{i1}^{\mathbf{E,A}}\left(z_{i1}^{\mathbf{E}**}\right)$ are determined in Equations (A.25) and (A.26), respectively. [36] Since the condition $f_i\theta > \mu_i^*$ holds, we can show that the left-hand side of the cutoff condition (A.29) increases with the productivity $z_{i1}^{\mathbf{E}**}$, which ensures the existence and uniqueness of the solution.

Due to the application fixed cost, we can show that the optimal application decision follows

[36] Comparing the cutoff conditions (A.20) and (A.29), we find that the relationship between $\tilde{z}_{i1}^{\mathbf{H}**}$ and $\tilde{z}_{i1}^{\mathbf{E}**}$ is ambiguous. First, the HNTE-env policy affects the gap in firm values between non-abating and abating firms, as shown in the left-hand side of (A.29). Second, it increases the real abatement fixed cost due to the tax shield effect, as shown in the right-hand side of (A.29). Thus, the relationship depends on which force dominates.

a cutoff strategy. The firm chooses to apply the HNTE certification upon the HNTE-env policy, if and only if its productivity exceeds a threshold of $\hat{z}_{i1}^{\mathbf{E}}$. We assume that the fixed cost ψ is sufficiently small such that $\hat{z}_{i1}^{\mathbf{E}} < z_{i1}^{\mathbf{E}**}$, which guarantees that firms applying for the HNTE certification under the HNTE-env policy include those with and without abatement. From the value function for the marginal firm, that are indifferent between applying or not, we can derive the condition for the application threshold, $\hat{z}_{i1}^{\mathbf{E}}$,

$$(1-\tau_{i1})\left[\frac{1}{\phi(\sigma-1)}-1\right]\left(\omega_i^{\mathbf{E,N}}-\omega_i\right)\cdot\left[\frac{\exp\left(\rho\hat{z}_{i1}^{\mathbf{E}}\right)}{1+f_i\theta}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}=\psi. \tag{A.30}$$

where $\omega_i^{\mathbf{E,N}}=\omega_i^{\mathbf{H}}>\omega_i$ given a positive $\lambda(0)$. Thus, we can show that $\hat{z}_{i1}^{\mathbf{E}}>\hat{z}_{i1}^{\mathbf{H}}$. In other words, as the application cutoff decreases with the tax benefit, the downstream firms, given other things equal, are less likely to apply for the HNTE certification under the HNTE-en policy.

Combining the analysis above, we can write the optimal R&D and abatement decision under the HNTE-env policy as follows

$$\xi_{i2}^{\mathbf{E}}=\begin{cases}\xi_i^{\mathbf{E}}, & \text{if } z_{i1}>z_{i1}^{\mathbf{E}**}\\ 0, & \text{otherwise}\end{cases}, \tag{A.31}$$

$$d_{i1}^{\mathbf{E}}=\begin{cases}\omega_i^{\mathbf{E,A}}\left[\frac{\exp(\rho z_{i1})}{1+\mu_i^{\mathbf{E}}}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, & \text{if } z_{i1}>z_{i1}^{\mathbf{E}**}\\ \omega_i^{\mathbf{E,N}}\left[\frac{\exp(\rho z_{i1})}{1+f_i\theta}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, & \text{if } \hat{z}_{i1}^{\mathbf{E}}<z_{i1}<z_{i1}^{\mathbf{E}**}\\ \omega_i\left[\frac{\exp(\rho z_{i1})}{1+f_i\theta}\right]^{\frac{\sigma-1}{1-\phi(\sigma-1)}}, & \text{if } z_{i1}<\hat{z}_{i1}^{\mathbf{E}}\end{cases}. \tag{A.32}$$

Since $\lambda(0)>\lambda\left(\xi_i^{\mathbf{E}}\right)$, it can be shown that $\omega_i^{\mathbf{E,N}}<\omega_i^{\mathbf{E,A}}<\widetilde{\omega}_i$. By comparing the above two equations with the optimal decisions (A.22) and (A.23) under the HNTE policy, we can derive firms' responses to HNTE-env reform. In particular, for firms that apply for the HNTE certification under the new policy regime ($z_{i1}>\hat{z}_{i1}^{\mathbf{E}}$), they choose a lower R&D investment, regardless of its productivity. Since the output y_{i2} in the second period is positively correlated with the productivity, z_{i2}, and thereby the R&D investment in the first period, then the downstream firms applying for the certification would reduce their output due to the decline in R&D investment. Moreover, for firms with sufficiently large productivity, they choose a higher degree of abatement intensity than the case without environmental criteria, i.e., $\xi_i^{\mathbf{E}}>\xi_i^{*}$. Thus, we can show that the average pollution $e_{i2}=(1-\xi_{i2})\theta y_{i2}$ would decrease for downstream firms.

Lastly, we discuss the proof regarding the heterogeneous policy effects for firms with dif-

ferent sizes. For large firms with productivity $z_{i1} > \max\left\{z_{i1}^{\mathbf{E}**}, z_{i1}^{\mathbf{H}**}\right\}$, they always choose to abate before and after the HNTE-env policy. Their changes in the optimal decisions are given by

$$\Delta \log d_{i1}^{\mathbf{Large}} = \frac{1}{1-\phi(\sigma-1)}\left[(\sigma-1)\log\frac{1+\mu_i^*}{1+\mu_i^{\mathbf{E}}} + \log\frac{1-\tau_{i2}+\left[1-\lambda\left(\xi_i^{\mathbf{E}}\right)\right]\delta}{1-\tau_{i2}+\delta}\right], \tag{A.33}$$

$$\Delta \log \xi_{i2}^{\mathbf{Large}} = \log \xi_i^{\mathbf{E}} - \log \xi_i^*, \tag{A.34}$$

$$\Delta \log e_{i2}^{\mathbf{Large}} = \log\frac{1-\xi_i^{\mathbf{E}}}{1-\xi_i^*} + \sigma\phi \cdot \Delta \log d_{i1}^{\mathbf{Large}}, \tag{A.35}$$

where, the equation (A.35) employs the conditions $\log e_i = \log\left[\theta\left(1-\xi_i\right)\log y_{it}\right]$ and $\log y_{it} = -\sigma \log p_{it} = -\sigma\left(\log\frac{\sigma}{1-\sigma} - \log c_{it}\right)$. Similarly, for small firms with productivity $\hat{z}^{\mathbf{E}} < z_{i1} < \min\left\{z_{i1}^{\mathbf{H}**}, z_{i1}^{\mathbf{E}**}\right\}$, they never choose to abate before and after the HNTE-env policy. Their changes in the optimal decisions after the policy reform are given by

$$\Delta \log d_{i1}^{\mathbf{Small}} = \frac{1}{1-\phi(\sigma-1)} \cdot \log\frac{1-\tau_{i2}+\left[1-\lambda(0)\right]\delta}{1-\tau_{i2}+\delta}, \tag{A.36}$$

$$\Delta \log \xi_{i2}^{\mathbf{Small}} = 0, \tag{A.37}$$

$$\Delta \log e_{i2}^{\mathbf{Small}} = \sigma\phi \cdot \Delta \log d_{i1}^{\mathbf{Small}}. \tag{A.38}$$

By comparing Equations (A.33) and (A.36), the decline in $d_{i1}^{\mathbf{Large}}$ comes from two components: the first is a higher abatement cost, and the second is the probability of environmental penalty, $\lambda\left(\xi_i^{\mathbf{E}}\right)$, which leads to the loss of tax credit; whereas the decline $d_{i1}^{\mathbf{Small}}$ sorely comes from the probability of environmental penalty, $\lambda(0)$. Therefore, under a sufficiently large penalty probability levied on those without abatement, $\lambda(0)$, we can prove that $\Delta \log d_{i1}^{\mathbf{Small}}$ is more negative (larger in magnitude) than $\Delta \log d_{i1}^{\mathbf{Large}}$. By comparing Equations (A.35) and (A.38), the decline in $e_{i1}^{\mathbf{Large}}$ can be decomposed into two parts: the first is due to a higher intensity of pollution abatement, and the second comes from the decline in R&D investment, which leads to the shrink in output of the second period. Thus, given a sufficiently small $\sigma\phi$ (low TFP to R&D elasticity or demand elasticity), we can derive that $\Delta \log e_{i1}^{\mathbf{Large}} < \Delta \log e_{i1}^{\mathbf{Small}} < 0$.

Under a sufficiently large $\lambda(0)$ or small $\sigma\phi$, we can derive a similar proposition on the heterogeneity if we further consider the *middle* group that has the productivity between $z_{i1}^{\mathbf{E}**}$, and $z_{i1}^{\mathbf{h}**}$. We consider the case with $z_{i1}^{\mathbf{E}**} < z_{i1}^{\mathbf{H}**}$, and the analysis is similar in the opposite one. For any firms with $z_{i1} \in \left(z_{i1}^{\mathbf{E}**}, z_{i1}^{\mathbf{H}**}\right)$, they switch from non-abating firms to abating ones after

the HNTE-env policy, and their changes in the optimal decisions are given by

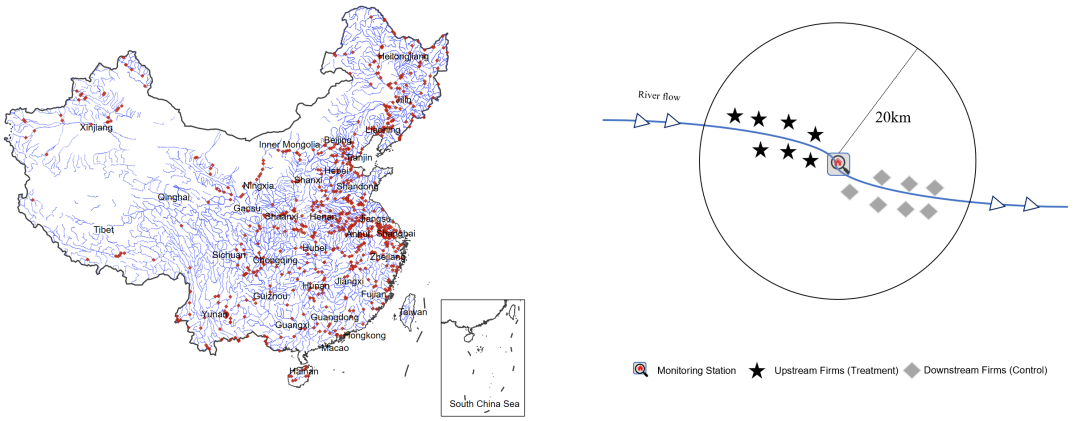
$$\Delta \log d_{i1}^{\mathbf{Middle}} = \frac{1}{1-\phi(\sigma-1)} \left[(\sigma-1) \log \frac{1+f_i\theta}{1+\mu_i^{\mathbf{E}}} + \log \frac{1-\tau_{i2}+\left[1-\lambda\left(\xi_i^{\mathbf{E}}\right)\right]\delta}{1-\tau_{i2}+\delta} \right], \tag{A.39}$$

$$\Delta \xi_{i2}^{\mathbf{Middle}} = \xi_i^{\mathbf{E}} - 0 = \xi_i^{\mathbf{E}}, \tag{A.40}$$

$$\Delta \log e_{i2}^{\mathbf{Middle}} = \log\left(1-\xi_i^{\mathbf{E}}\right) + \sigma\phi \cdot \Delta \log d_{i1}^{\mathbf{Middle}}, \tag{A.41}$$

Since $f_i\theta > \mu_i^*$ and $\lambda(0) > \lambda\left(\xi^{\mathbf{E}}\right)$, we can demonstrate that $\Delta \log d_{i1}^{\mathbf{Small}} < \Delta \log d_{i1}^{\mathbf{Middle}}$. Moreover, because of $\log\left(1-\xi_i^{\mathbf{E}}\right) < 0$, a sufficiently small $\sigma\phi$ enables us to establish that $\Delta \log e_{i1}^{\mathbf{Middle}} < \Delta \log e_{i1}^{\mathbf{Small}}$. Nevertheless, compared to larger firms, small ones tend to reduce more R&D investment, as long as they have more difficulty in affording the abatement fixed cost, and thus face a sufficiently large probability of being punished. Moreover, the declines in pollution for small firms are only caused by the decline in their outputs. If the TFP to R&D elasticity or demand elasticity is sufficiently low (the abatement effect dominates the output effect), small firms will emit more than larger ones after the HNTE-env policy.

B Empirical Tables and Figures



(a) Distribution of Water Quality Monitoring Stations (River)

(b) Upstream and Downstream Firms

Figure B.1: Identification of Upstream and Downstream Firms

Notes: The data cover a population of 970 water quality monitoring stations before 2010. We exclude the monitoring stations that are built on lakes and reservoirs, or largely overlapped with each other. The remaining 720 monitoring stations are presented on the China map. The red dots represent the position of the monitoring stations. For each monitoring station, we draw a circle centered at the monitoring station with a radius of 20 kilometers. With this neighborhood, firms on the upstream side of the river are identified as upstream firms, and firms on the downstream side are identified as downstream firms.

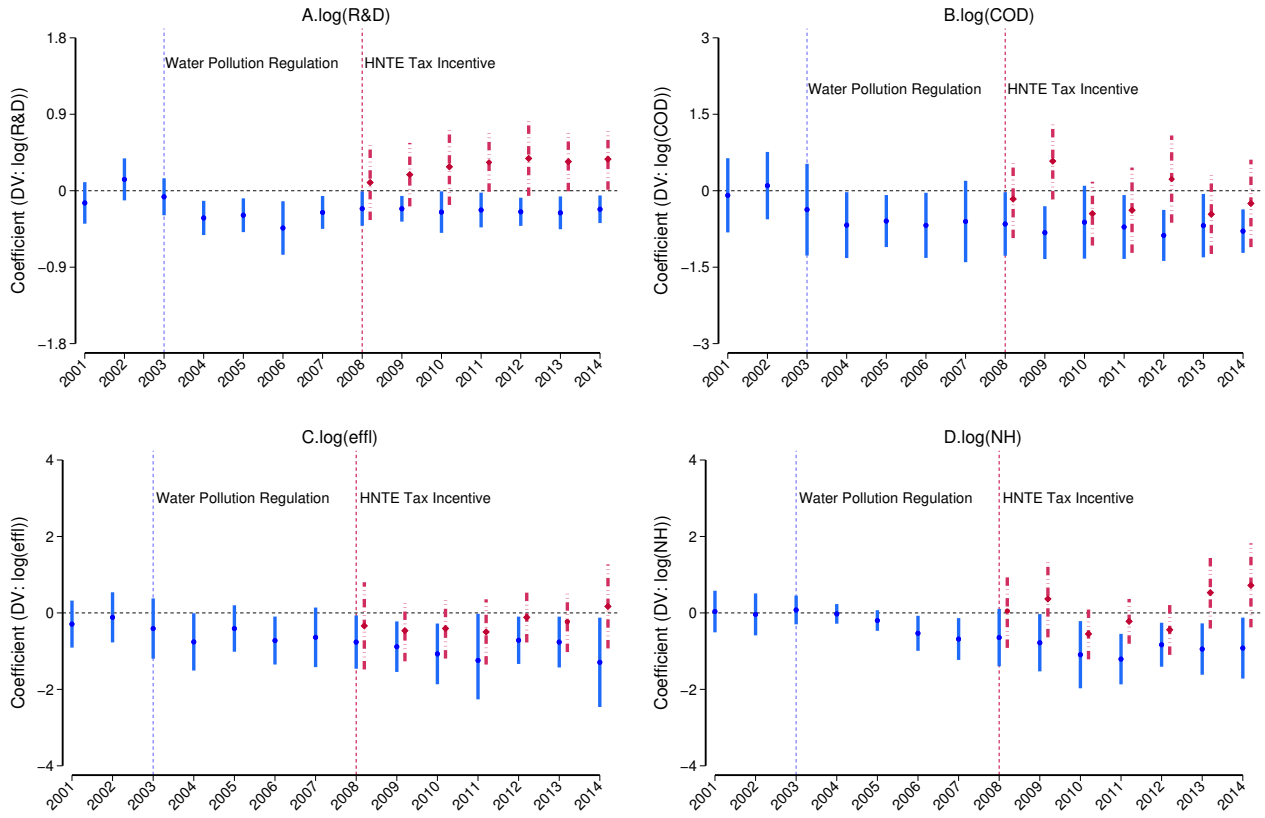


Figure B.2: Dynamic Effects on R&D and Environment

Notes: Figure 2A, B, C, and D plot the dynamic effects on R&D, COD, industrial effluent, and NH discharge respectively. In Figure 2A, B, C, and D, the y axis denotes the discontinuities in R&D, COD, industrial effluent, and NH discharge at logarithmic level between upstream and downstream firms, respectively. The x axis denotes the timeline between 2000 and 2014. The blue dots and lines are estimated based on the subsample of non-HNTE-env firms, while the red dots and dashed lines are estimated based on the subsample of HNTE-env firms. Each dot represents an RDD estimate in each year, with firm-level covariates, monitoring station indicators, and two-digit industry indicators absorbed. The corresponding range bars indicate the confidence intervals at 95 percent significance level.

Table B.1: Categorization of Polluting and Non-Polluting Industries

Polluting Industries		**Non-Polluting Industries**	
Code	Name	Code	Name
6	Coal Mining and Washing	7	Oil and Natural Gas Extraction
8	Black Metal Mining and Selection	9	Non-ferrous Metal Mining and Selection
10	Non-metallic Mining and Selection	11	Other Mining
14-6	Fermentation	13	Agricultural and Sideline Food Processing
15	Beverage	14	Food
17	Textile	16	Tobacco
19	Leather and Fur	18	Textiles and Apparel
22-1; 22-2	Pulp; Paper	20	Wood Processing and Bamboo, Rattan, and Grass Products
25	Petroleum Processing, Coking, and Nuclear Fuel	21	Furniture
26	Chemical Raw Materials and Chemical Products	22	Pulp and Paper
27-1; 27-2; 27-4;	Medicine; Pharmaceutical	23	Printing and Duplication
28	Chemical Fiber	24	Educational and Sports
31	Non-Metallic Mineral	27	Pharmaceutical
32-1; 32-2	Iron and Steel Smelting	29	Rubber
33-1	Common Nonferrous Metal Smelting	30	Plastic Products
44-1	Fossil Fuel Power Generation	32	Black Metal Smelting and Rolling
		33	Non-ferrous Metal Smelting and Rolling
		34	Metal Products
		35	General Equipment
		36	Specialized Equipment
		37	Transportation Equipment
		38	Electrical Machinery and Equipment
		39	Electrical Machinery and Equipment
		40	Communication Devices, Computers, and Other electronic equipment
		41	Instruments, Meters, and Office Machinery
		42	Crafts
		43	Recycling of Waste Materials
		44	Power Generation
		45	Gas Production and Supply
		46	Water Production and Supply

Notes: The classification of water-polluting industries is established by the National Ministry of Environmental Protection. The industries identified as key polluters are responsible for the majority of water pollution emissions. The definition of the code is based on the *Classification and Code of National Economic Industries (GB/T 4754—2002)*.

Table B.2: Summary Statistics

	Upstream (1)	Downstream (2)
A. Vars from SSTA database		
HNTE status	0.152	0.113
	(0.359)	(0.317)
RDWD status	0.164	0.147
	(0.371)	(0.354)
ln(R&D)	2.841	2.840
	(0.229)	(0.227)
Observations	23,396	15,001
B. Var from SAT database		
HNTE status	0.049	0.050
	(0.216)	(0.218)
Observations	77,835	42,846
C. Var from ESR database		
ln(COD)	2.297	2.734
	(1.995)	(2.125)
ln(Effluent)	4.434	4.711
	(2.513)	(2.482)
ln(NH)	0.212	0.675
	(0.594)	(1.096)
Observations	24,959	15,247

Notes: All variables are measured at firm level and constructed by the authors using data from *Surveys of Science and Technology Activities of Industrial Firms*, *State Administration of Tax* (SAT), and *Environmental Survey and Reporting* (ESR) databases.

Table B.3: Upstream-Downstream Discontinuity: Robustness

Robustness check 1: Firms within four-digit industry comparison—SSTA database (2008-2014)				
	HNTE status	**HNTE status**	**log(HNTE subsidy)**	**log(HNTE subsidy)**
	(1)	**(2)**	**(3)**	**(4)**
Firms in polluting industries				
RDD Estimate	0.354***	0.127***	2.781***	1.429***
	(0.074)	(0.043)	(0.606)	(0.384)
Bandwidth	3.099	4.611	2.948	4.051
Firm Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Year-station FE	No	Yes	No	Yes
Kernel Type	Triangular	Triangular	Triangular	Triangular
Observations	32,722	32,539	32,722	32,539
Robustness check 2: Excluding firms that migrate in the upstream-downstream direction				
	HNTE status	**HNTE status**	**log(HNTE subsidy)**	**log(HNTE subsidy)**
	(5)	**(6)**	**(7)**	**(8)**
Firms in polluting industries				
RDD Estimate	0.376***	0.117***	2.968***	1.393***
	(0.077)	(0.043)	(0.629)	(0.390)
Bandwidth	3.105	4.680	2.969	4.108
Firm Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Year-station FE	No	Yes	No	Yes
Kernel Type	Triangular	Triangular	Triangular	Triangular
Observations	32,447	32,266	32,447	32,266
Robustness check 3: Data from a different survey—State Administration of Tax (2009-2014)				
	HNTE status	**HNTE status**	**log(HNTE subsidy)**	**log(HNTE subsidy)**
	(5)	**(6)**	**(7)**	**(8)**
Firms in polluting industries				
RDD Estimate	0.072***	0.085***	0.113**	0.451***
	(0.016)	(0.020)	(0.054)	(0.130)
Bandwidth	4.045	3.346	7.864	3.892
Firm Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Year-station FE	No	Yes	No	Yes
Kernel Type	Triangular	Triangular	Triangular	Triangular
Observations	119,923	119,851	119,923	119,851

Notes: "HNTE status" refers to a firm possesses the HNTE certification after the HNTE-env reform. "HNTE subsidy" refers to the tax credits that a firm can claim from the HNTE-env program. The MSE-optimal bandwidth is based on the default kernel type suggested by Calonico et al. (2014). Firm controls include firm's age and total assets. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table B.4: Upstream-Downstream Discontinuity: Water Pollutant Discharge (2008-2014)

	log(R&D)	log(COD)	log(Effluent)	log(NH)
	(1)	(2)	(3)	(4)
Panel A: Discontinuity in pollution control among non-HNTE-env firms				
RDD Estimate	-0.986***	-1.611***	-1.351***	-1.074***
	(0.111)	(0.388)	(0.234)	(0.153)
Bandwidth	4.231	3.911	4.461	8.393
Firm Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year-station FE	Yes	Yes	Yes	Yes
Kernel Type	Triangular	Triangular	Triangular	Triangular
Observations	25,499	9,958	10,015	8,049
Panel B: Discontinuity in pollution control among HNTE-env firms				
RDD Estimate	0.830***	0.189	0.554	0.146
	(0.225)	(0.691)	(1.490)	(0.406)
Bandwidth	6.688	6.512	3.535	5.332
Firm Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year-station FE	Yes	Yes	Yes	Yes
Kernel Type	Triangular	Triangular	Triangular	Triangular
Observations	4,170	2,054	2,040	1,768

Notes: Column (1) reports estimate on firms' R&D investment. Columns (2)-(4) report estimates on a range of water pollutants: chemical oxygen demand (COD), ammonia nitrogen (NH3, NH4+), and industrial effluent, respectively. The MSE-optimal bandwidth is based on the default kernel type suggested by Calonico et al. (2014). Firm controls include firm's age and total assets. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table B.5: Upstream-Downstream Discontinuity: Placebo Test on Air Pollution (2003-2007)

	log(**SO2**)	log(**NOx**)	log(**soot**)	log(**wastegas**)
	(5)	**(6)**	**(7)**	**(8)**
RDD Estimate	-0.090	-0.061	-0.579	0.104
	(0.475)	(0.658)	(0.433)	(0.395)
Bandwidth	4.434	4.171	4.959	3.644
Firm Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year-station FE	Yes	Yes	Yes	Yes
Kernel Type	Triangular	Triangular	Triangular	Triangular
Observations	19,525	6,295	18,773	19,789

Notes: Columns (1)-(4) report estimates on a range of air pollutants: sulfur dioxide (SO_2), nitrogen oxide (NOx), industrial soot, and wastegas, respectively. The MSE-optimal bandwidth is based on the default kernel type suggested by Calonico et al. (2014). Firm controls include firm's age and total assets. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table B.6: Intensive Effects of the HNTE-env Policy on Firms' R&D Performance

	Upstream	**Downstream**		
	log(**Patent**)	log(**Patent**)		log(**Patent**)
	(1)	**(2)**		**(3)**
$Year2008_t \times HNTEenv_i$	0.097	-0.497***	$Year2008_t \times HNTEenv_i \times Down_i$	-0.578***
	(0.060)	(0.103)		(0.110)
Firm Controls	Yes	Yes	Firm Controls	Yes
Firm FE	Yes	Yes	Firm FE	Yes
Industry FE	Yes	Yes	Industry FE	Yes
Year-Station FE	Yes	Yes	Year-Station FE	Yes
$\mathbf{R}^2$	0.673	0.667	$\mathbf{R}^2$	0.653
Observations	39,877	22,251	Observations	63,137

Notes: "Patent" refers to the total number of patents granted to the firms, which includes inventions, utility models, and designs. $Year2008_t$ is an indicator, which equals 1 for the period during 2008-2014, and 0 for the period during 2005-2007. $HNTEenv_i$ equals 1 if a firm is certified as an HNTE both before and after 2008, and 0 if it has never been granted HNTE status during the sample period. The treatment group includes the firms that maintained a stable HNTE status before and after 2008. The only relevant shock affecting them was the introduction of environmental criteria into the HNTE policy. $Large_i$ equals one for large firms with sales above 20 million CNY, and equals zero for small firms with sales below 20 million CNY. Firm controls include the firm's age and total assets. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

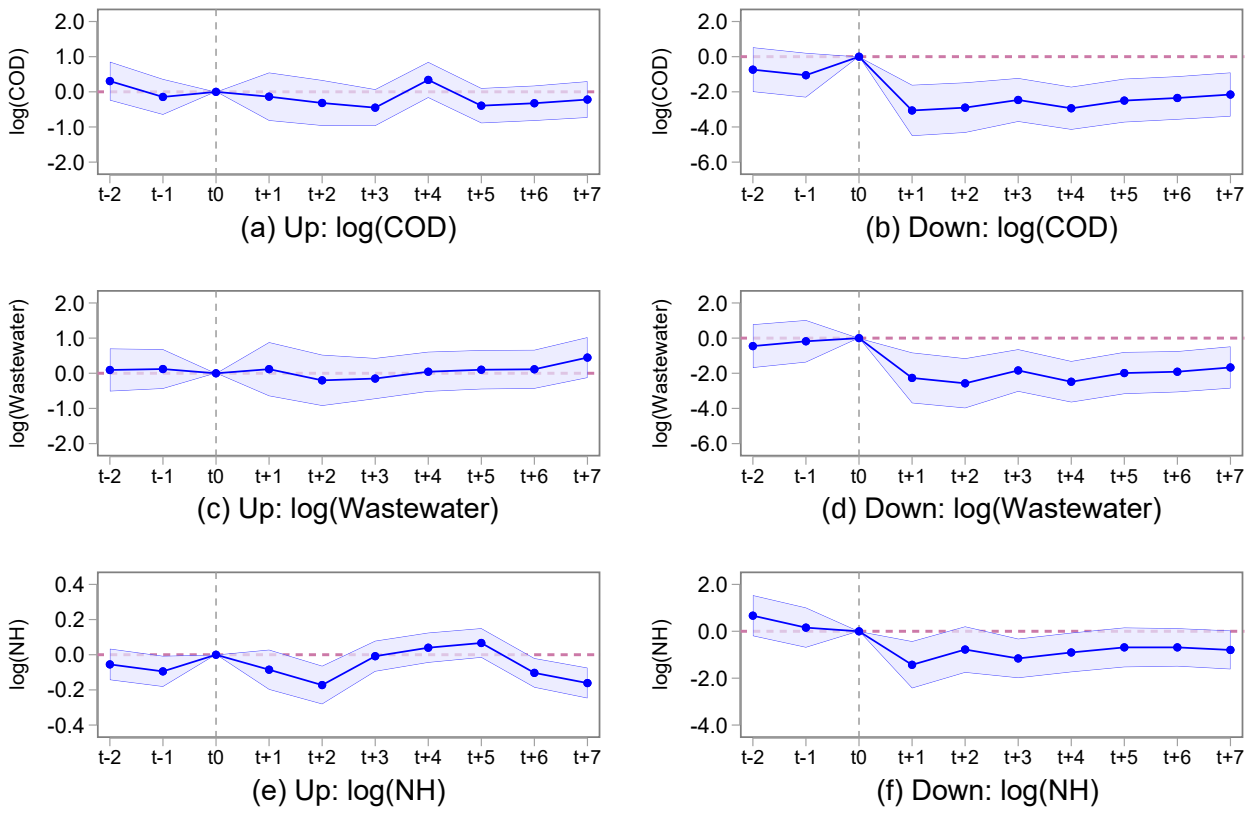


Figure B.3: Parallel Trend: Dynamic Effects of HNTE-env Policy on Firms' Pollution Emissions

Notes: (a) and (b) plot the dynamic effects of HNTE-env policy on upstream and downstream firms' COD discharge, respectively. (c) and (d) plot the dynamic effects of HNTE-env policy on upstream and downstream firms' wastewater discharge, respectively. (e) and (f) plot the dynamic effects of HNTE-env policy on upstream and downstream firms' NH discharge, respectively. All the outcome variables are presented in logarithmic value. In every estimation, firm-level covariates, firm fixed effects, and the interaction of station-year fixed effects are absorbed. Each dot represents the estimated coefficient for the corresponding period, relative to the last year prior to the treatment period ($t0$).

Table B.7: Policy Intensive Effects on Pollution Intensity: Large vs. Small Firms

	Upstream			Downstream		
	COD_int	**Wastewater_int**	**NH_int**	**COD_int**	**Wastewater_int**	**NH_int**
	(1)	**(3)**	**(5)**	**(2)**	**(4)**	**(6)**
$Year2008_t \times Large_i \times HNTEenv_i$						
	-0.056	0.034	-0.005	-0.598**	-0.848*	-0.235***
	(0.125)	(0.177)	(0.025)	(0.290)	(0.458)	(0.065)
$Year2008_t \times HNTEenv_i$						
	0.145	0.129	0.001	-0.084	-0.171	-0.027
	(0.093)	(0.132)	(0.020)	(0.267)	(0.424)	(0.059)
$Year2008_t \times Large_i$						
	0.047	0.036	0.010	0.059	-0.026	0.022**
	(0.032)	(0.045)	(0.007)	(0.040)	(0.063)	(0.011)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
YearStation FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{R}^2$	0.899	0.940	0.750	0.902	0.929	0.770
Observations	7,436	7,681	5,516	4,611	4,744	3,391

Notes: The dependent variables are the emission intensities of COD, industrial effluent, and NH, each measured as total pollutant emissions per unit of output. $Year2008_t$ is an indicator, which equals 1 for the period during 2008-2014, and 0 for the period during 2005-2007. $HNTEenv_i$ equals 1 if a firm is certified as an HNTE both before and after 2008, and 0 if it has never been granted HNTE status during the sample period. The treatment group includes the firms that maintained a stable HNTE status before and after 2008. The only relevant shock affecting them was the introduction of environmental criteria into the HNTE policy. $Large_i$ equals one for large firms with sales above 20 million CNY, and equals zero for small firms with sales below 20 million CNY. Firm controls include firm's age and total assets. Standard errors are reported below the estimates. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

C Full Quantitative Model

To better match the data moments, we incorporate the following elements into the full quantitative model.

1. **The productivity shock.** The TFP evolution follows

$$z_{it} = \rho z_{it-1} + \phi \log\left(d_{it-1}\right) + u_{it}, \tag{C.1}$$

where d_{it-1} is the R&D investment made in the last period; $\rho \in (0,1)$ indicates the persistence of the productivity process; $u_{it} \sim$ i.i.d $N(0,\sigma)$. Thus, the expectation of TFP in the second period becomes $\mathbb{E}\left[\exp\left(z_{it}\right)\right] = \exp\left(\rho z_{it-1} + \frac{\sigma^2}{2}\right) \cdot d_{it-1}^{\phi}$.

2. **The adjustment cost of R&D investment.** We follow the investment literature and model the adjustment cost of R&D investment with a quadratic form that is proportional to revenue π_{i1} and that depends on the parameter b:

$$g\left(d_{it}, \pi_{it}\right) = \frac{b\pi_{it}}{2}\left[\frac{d_{it}}{\pi_{it}}\right]^2. \tag{C.2}$$

Thus, the optimal condition of R&D will incorporate an additional term, $-b\left[\frac{d_{it}}{\pi_{it}}\right]$. Firms are heterogeneous in their R&D efficiency; accordingly the parameter of the adjustment cost function b is assumed to follow a distribution with a mean μ_b and a standard deviation σ_b.

3. **Heterogeneity in abatement fixed cost.** We assume the fixed cost for pollution abatement and HNTE certification could be heterogeneous across firms, and follow a distribution with parameters to be estimated. The heterogeneity in fixed costs helps to improve the model fit on moments about HNTE status and pollution emissions.

4. **Tax structure.** To match the data moments, we assume the tax in the second period has the following structure that mirrors the incentives in the HNTE policy:

$$t_{i2}^{*} = \begin{cases} t_{i2} & \text{if } d_{i1}/\pi_{i1} < \alpha \\ t_{i2} - \delta & \text{if } d_{i1}/\pi_{i1} \geq \alpha \end{cases}, \tag{C.3}$$

where α is the R&D intensity required to obtain the HNTE certification. We follow Chen et al. (2021) and consider the threshold, $\alpha = 3\%$, in later estimation.

In the following subsections, we describe the details of the quantitative model.

C.1 Firms' Decision without HNTE Policy

Given the initial state of productivity z_{i1}, the firm's R&D decision d_{i1} in period 1, the abatement decision ξ_{i2} and the pricing decision p_{i2} in period 2 jointly solve the following optimization problem

$$\mathbb{V}_i(z_{i1}) = \max_{\{d_{i1}, p_{i2}, \xi_{i2}\}} (1-\tau_{i1}) \left[\Pi(z_{i1}) - d_{i1} - g\left(d_{i1}, \pi_{i1}\right)\right] + \beta(1-\tau_{i2})\mathbb{E}\left[\pi(p_{i2}, \xi_{i2}|z_{i2})\right], \quad \text{(C.4)}$$

where $\Pi(z_{i1}) \equiv \max_{\{p_{i1}, \xi_{i1}\}} \pi(p_{i1}, \xi_{i1}|z_{i1}) = \max\left\{\pi^{\mathbf{A}}(z_{i1}), \pi^{\mathbf{N}}(z_{i1})\right\}$ is the profit function after the abatement and pricing decisions in period 1; $\tau_{it} \in (0,1)$ is the corporate tax in period t. From the TFP evolution process (C.1), the productivity in period 2, z_{i2}, depends on the R&D activity in the first period, i.e., $\mathbb{E}\left[\exp\left(z_{i2}\right)\right] = \exp\left(\rho z_{i1} + \frac{\sigma^2}{2}\right) \cdot d_{it-1}^{\phi}$.

Thus, the optimal conditions for the firm's R&D investment decision for firms without/with abatement in the second period are written as

$$-\left[1 + b\frac{d_{it}^{\mathbf{N}}}{\pi_{i1}}\right] + \beta\frac{(1-\tau_{i2})}{(1-\tau_{i1})}\phi\left(\sigma-1\right)\gamma_{i2}\left[\frac{\exp(\rho z_{i1}+\frac{\sigma^2}{2})}{1+f_i\theta}\right]^{(\sigma-1)}\left(d_{i1}^{\mathbf{N}}\right)^{\phi(\sigma-1)-1} = 0, \quad \text{(C.5)}$$

$$-\left[1 + b\frac{d_{i1}^{\mathbf{A}}}{\pi_{i1}}\right] + \beta\frac{(1-\tau_{i2})}{(1-\tau_{i1})}\phi\left(\sigma-1\right)\gamma_{i2}\left[\frac{\exp(\rho z_{it-1}+\frac{\sigma^2}{2})}{1+\mu_i^*}\right]^{(\sigma-1)}\left(d_{i1}^{\mathbf{A}}\right)^{\phi(\sigma-1)-1} = 0, \quad \text{(C.6)}$$

From the above two conditions, we can show that the optimal R&D increases with TFP (or firm size) z_{i1}. Moreover, It declines with the environmental regulation f_i and consequently with μ_i^*. Denote d_{it}^* as the optimal R&D investment without the HNTE policy. Thus, the firms' optimal decision follows the cutoff strategy. If the firm values $\mathbb{V}_i^{\mathbf{A}}(d_{i1}^{\mathbf{A}}, z_{i1}^{**}) > \mathbb{V}_i^{\mathbf{N}}(d_{i1}^{\mathbf{N}}, z_{i1}^{**})$, the firm decides not to abate and chooses the R&D investment that satisfies Equation. (C.5), i.e., $d_{it}^* = d_{it}^{\mathbf{N}}$; otherwise, the firm decides to abate with intensity ξ_i^* given by Equation (A.1), and choose the R&D investment that satisfies Equation. (C.6), i.e., $d_{it}^* = d_{it}^{\mathbf{A}}$.

C.2 Firms' Decision under HNTE Policy

We now discuss the optimal R&D decisions under the HNTE policy after incorporating more necessary elements. If the firm does not apply the HNTE certification, the firm value remains as that in the last subsection. If the firm decides to apply the HNTE certification the firm value becomes:

$$\mathbb{V}_i^{\mathbf{H}}(z_{i1}) = \max_{\{d_{i1}, p_{i2}, \xi_{i2}\}} (1-\tau_{i1}) \left[\Pi(z_{i1}) - d_{i1} - g\left(d_{i1}, \pi_{i1}\right)\right] + \beta(1-\tau_{i2}+\delta)\mathbb{E}\left[\pi(p_{i2}, \xi_{i2}|z_{i2})\right], \quad \text{(C.7)}$$

Analog to analysis for the case without the HNTE policy, the optimal conditions for firms

applying for the HNTE certification without and with abatement are respectively

$$-\left[1+b\frac{d_{it}^{\mathbf{H,N}}}{\pi_{i1}}\right]+\beta\frac{(1-\tau_{i2}+\delta)}{(1-\tau_{i1})}\phi\left(\sigma-1\right)\gamma_{i2}\left[\frac{\exp(\rho z_{i1}+\frac{\sigma^2}{2})}{1+f_i\theta}\right]^{(\sigma-1)}\left(d_{i1}^{\mathbf{H,N}}\right)^{\phi(\sigma-1)-1}=0, \tag{C.8}$$

$$-\left[1+b\frac{d_{i1}^{\mathbf{H,A}}}{\pi_{i1}}\right]+\beta\frac{(1-\tau_{i2}+\delta)}{(1-\tau_{i1})}\phi\left(\sigma-1\right)\gamma_{i2}\left[\frac{\exp(\rho z_{i1}+\frac{\sigma^2}{2})}{1+\mu_i^*}\right]^{(\sigma-1)}\left(d_{i1}^{\mathbf{H,A}}\right)^{\phi(\sigma-1)-1}=0, \tag{C.9}$$

Denote $d_{it}^{\mathbf{H}*}$ as the optimal R&D investment if the firm applies for the HNTE certification. Thus, the tax credit encourages firms to increase R&D investment compared to the case without the HNTE policy. Similarly, the optimal R&D and abatement decision follows a cutoff strategy. In particular, the firms' optimal decision follows the cutoff strategy. If firm values $\mathbb{V}_i^{\mathbf{H,N}}\left(d_{i1}^{\mathbf{H,N}},z_{i1}^{\mathbf{H}**}\right)>\mathbb{V}_i^{\mathbf{H,A}}\left(d_{i1}^{\mathbf{H,N}},z_{i1}^{\mathbf{H}**}\right)$, the firm decides not to abate and choose the R&D investment that satisfies Equation, i.e, $d_{it}^{\mathbf{H}*}=d_{i1}^{\mathbf{H,N}}$. (C.8); otherwise, the firm decides to abate with $\xi_{i2}=\xi_i^*$ given by Equation (A.1), and choose the R&D investment that satisfies Equation (C.9), i.e, $d_{it}^{\mathbf{H}*}=d_{i1}^{\mathbf{H,A}}$.

To make the model better match the data moments, we specify a minimum R&D to sales ratio required for the HNTE certification, denoted by α. Moreover, the application of the HNTE certification needs the payment of a fixed cost, that is assumed to be proportion to the sales in the first period, $\psi\times\Pi_{i1}$. We then calculate the optimal profit of the firm conditioning on bunching at the notch, i.e., $d_{i1}^{\mathbf{B}}=\alpha\Pi_{i1}$.

$$\mathbb{V}_i^{\mathbf{H}}\left(d_{i1}^{\mathbf{B}},z_{i1}\right)=(1-\tau_{i1})\left(1-\alpha-\frac{b\alpha^2}{2}\right)\Pi_{i1}\left(z_{i1}\right)+\beta\left(1-\tau_{i2}+\delta\right)\mathbb{E}\left[\Pi_{i2}\left(z_{i2}^{\mathbf{B}}\right)\right], \tag{C.10}$$

where $\Pi_{it}=\Pi(z_{it})$ represents the profit function after the abatement and pricing decisions in each period, and the productivity in the second period depends on the R&D input at the notch, $d_{i1}^{\mathbf{H,B}}=\alpha\Pi_{i1}$. That is, $z_{i2}^{\mathbf{B}}=\rho z_{i1}+\phi\log(d_{i1}^{\mathbf{B}})+u_{it}$.

Case 1. If $d_{it}^{\mathbf{H}*}$ is no lower than the minimum requirement, i.e., $d_{it}^{\mathbf{H}*}\geq\alpha\Pi_{i1}$, then application and R&D decision is to solve the following discrete choice problem

$$\max\left\{\mathbb{V}_i^{\mathbf{H}}(d_{it}^{\mathbf{H}*},z_{i1})-\psi\Pi_{i1},\mathbb{V}_i(d_{it}^*,z_{i1})\right\}. \tag{C.11}$$

The optimal application decision follows a cutoff strategy. The firm will choose to apply the HNTE certification if the firm values satisfy $\mathbb{V}_i^{\mathbf{H}}(d_{it}^{\mathbf{H}*},z_{i1})-\psi\Pi_{i1}>\mathbb{V}_i(d_{it}^*,z_{i1})$; otherwise, the firm choose not to apply the HNTE certification.

Case 2. If $d_{it}^{\mathbf{H}*}$ is lower than the minimum requirement, i.e., $d_{it}^{\mathbf{H}*}<\alpha\Pi_{i1}$, then application

and R&D decision is to solve the following discrete choice problem

$$\max\left\{\mathbb{V}_i^{\mathbf{H}}(d_{it}^{\mathbf{B}}, z_{i1}) - \psi\Pi_{i1}, \mathbb{V}_i(d_{it}^{*}, z_{i1})\right\}. \tag{C.12}$$

Similarly, firms' optimal application decision follows a cutoff strategy. The firm will bunch at the notch and then apply the HNTE if $\mathbb{V}_i^{\mathbf{H}}(d_{it}^{\mathbf{B}}, z_{i1}) - \psi\Pi_{i1} > \mathbb{V}_i(d_{it}^{*}, z_{i1})$; otherwise, the firm will choose not to apply the HNTE certification.

C.3 Firms' Decision under HNTE-env Policy

Similar to the simple model, we assume that with a positive probability, $\lambda(\xi_{i2})$, they will be punished by the authorities due to more intensive pollution. We further assume that $\lambda'(\xi_{i2}) < 0$. As discussed previously, once the firm is punished due to pollution, it will be revoked the HNTE certificate gained. In this case, they switch back to being a normal firm. We add the subscript **E** to variables corresponding to the HNTE-env policy. The expected value for a downstream firm that applies for the HNTE certification under the HNTE-env policy becomes

$$\mathbb{V}_i^{\mathbf{E}}(z_{i2}) = [1 - \lambda(\xi_{i2})]\,\mathbb{V}_i^{\mathbf{H}}(z_{i2}) + \lambda(\xi_{i2})\,\mathbb{V}_i(z_{i2}), \tag{C.13}$$

where $\widetilde{V}_i$ and V_i satisfy equations (C.7) and (C.4), and represents the firm value for those staying in HNTE status and those switching to be a normal firm, respectively. The expected value $\mathbb{V}_i^{\mathbf{E}}(z_{i2})$ can be further written as

$$\mathbb{V}_i^{\mathbf{E}}(z_{i1}) = \max_{\{d_{i1}, p_{i2}, \xi_{i2}\}} (1-\tau_{i1})\left[\Pi(z_{i1}) - d_{i1} - g(d_{it}, \Pi_{it})\right] + \beta\left\{1 - \tau_{i2} + [1 - \lambda(\xi_{i2})]\delta\right\}\mathbb{E}\left[\pi(p_{i2}, \xi_{i2}|z_{i2})\right]. \tag{C.14}$$

Analog to analysis for the case with the HNTE policy, the optimal conditions for the firm's R&D investment decision for firms without/with abatement in the second period are written as

$$1 + b\frac{d_{it}^{\mathbf{E,N}}}{\pi_{i1}} = \beta\frac{(1-\tau_{i2}+[1-\lambda(0)]\delta)}{(1-\tau_{i1})}\phi(\sigma-1)\gamma_{i2}\left[\frac{\exp(\rho z_{i1}+\frac{\sigma^2}{2})}{1+f_i\theta}\right]^{(\sigma-1)}\left(d_{i1}^{\mathbf{E,N}}\right)^{\phi(\sigma-1)-1}, \tag{C.15}$$

$$1 + b\frac{d_{i1}^{\mathbf{E,A}}}{\pi_{i1}} = \beta\frac{\left(1-\tau_{i2}+\left[1-\lambda\left(\xi_i^E\right)\right]\delta\right)}{(1-\tau_{i1})}\phi(\sigma-1)\gamma_{i2}\left[\frac{\exp(\rho z_{i1}+\frac{\sigma^2}{2})}{1+\mu_i^E}\right]^{(\sigma-1)}\left(d_{i1}^{\mathbf{E,A}}\right)^{\phi(\sigma-1)-1}, \tag{C.16}$$

For the sake of brevity, we use the same notation $d_{it}^{\mathbf{E}*}$ to denote the optimal R&D investment if the firm applies for the HNTE certification under HNTE-env policy. Thus, the tax credit encourages firms to increase R&D investment compared to the case without the HNTE policy. Similarly, the optimal R&D and abatement decision follows a cutoff strategy. If firm values

$\mathbb{V}_i^{\mathbf{E,N}}\left(d_{it}^{\mathbf{E,N}}, z_{i1}\right) > \mathbb{V}_i^{\mathbf{E,A}}\left(d_{it}^{\mathbf{E,A}}, z_{i1}\right)$, the firm decides not to abate and choose the R&D investment that satisfies Equation. (C.15); otherwise, the firm decides to abate with $\xi_{i2} = \xi_i^{\mathbf{E}}$ given by Equation (A.24), and choose the R&D investment that satisfies Equation (C.16).

Under the HNTE-env policy, we can also calculate the optimal profit of the firm conditioning on bunching at the notch, i.e., $d_{i1}^{\mathbf{B}} = \alpha\Pi_{i1}$.

$$\mathbb{V}_i^{\mathbf{H}}\left(d_{i1}^{\mathbf{B}}, z_{i1}\right) = (1-\tau_{i1})\left(1-\alpha-\frac{b\alpha^2}{2}\right)\Pi_{i1}\left(z_{i1}\right) + \beta\left\{1-\tau_{i2}+\left[1-\lambda\left(\xi_{i2}\right)\right]\cdot\delta\right\}\mathbb{E}\left[\Pi_{i2}\left(z_{i2}^{\mathbf{B}}\right)\right], \tag{C.17}$$

Case 1. If $d_{it}^{\mathbf{E}*}$ is not lower than the minimum requirement, i.e., $d_{it}^{\mathbf{E}*} \geq \alpha\Pi_{i1}$, then application and R&D decision is to solve the following discrete choice problem

$$\max\left\{\mathbb{V}_i^{\mathbf{E}}(d_{it}^{\mathbf{E}*}, z_{i1}) - \psi\Pi_{i1}, \mathbb{V}_i(d_{it}^{*}, z_{i1})\right\}. \tag{C.18}$$

The optimal application decision follows a cutoff strategy. The firm will choose to apply the HNTE if the firm values satisfy $\mathbb{V}_i^{\mathbf{E}}(d_{it}^{\mathbf{E}*}, z_{i1}) - \psi\Pi_{i1} > \mathbb{V}_i(d_{it}^{*}, z_{i1})$; otherwise, the firm choose not to apply for the HNTE under the HNTE-env policy.

Case 2. If $d_{it}^{\mathbf{E}*}$ is lower than the minimum requirement, i.e., $d_{it}^{\mathbf{E}*} < \alpha\Pi_{i1}$, then application and R&D decision is to solve the following discrete choice problem

$$\max\left\{\mathbb{V}_i^{\mathbf{E}}(d_{it}^{\mathbf{B}}, z_{i1}) - \psi\Pi_{i1}, \mathbb{V}_i(d_{it}^{*}, z_{i1})\right\}. \tag{C.19}$$

The optimal application decision follows a cutoff strategy. The firm will bunch at the notch and then apply for the HNTE if $\mathbb{V}_i^{\mathbf{E}}(d_{it}^{\mathbf{B}}, z_{i1}) - \psi\Pi_{i1} > \mathbb{V}_i(d_{it}^{*}, z_{i1})$; otherwise, the firm will not apply the HNTE certification under the HNTE-env policy.

D Detailed Procedure of Structural Estimation

In this section, we provide more details on the structural estimation. We first explain how we compute the moments used in our structural estimation. For identification, the sample used for moment construction covers both upstream and downstream firms with R&D activities, that are located 20 kilometers around the water quality monitoring stations. We focus on the period after the HNTE-env reform, which enables us to identify the parameters related to the policy intensity.[37] Due to data quality, the sample period covers from 2011 to 2014.

$\mathbf{m}_0^D$, Firms' R&D and TFP Distribution Moments:

- Histogram of R&D intensity. We first collapse the cleaned data into the bins of R&D intensity with the width 0.1%. For each bin, we compute the count of firms, and then aggregate the bin counts into six categories: the intervals below the application threshold (3%): $[0.3, 1.2]$, $[1.2, 2.1]$, and $[2.1, 3]$,[38] and those above the potential bunch region: $[5, 6.3]$, $[6.3, 7.6]$, and $[7.6, 9]$. The variance-covariance matrix of these and later moments is computed by bootstrapping the counterfactual statistics, based on 5,000 rounds of computation on randomly drawn observations.

- Average R&D intensity over the interval $[3, 5]$. We compute this moment by averaging R&D for firms with R&D intensity falling between 3% and 5%.

- Fraction of HNTE firms. We compute this moment by dividing the number of firms with HNTE status (that successfully applied for the tax credit) by the total number of all observations in the area.

- Average TFP for non-HNTE and HNTE firms. We compute this moment by averaging the firm-level productivity for different types of firms. To make the values comparable, we normalize firms' productivity by the average of the corresponding industry in that area. We essentially follow Chen et al. (2021) to construct the firm-level productivity, $\hat{z}_{it}$.

  The details are described as follows: First, according to our model with constant elasticity demand, firms' value-added can be expressed as

$$\ln y_{it} = \left(\frac{\sigma - 1}{\sigma}\right) \left[\alpha_k \ln k_{it} + (1 - \alpha_k) \ln l_{it} + z_{it}\right], \tag{D.1}$$

[37] Another reason why we do not use the data before 2007 is that the parameter of environmental regulations may be time-variant since China's government gradually tightens related regulations over the years.

[38] We exclude observations that are very close to conducting no R&D, i.e., firms with R&D intensity lower than 0.25%.

where l_{it} and k_{it} represents the capital and labor input respectively. We assume the decision on labor input is static. Thus, the cost minimization for the labor input implies that the ratio of wage payment to value-added should satisfy

$$\ln\left(\frac{wl_{it}}{r_{it}}\right) = \ln\left[(1-\alpha_k)\left(\frac{\sigma-1}{\sigma}\right)\right] + \varepsilon_{it}, \tag{D.2}$$

where $\varepsilon_{it} \sim i.i.d$ with $E[v_{it}] = 0$, which represents measurement error or a transitive shock in factor prices. From Equation (D.2), we can derive a consistent estimate of $(1-\alpha_k)$ for each three-digit manufacturing sector. Lastly, given $\sigma = 5$, the residual measure of log TFP can be computed as follows:

$$\hat{z}_{it} = \frac{\sigma}{\sigma-1}\ln y_{it} - \hat{\alpha}_k \ln k_{it} - (1-\hat{\alpha}_k)\ln l_{it}. \tag{D.3}$$

$\mathbf{m}_0^E$, Firms' Pollution Moments:

- Average COD Emissions. As COD has been widely used as an omnibus indicator for water pollution, we compute moments related to COD emissions for our structural estimation. To make the values comparable, we normalize the firm-level COD emission by its annual output.[39] We then compute these moments by averaging the COD emission for non-HNTE and HNTE firms.

We then describe the detailed procedure of the structural estimation. For a given guess of the structural parameters of the model, Ω, we simulate 30,000 firms that differ in their initial productivity z_{i1}, as well as the distributions of firms' R&D adjustment cost, the application fixed cost and the pollution abatement fixed cost. Next, we solve firms' optimal R&D and abatement decisions conditional on applying for the HNTE or not. In particular, Equations (C.4) to (C.6) determine firms' R&D and abatement decisions conditional on not applying for the tax credit, and Equations (C.14) to (C.16) determine those conditional on applying for the certification. Combining with the optimal profit conditional on bunching at the notch (C.17), firms choose whether to apply for the HNTE certification under the HNTE-env policy based on Equations (C.18) and (C.19). By aggregating the optimal R&D investment and pollution abatement of these 30,000 simulated firms, we then derive R&D and pollution moments discussed above. To improve accuracy, we repeat the above simulation 10 times and compute the average of moments generated by these simulations, denoted by $\mathbf{m}^D(\Omega)$ and $\mathbf{m}^E(\Omega)$. Lastly, we calculate the criterion function as discussed in Section 5.1. The optimal estimate of Ω can be solved by minimizing the criterion function.

[39] We exclude outliers that are very close to non-emission or release extremely high emissions, i.e., those with COD emission per output outside the 5th and 95th percentile.

E Robustness of Structural Estimation

In this section, we conduct some robustness checks for the model specifications or parameter assumptions in the baseline estimations.

Robustness on the penalty function. We first consider the robustness of the formulation of the penalty function. In the baseline estimation, we assume a linear form of the penalty probability function. In reality, the relationship between pollution emission and the penalty probability could be linear, convex, or concave depending on the behavior of the authorities and individual firms. To this end, we consider a flexible form of the penalty function, i.e.,

$$\lambda_i(\xi) = \lambda_i \cdot (1-\xi)^{\kappa}, \tag{E.1}$$

where $\kappa > 0$ measures the convexity of the penalty function. We then jointly estimate the coefficients of the penalty function, λ and η, as well as other parameters in the baseline model. Column (2) of Table E.1 reports parameter estimates and standard errors for our model. It suggests that the estimate of κ is 1.044 and exhibits no statistical difference from one. Column (3) of Table E.2 further compares the simulated moments with the baseline and data. From the table, we do not find a significant improvement in the fit of data moments, despite introducing a more complex form of penalty function. These results suggest that our main estimates are robust to alternative specifications of penalty functions.

Robustness on TFP elasticity. In the baseline estimation, we set the TFP to R&D investment elasticity as $\phi = 0.9$, based on the estimate by Chen et al. (2021). Their result essentially relies on the R&D and TFP moments from both polluting and non-polluting industries and never targets the data moments related to pollution emissions. One may concern that the return on R&D may vary across industries with different polluting intensities. To overcome this issue, in this section, we allow the value of TFP elasticity to be jointly estimated with other parameters in the baseline model.

Column (3) of Table E.1 reports parameter estimates and standard errors for our model. The tables suggest that the estimate of ϕ is pretty close to 0.09 with the standard error 0.001. Moreover, Column (4) of Table E.2 compares the simulated moments with the baseline and data. As predicted, the simulated moments remain similar to those in the baseline model. This exercise suggests that the specification of TFP elasticity does not bias our baseline estimates.

Robustness on upstream penalty parameter. In the baseline estimation, we normalize the penalty parameter λ_u for upstream firms as zero to reduce the complexity of the optimization

process. Now, we let the penalty parameter for upstream firms, λ_u, be jointly determined with other parameters in the baseline estimation.

Column(4) of Table E.1 reports parameter estimates and standard errors for our model. The table suggests that the estimate of λ_u is only 0.001 and does not exhibit significance from zero. In addition, the estimate of λ_d stays in a similar range around 0.40 as that in the baseline estimation. Column(5) of Table E.2 further compares the simulated moments with the baseline and data. We find that the simulated moments present little changes, compared to those in the baseline model. The above results rationalize our baseline specification and again confirm the fact that downstream firms suffer a large likelihood of being punished and revoked the HNTE certification.

Allowing firms' relabeling behavior. Lastly, we explore the robustness of the structural estimation by allowing firms to relabel non-R&D costs as R&D. As modeled in Section 5.1, firms can apply for the HNTE certification only if its reported R&D level higher than the threshold, $\alpha \times \Pi_{i1}$. Thus, the firm with real R&D intensity lower than the threshold has the incentive to misreport their R&D expenditure. We denote a firm's reported level of R&D spending by $d_{i1}^{\mathbf{P}}$, and the real level by $d_{i1}^{\mathbf{K}}$. We assume that firms face an expected misreporting cost, $M\left(d_{i1}^{\mathbf{K}}, d_{i1}^{\mathbf{P}}\right)$.[40] The misreporting cost takes the form as follows:

$$M\left(d_{i1}^{\mathbf{K}}, d_{i1}^{\mathbf{P}}\right) = d_{i1}^{\mathbf{P}} \cdot \tilde{M}'\left(\ell\right), \tag{E.2}$$

which is the product of the reported R&D level, $d_{i1}^{\mathbf{P}}$, and the percentage of misreported level $\ell = \frac{d_{i1}^{\mathbf{P}} - d_{i1}^{\mathbf{K}}}{d_{i1}^{\mathbf{K}}}$; and $\tilde{M}$ satisfies $\tilde{M}(0) = 0$ and $\tilde{M}'(\cdot) \geq 0$. It is easy to verify that the optimal reporting level for firms deciding to relabel, is the threshold level, $d_1^{\mathbf{P}} = \alpha \times \Pi_1$. Conditional on relabeling and bunching at the application threshold, the optimal R&D decisions for non-abating and abating firms solve the following problem:

$$1 + b\frac{d_{it}^{\mathbf{N}}}{\pi_{i1}} - d_{i1}^{\mathbf{P}} \cdot \tilde{M}'\left(\ell^{\mathbf{N}}\right) = \beta \frac{(1-\tau_{i2}+[1-\lambda(0)]\delta)}{(1-\tau_{i1})} \tilde{\phi}\gamma_{i2} \left[\frac{\exp(\rho z_{i1} + \frac{\sigma^2}{2})}{1+f_i\theta}\right]^{(\sigma-1)} \left(d_{i1}^{\mathbf{N}}\right)^{\tilde{\phi}-1}, \tag{E.3}$$

$$1 + b\frac{d_{i1}^{\mathbf{A}}}{\pi_{i1}} - d_{i1}^{\mathbf{P}} \cdot \tilde{M}'\left(\ell^{\mathbf{A}}\right) = \beta \frac{\left(1-\tau_{i2}+\left[1-\lambda\left(\xi_i^E\right)\right]\delta\right)}{(1-\tau_{i1})} \tilde{\phi}\gamma_{i2} \left[\frac{\exp(\rho z_{i1} + \frac{\sigma^2}{2})}{1+\mu_i^E}\right]^{(\sigma-1)} \left(d_{i1}^{\mathbf{A}}\right)^{\tilde{\phi}-1}, \tag{E.4}$$

where, $\tilde{\phi} = \phi\left(\sigma - 1\right)$; $\ell^{\mathbf{N}}$ and $\ell^{\mathbf{A}}$ represent the percentage of misreported R&D level in the case with non-abating and abating decisions. Therefore, we can also calculate the optimal profit of firms with relabeling behavior. Denote $d_{it}^{\mathbf{K},*}$ as firms optimal R&D decision with relabeling be-

[40] The misreporting cost could be understood as the potential loss upon being caught and punished by the tax authority.

havior, and d_{it}^* as that without relabeling. For the firms with $d_{it}^* < \alpha\Pi_{i1}$, the optimal application decision follows a cutoff strategy. The firm will choose to misreport and apply for the HNTE if the firm values satisfy $\mathbb{V}_i^E\left(d_{i1}^{\mathbf{K},*}\right) - \psi\Pi_{i1} - M\left(d_{i1}^{\mathbf{K},*}, \alpha\Pi_{i1}\right) > \mathbb{V}_i\left(d_{i1}^*\right)$; otherwise, these firm does not apply with misreporting the R&D level. The specifications of other options are the same as that in the baseline model.

We follow Chen et al. (2021) and adopt the following form for the relabeling cost: $\frac{\exp\{\eta\cdot\ell\}-1}{\eta}$, where ℓ is the fraction of reported R&D corresponding to relabeling, and η is the shape parameter that we need to estimate.

Column (5) of Table E.1 reports parameter estimates and standard errors for the extended model. It shows the estimate of relabeling cost parameter, η is around 10.013, and that of certification cost increases from 1.31 to 1.54. Despite these, the estimate of other key parameters, including the environment control f_d penalty parameter λ_d, are still statically significant with slightly larger magnitudes compared to those in the baseline estimation. Column (6) of Table E.2 further compares the simulated moments with the baseline and data. The moments implied by the extended model come slightly closer to the data. The average distance between simulated and data moments becomes approximately 14.56%, which is similar to that of the baseline estimation. From the above results, the abstraction from firms' relabeling behaviors does not seriously bias our baseline estimation. In Section F, we further show that the simulation results based on the extended model with relabeling behaviors are close to those in the baseline simulation.

Table E.1: Robustness of Structural Estimates

Parameters	Baseline	Penalty Function	TFP Elasticity	Upstream Parameter	Relabel Behavior
R&D adjust. cost: μ_b	7.410	7.411	7.422	7.410	7.420
	(0.028)	(0.027)	(0.113)	(0.031)	(0.031)
R&D adjust. cost: σ_b	1.827	1.827	1.829	1.827	1.839
	(0.031)	(0.030)	(0.038)	(0.034)	(0.035)
Applicat. fixed cost: μ_ψ	1.313	1.311	1.321	1.312	1.534
	(0.037)	(0.036)	(0.119)	(0.047)	(0.067)
Applicat. fixed cost: μ_ψ	0.358	0.358	0.358	0.358	0.365
	(0.016)	(0.012)	(0.018)	(0.020)	(0.018)
Env. regulation: f_d	0.848	0.851	0.845	0.848	0.884
	(0.032)	(0.034)	(0.035)	(0.035)	(0.034)
Abatement fixed cost: μ_ζ	0.483	0.483	0.486	0.483	0.510
	(0.029)	(0.030)	(0.039)	(0.032)	(0.029)
Penalty para.: λ_d	0.400	0.400	0.400	0.400	0.467
	(0.094)	(0.133)	(0.109)	(0.106)	(0.094)
Penalty fun. coef.: κ		1.044			
		(0.519)			
TFP elasticity: ϕ			0.090		
			(0.003)		
Upstream penalty para.: λ_u				0.010	
				(0.039)	
Relabel cost para.: η					10.065
					(1.678)

Notes: The estimates of other structural parameters are based on calibrated values discussed in Section 5.1. See appendix E for the details of each of these robustness checks.

Table E.2: Simulated vs. Targeted Data Moments
(Robustness Checks)

	Data	Baseline	Penalty Function	TFP Elasticity	Upstream Para.	Relabel Behavior
Upstream Firms						
Below the notch (%): $[0.3, 1.2]$	0.266	0.247	0.247	0.247	0.247	0.250
$[1.2, 2.1]$	0.154	0.203	0.203	0.203	0.203	0.187
$[2.1, 3.0]$	0.131	0.123	0.123	0.123	0.123	0.127
Above the notch (%): $[5.0, 6.3]$	0.092	0.085	0.085	0.085	0.085	0.084
$[6.3, 7.6]$	0.051	0.062	0.062	0.061	0.062	0.061
$[7.6, 9.0]$	0.030	0.045	0.045	0.045	0.045	0.045
Mean R&D intensity $[3.0, 5.0]$	0.039	0.038	0.038	0.038	0.038	0.038
Fraction of HNTE Firms (%)	0.155	0.153	0.153	0.153	0.152	0.151
Average TFP (HNTE Firms)	0.115	0.091	0.091	0.092	0.091	0.094
Average TFP (non-HNTE Firms)	-0.021	-0.023	-0.023	-0.023	-0.023	-0.022
COD Emission (HNTE Firms)	0.087	0.087	0.087	0.087	0.086	0.088
COD Emission (non-HNTE Firms)	0.131	0.142	0.142	0.142	0.142	0.145
Downstream Firms						
Below the notch (%): $[0.3, 1.2]$	0.242	0.247	0.247	0.247	0.247	0.250
$[1.2, 2.1]$	0.175	0.207	0.207	0.207	0.207	0.194
$[2.1, 3.0]$	0.129	0.128	0.127	0.127	0.127	0.131
Above the notch (%): $[5.0, 6.3]$	0.095	0.085	0.085	0.085	0.085	0.084
$[6.3, 7.6]$	0.049	0.060	0.060	0.060	0.060	0.060
$[7.6, 9.0]$	0.030	0.045	0.045	0.044	0.045	0.044
Mean R&D intensity: $[3.0, 5.0]$	0.039	0.038	0.038	0.038	0.038	0.038
Fraction of HNTE Firms (%)	0.140	0.131	0.134	0.131	0.132	0.127
Average TFP (HNTE Firms)	0.117	0.107	0.107	0.107	0.107	0.113
Average TFP (non-HNTE Firms)	-0.019	-0.023	-0.023	-0.023	-0.023	-0.022
COD Emission (HNTE Firms)	0.093	0.099	0.099	0.100	0.099	0.090
COD Emission (non-HNTE Firms)	0.172	0.165	0.165	0.165	0.165	0.163

Notes: This table compares the moments generated by our simulations with those from the data. The details of targeted moments are discussed in Section 5.1. The table shows using the alternative parameter sets shown in Table E.1 does not significantly improve the model fit of the baseline estimation.

F More Simulation Results

Selection effect of environment policies Panels A and B of Figure F.1 graphically present the policy effects of the increase in penalty probability parameter, λ_d, on the average productivity and R&D adjustment cost for HNTE firms. The figure shows that a higher probability of environmental penalty selects firms with higher productivity and lower adjustment costs; whereas a more intensive tax credit on HNTE firms induces the opposite effect. This is because the introduction of environmental criteria depresses the incentive for firms with lower productivity and higher adjustment costs to apply for the tax subsidy. In this sense, the environment penalty could mitigate the resource misallocation to less efficient firms caused by the uniform tax credit.

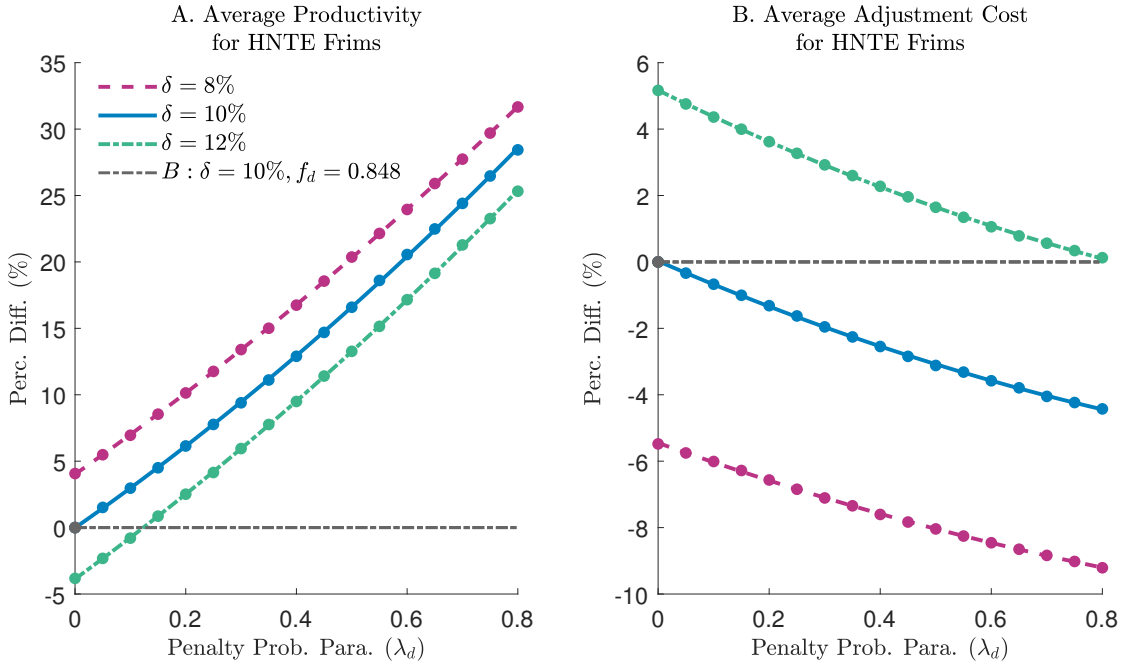


Figure F.1: Simulated counterfactual policies: Selection Effect

Notes: These panels present the policy effects of alternative tax credit and environment penalties on the average productivity and adjustment cost for HNTE firms. The x-axis represents the parameter of the penalty probability function, λ_d, and the y-axis denotes the difference percentage of corresponding variables compared to those in the benchmark case with the penalty probability parameter $\lambda_d = 0$ and the tax credit $\delta = 10\%$. The dots in each panel represent the average change in corresponding statistics, and the polynomial curves are the fitted trends. The red, blue, and green color corresponds to the case with tax credit, 8%, 10%, and 12%, respectively.

Simulating separating environmental regulations Figure F.2 presents the policy effects of implementing different extents of environmental regulations. The benchmark model corresponds to the policy regime with the tax credit with $\delta = 10\%$, zero probability of being revoked from the tax credit ($\lambda_d = 0$), and the baseline level of environmental regulations ($f_d = 0.848$).

The x-axis denotes the parameter of the environmental regulations, f_d. The y-axis denotes the differences in the percentage of corresponding variables for downstream firms compared with those in the benchmark model. The red, blue, and green lines correspond to the cases with tax credits of 8%, 10%, and 12%, respectively. Panels A and B of Figure F.2 present the extensive and intensive effects of tighter environmental regulations. Panel A shows that a larger f_d slightly reduces the fraction of HNTE firms since it narrows the dispersion of firm values for HNTE and non-HNTE firms. Panel B shows that the R&D investment of incumbent HNTE firms decreases with tightening environmental regulations, which results in higher marginal costs and lower marginal returns from conducting R&D.

Simulating economic cost and health benefit Figure F.3 graphically displays the economic cost due to TFP loss and health benefit from the water quality improvement, under different levels of penalty probability parameters, λ_d. The calculation procedure is the same as that in Section 5.3. The x-axis represents the parameter of penalty probability function, λ_d, and the y-axis denotes the net benefit in the billion yuan compared to those in the benchmark case with $\lambda_d = 0$, and tax credit $\delta = 10\%$. The figure suggests the economic cost (blue line) and health benefit (green line) simultaneously increase with the penalty parameter, λ_d. The gap between the two curves measures the net benefit of the environment policy; see more discussion in Section 5.3.

Moreover, Figure F.4 graphically displays the economic loss and health benefit for different levels of parameters of environment regulations, f_d. The x-axis represents the extent of environmental regulations, f_d, and the y-axis denotes net benefit in the billion yuan compared to those in the benchmark case with $\lambda_d = 0$, tax credit $\delta = 10\%$, and the baseline level of environmental regulations $f_d = 0.848$. The simulation results indicate that the economic loss caused by tighter environmental regulations is larger than the health benefits, implying a monotonically negative effect on social welfare; see more discussion in Section 5.3.

Simulating policies with firms' relabeling behavior In this part, we simulate the alternative tax credit and environment penalty for the extended model with firms' relabeling behavior. The model details are described in Section E, and the estimates of parameters are shown in Table E.1. Analog to Section 5.3, we plot the policy effects of introducing different extents of environment penalty to R&D subsidy, as shown in Figure 2. The x-axis denotes the parameter of the punishment function, λ_d. A larger λ_d indicates a higher environmental uncertainty for HNTE appliers. The y-axis represents the difference percentage of corresponding variables for downstream firms compared to those in the benchmark. The red, blue, and green lines correspond to the case with tax credit, 8%, 10%, and 12%, respectively.

Panel A and B of Figure F.5 show the extensive and intensive effect of the R&D policies.

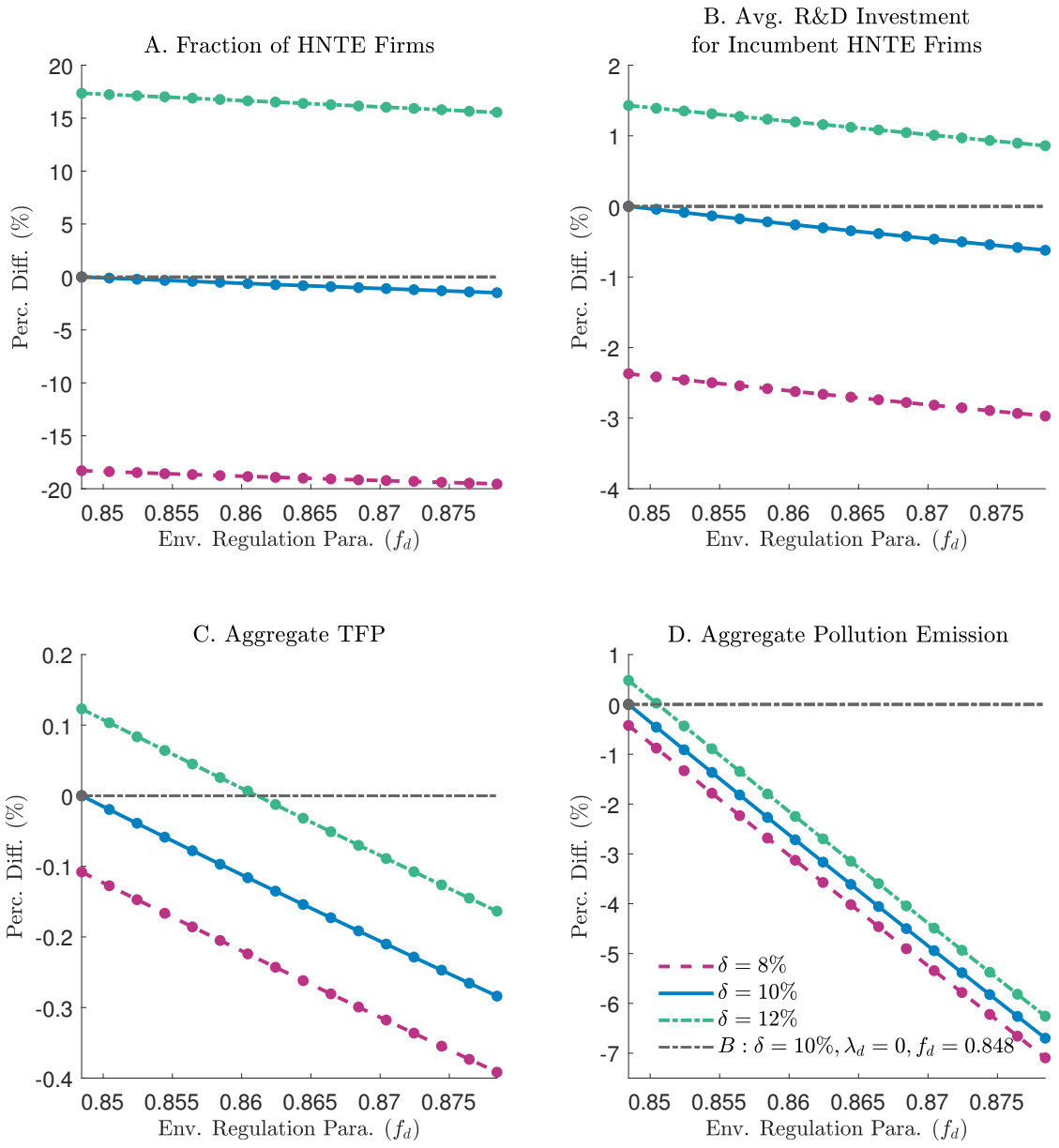


Figure F.2: Simulated counterfactual policies: Alternative environmental regulations

Notes: These panels present the policy effects of alternative tax credits and traditional environmental regulations on aggregate outcomes of interest. The x-axis represents the parameter of the environmental regulations, f_d, and the y-axis denotes the difference percentage of corresponding variables compared to those in the benchmark case with the tax credit $\delta = 10\%$, zero probability of being eliminated from the tax credit ($\lambda_d = 0$), and the baseline level of environment regulations ($f_d = 0.848$). Incumbent HNTE firms refer to those applying for HNTE status in the benchmark case. The dots in each panel represent the average change in corresponding statistics, and the polynomial curves are the fitted trends. The red, blue, and green color corresponds to the case with tax credits, 8%, 10%, and 12%, respectively.

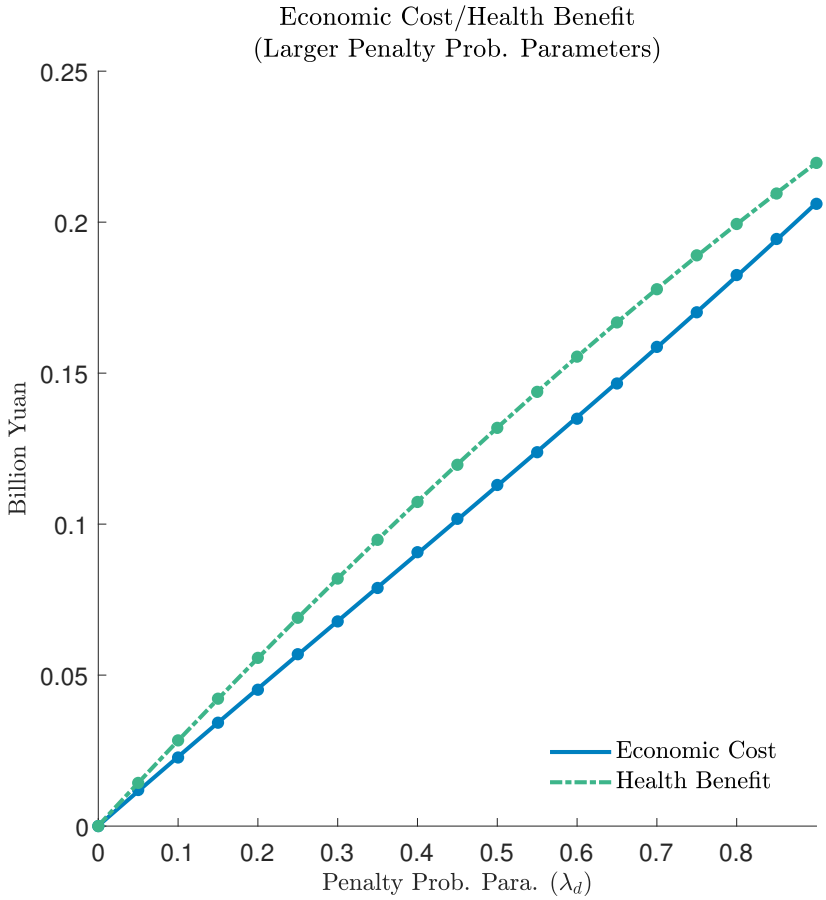


Figure F.3: Simulated Economic Cost and Health Benefit (Larger Penalty Prob. Parameters)

Notes: The figure presents the economic cost due to TFP loss and health benefits from the water quality improvement; See Section 5.3 for the details of the calculation. The x-axis represents the coefficient of penalty probability function, λ_d, and the y-axis denotes net benefit in the billion yuan compared to those in the benchmark case with $\lambda_d = 0$, and tax credit $\delta = 10\%$. The dots in each panel represent the average change in corresponding statistics, and the polynomial curves are the fitted trends.

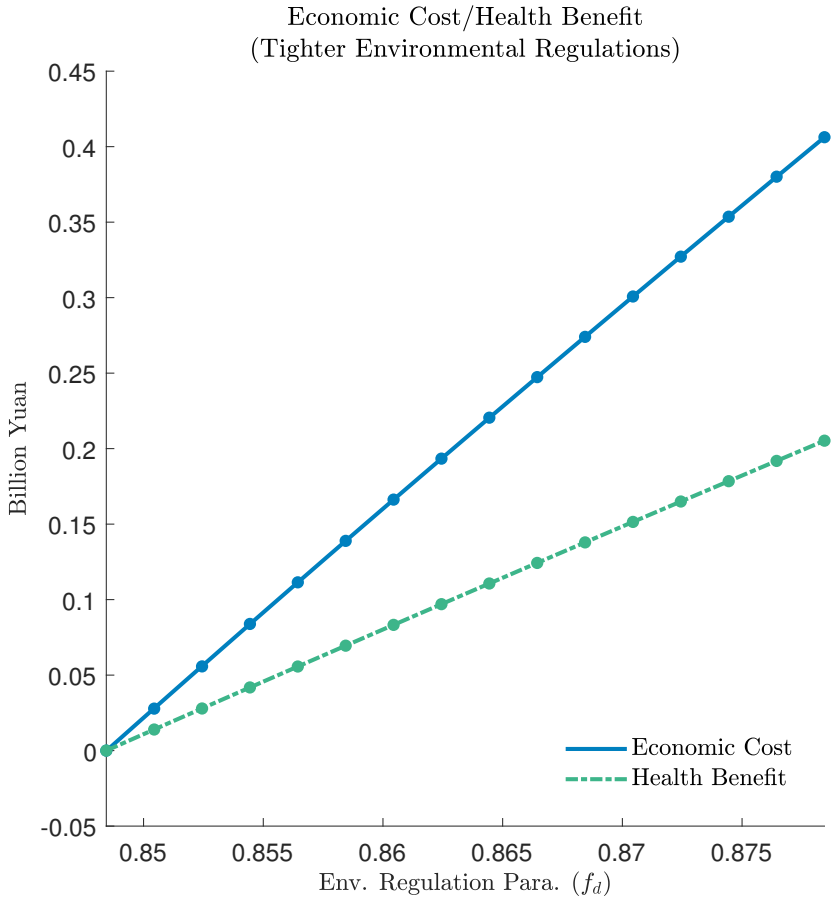


Figure F.4: Simulated Economic Cost and Health Benefit (Tighter Environmental Regulations)

Notes: The figure presents the economic cost due to TFP loss and health benefits from the water quality improvement; See Section 5.3 for the details of the calculation. The x-axis represents the extent of environmental regulations, f_d, and the y-axis denotes the net benefit in the billion yuan compared to those in the benchmark case with $\lambda_d = 0$, tax credit $\delta = 10\%$, and the baseline level of environmental regulations $f_d = 0.848$. The dots in each panel represent the average change in corresponding statistics, and the polynomial curves are the fitted trends.

Panel C and D of Figure F.5 display the aggregate policy implications for productivity growth on aggregate water pollution emission. The figure shows similar patterns as those in the baseline model. Under the estimate based on the extended model with relabeling behavior, relative to the benchmark, the fraction of HNTE firms in the downstream region declines by 12.96%, and the average real R&D investment for incumbent HNTE firms declines by 1.28%. In addition, with firms' relabeling behavior, our simulation suggests that the TFP loss is approximately 0.061% and overall pollution reduction is about 4.06% compared to the benchmark. The magnitudes of these simulated outcomes are close to the baseline estimation. Overall, our simulation results are robust to incorporating firms' relabeling decisions.

Moreover, we further explore the effect of the environmental penalty on firms' misreporting decisions. Panel A and B of Figure F.6 show the policy effect on the fraction of misreporting firms and the average fraction of R&D evasion to real R&D for these misreporting firms. Panel A shows that with the increase in the environment penalty parameter, fewer firms choose to misreport and apply for the HNTE; whereas the tax credit induces the opposite effect. A similar result can be found in Panel B, a higher penalty parameter leads to a lower fraction of R&D evasion. The underlying reason is that potential misreporting firms face a higher probability of being eliminated from the tax credit, and thereby optimally choose not to apply with relabeling R&D expenditure. The above results suggest that in addition to the environmental effect, introducing environmental criteria could alleviate the misallocation of R&D toward firms with relabeling behaviors. In this sense, the environment criteria is an effective complementary to the R&D tax credit.

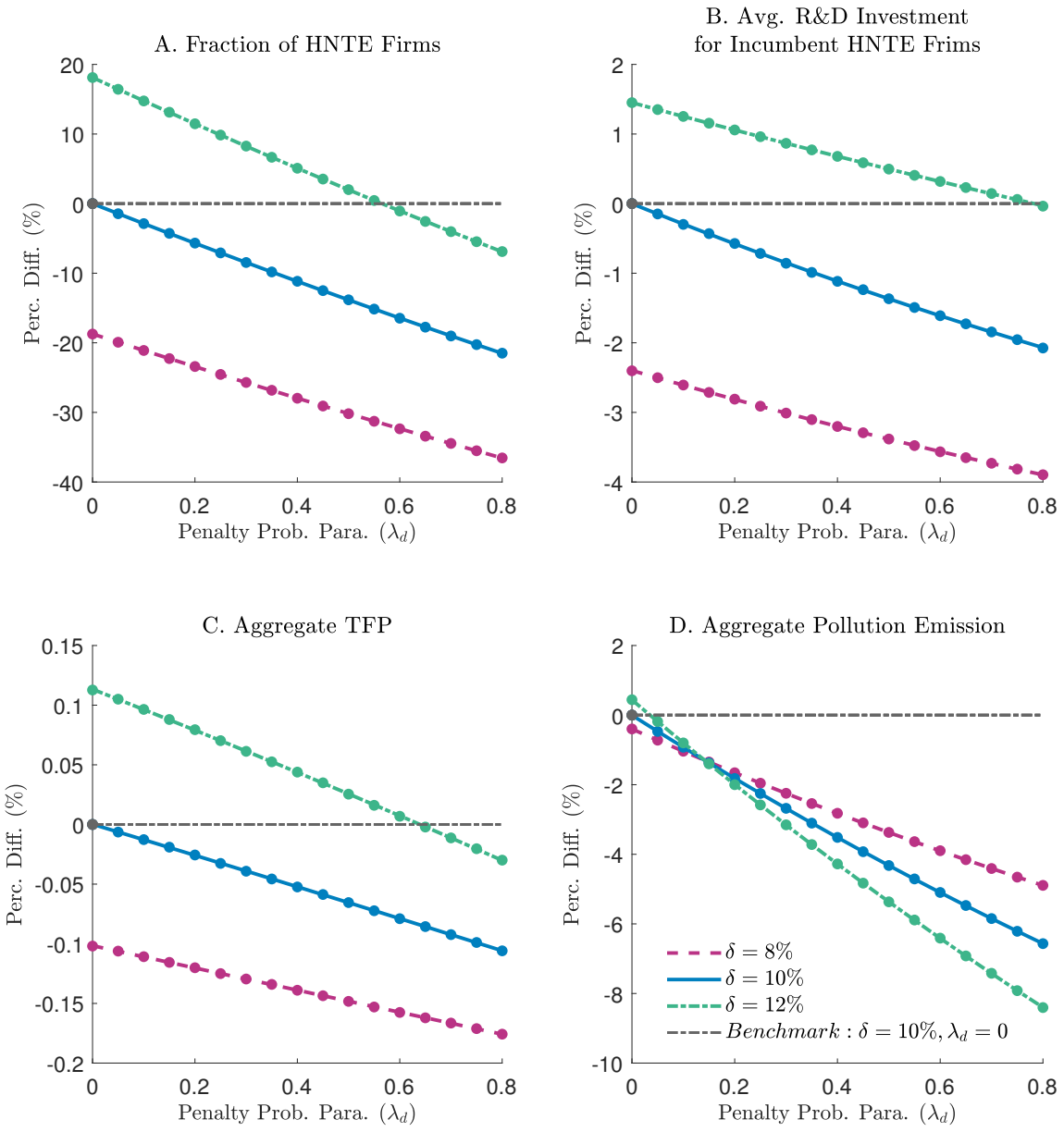


Figure F.5: Simulated counterfactual policies with firms' relabeling behavior

Notes: These panels present the policy effects of alternative tax credit and environment penalties on aggregate outcomes of interest, based on the extended model with firms' relabeling behavior. The x-axis represents the parameter of the penalty probability function, λ_d, and the y-axis denotes the difference percentage of corresponding variables compared to those in the benchmark case with the penalty probability parameter $\lambda_d = 0$ and the tax credit $\delta = 10\%$. Incumbent HNTE firms refer to those choosing to apply for HNTE status in the benchmark case. The dots in each panel represent the average change in corresponding statistics, and the polynomial curves are the fitted trends. The red, blue, and green color corresponds to the case with tax credit, 8%, 10%, and 12%, respectively.

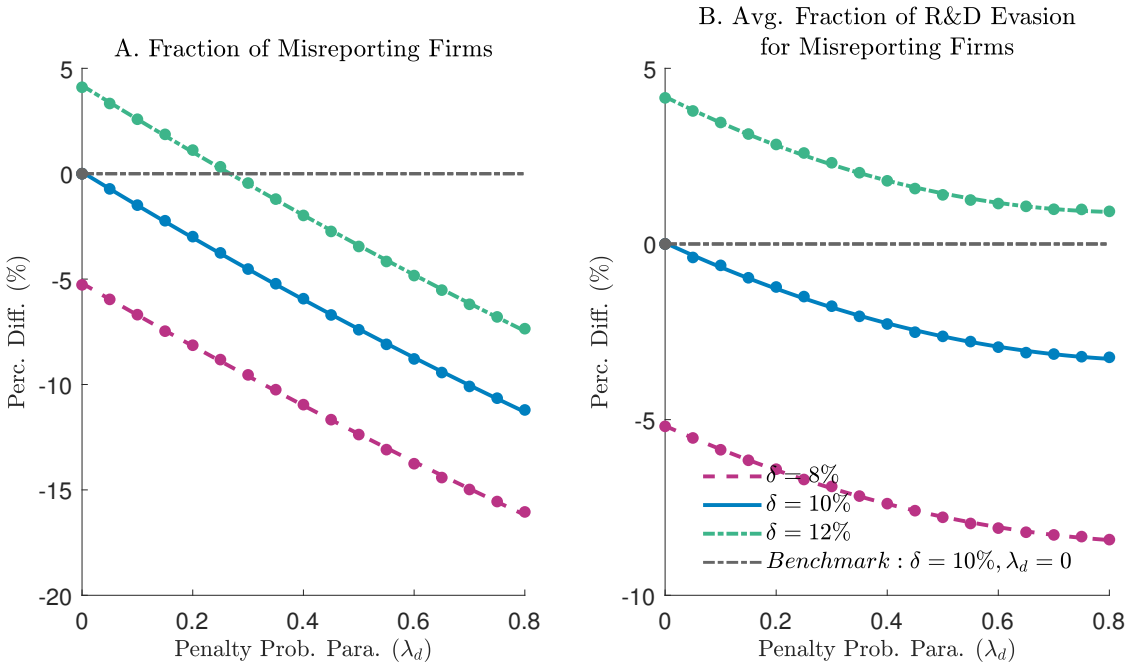


Figure F.6: Simulated counterfactual policies with firms' relabeling behavior

Notes: These panels present the policy effects of alternative tax credit and environment penalties on firms' relabeling decisions. The x-axis represents the parameter of the penalty probability function, λ_d, and the y-axis denotes the difference percentage of corresponding variables compared to those in the benchmark case with the penalty probability parameter $\lambda_d = 0$ and the tax credit $\delta = 10\%$. The dots in each panel represent the average change in corresponding statistics, and the polynomial curves are the fitted trends. The red, blue, and green color corresponds to the case with tax credit, 8%, 10%, and 12%, respectively.

G Details on Externalities and Policy Decomposition

In this section, we extend the illustrative model to examine the aggregate welfare implications of different policies. By incorporating environmental externalities into the model, we aim to analytically discuss whether the EPI scheme serves as a more effective policy tool to address market failures and enhance social welfare.

G.1 Aggregation

Final Goods Sector As discussed in Section 3, individual firms i engage in monopolistic competition and produce (intermediate) goods. We now introduce a final good producer in each region that assembles the output of all firms according to a CES technology,

$$Y_t = \left[\int_i y_{it}^{\frac{\sigma-1}{\sigma}} \mathrm{d}i\right]^{\frac{\sigma}{\sigma-1}}. \tag{G.1}$$

where $\sigma > 1$ is the demand elasticity. The final good producer maximizes $P_t Y_t$ subject to the budget constraint $\int_i p_{it} y_{it} \mathrm{d}i = w_t L_t$, where the aggregate labor L_t supplied by a representative household, and we assume that there is an outside sector that pins down worker wages such that $w_t = 1$. The optimal conditions imply that the demand function of y_{it} is

$$y_{it} = (p_{it})^{-\sigma} B_t, \tag{G.2}$$

where $B_t = L_t P_t^{\sigma-1}$ is the aggregate demand shifter, and P_t is the price index that satisfies

$$P_t^{1-\sigma} = \int_i p_{it}^{1-\sigma} \mathrm{d}i \tag{G.3}$$

The optimal pricing decisions (A.2) and (A.3) imply that aggregate price index is given as follows

$$P_t^{1-\sigma} = \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \int_i \left(\frac{1+\mu_i}{\exp(z_{it})}\right)^{1-\sigma} \mathrm{d}i = \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \frac{1}{Z_t^{1-\sigma}} \tag{G.4}$$

where $\mu_i = f_i\theta$ is the marginal pollution cost for firms without abatement and $\mu_i = \mu_i^* < f_i\theta$ is the marginal pollution cost for those with abatement; firms' optimal abatement decisions are characterized in Appendix A. In addition,

$$Z_t^{\sigma-1} = \int_i \left(\frac{\exp z_{it}}{1+\mu_i}\right)^{\sigma-1} \mathrm{d}i$$

measures aggregate productivity, and is calculated as the integral of firms' log-productivity

divided by their marginal pollution cost. Note that firms' optimal pricing decisions (A.2) and (A.3) indicate that tighter environmental regulations, f_i, raise the marginal cost of producing one unit of output, or equivalently, reduce the marginal return on one unit of input. As a result, individual firms will set a higher price at the optimum. Given a downward-sloping demand curve, firms will reduce the optimal output level. This results in an increase in the aggregate price index P_t, and a decline in the aggregate productivity Z_t.

Substituting (G.2) into the CES production function (G.1), the aggregate output Y_t for the local economy can be expressed as

$$Y_t = \frac{\sigma - 1}{\sigma} L_t Z_t. \tag{G.5}$$

The above equation suggests that the aggregate output Y_t is proportional to the input I_t, and strictly increases with the aggregate productivity Z_t.

Given that the individual firms' emissions e_{it} are proportional to the firm's output, $e_{it} = (1 - \xi_{it})\theta y_{it}$, the aggregate pollution emissions are given by

$$E_t = \int_i e_i \mathrm{d}i = \theta \int_i (1 - \xi_{it}) y_{it} \mathrm{d}i \tag{G.6}$$

Households We consider a representative household that inelastically supplies $L_t = \bar{L}$ units of inputs for the production sector. We assume that the household consumes goods supplied by the final goods producer, and suffers a disutility due to pollution emission from the firm side.[41] Based on the firm optimization problem above, the price of the final good is $P_t = \frac{\sigma}{\sigma-1} Z_t^{-1}$, and the disposable income is $w_t L_t$. Therefore, the level of aggregate consumption is

$$C_t = \frac{w_t L_t}{P_t} = \frac{\sigma - 1}{\sigma} \bar{L} Z_t. \tag{G.7}$$

Further, the household's utility in each period is defined as

$$\mathbf{U}_t(C_t, E_t) = \eta_z Z_t - \eta_e \log E_t \tag{G.8}$$

where $\eta_z = \frac{\sigma-1}{\sigma} \bar{L} > 0$ is a constant depending on labor endowment and demand elasticity; the parameter $\eta_e > 0$ captures the marginal disutility caused by one percent increase in pollution emissions. As the initial productivity distribution in the first period is exogenously given, we can simply focus on the utility value in the second period. In Section 5.3, we employ the share

[41] To sharpen the analysis, we abstract from the consumption of the public goods supplied by the government. Our analysis remains similar if we introduce the public good. In particular, we can assume that the consumer consumes two types of goods, a private good C and a public good G with utility $\mathbf{U}_t = C_t^{1-\gamma} G_t^{\gamma}$. The government purchases the final good and transforms it into public good with a linear technology, and finances government expenditure with a tax on household income. After some algebra, we can show that the household's utility from consumption, $\mathbf{U}_t$, is proportional to LZ_t.

of economic activities in the downstream area compared to the entire country to pin down the relative importance of productivity loss versus environmental benefit.

The above utility function essentially captures the *environmental externality*. That is, when making optimal decisions, the individual firms do not take into account the negative effect of their pollution emissions on the household's utility. This implies that, without environmental regulations ($f_i = 0$) or other incentives, individual firms will emit pollution greater than the socially desirable level. Moreover, from a social perspective, the optimal level of R&D investment may also deviate from the choices made by individual firms. This is because individual firms make their decisions based on their own initial productivity and expected returns, rather than considering their collective effect on aggregate consumption.[42] In the next subsection, we analytically examine how different types of policies amplify or mitigate the externalities at play.

G.2 Policy Decomposition

Based on the above aggregation and the definition of a representative household's utility, we now examine the effects of different policy tools. To sharpen the analysis, we decompose the policy effects using the illustrative model presented in Section 3.

The Impact of HNTE Policies In our model, any firm certified as an HNTE firm can receive a tax reduction denoted by δ. As outlined in Section 3.2, firms' application decisions follow a trigger strategy. In particular, there exists a productivity cutoff $\hat{z}_{i1}^{\mathbf{H}}$, satisfying $\mathbb{V}_i^{\mathbf{H}}(\hat{z}_{i1}^{\mathbf{H}}) - \psi = \mathbb{V}_i(\hat{z}_{i1}^{\mathbf{H}})$, above which the firm chooses to apply for the HNTE certification, pays the fixed application cost ψ and thus enjoys the tax cut. Moreover, under a sufficiently small fixed cost ψ, the cutoff of applying for the HNTE certification $\hat{z}_{i1}^{\mathbf{H}}$ will be lower than the cutoff of abatement $z_{i1}^{\mathbf{H}**}$. Thus, the aggregate policy effect is the sum of the effects on each individual with productivity in different intervals.

Taking the derivative on household utility function in the second period with respect to the tax credit δ, we have

$$\frac{\partial \mathbf{U}_2}{\partial \delta} = \eta_z \frac{\partial Z_2}{\partial \delta} - \eta_e \frac{\partial \log E_2}{\partial \delta} \tag{G.9}$$

The above equation presents a decomposition of the costs and benefits of the HNTE program. To begin with, we examine its effect on aggregate productivity, Z_2. Equation (G.10) indicates that a higher R&D tax credit raises the aggregate productivity through two channels: First, the HNTE policies encourage firms to expand their R&D expenditure, which raises the aggregate productivity Z_2. Recall that $\exp(z_{it})$ follows a process of $z_{it} = \rho z_{it-1} + \phi \log(d_{it-1})$; thus, the

[42] Another pertinent reason, though beyond the scope of this paper, is that individual firms may not consider the spillover effects on the growth of aggregate productivity.

increase in first-period R&D investment enhances the productivity of individual firms. Second, firms that switch to abate ($\frac{\partial z_{i1}^{\mathbf{H}**}}{\partial \delta} < 0$) face a lower pollution cost per unit of output, enabling them to set lower prices and expand production levels.

$$\frac{\partial Z_2}{\partial \delta} = \underbrace{\Delta\hat{\chi}_{\mathbf{H}} \frac{\partial \mathrm{F}(\hat{z}_{i1})}{\partial \delta} + \int_{\hat{z}^{\mathbf{H}}}^{z_{\min}} \left[\left(\frac{\exp z_{it}}{1+\mu_i} \right)^{\sigma-1} \phi \frac{\partial d_{i1}}{\partial \delta} \right] \mathrm{dF}(z_{i1})}_{\text{R\&D Expansion Effect (+)}} + \underbrace{\Delta\chi^{\mathbf{H}**} \frac{\partial \mathrm{F}(z_{i1}^{\mathbf{H}**})}{\partial \delta}}_{\text{Production Distortion Effect (+)}} > 0, \tag{G.10}$$

where $\Delta\hat{\chi}_{\mathbf{H}} = \lim_{\epsilon \to 0^+} \left[\left(\frac{\exp z_{i2}(\hat{z}_{i1}^{\mathbf{H}} - \epsilon)}{1+f_i\theta} \right)^{\sigma-1} - \left(\frac{\exp z_{i2}(\hat{z}_{i1}^{\mathbf{H}} + \epsilon)}{1+f_i\theta} \right)^{\sigma-1} \right] < 0$ represents the productivity gap between non-HNTE and HNTE firms around the application threshold $\hat{z}_{i1}$; $\Delta\chi^{\mathbf{H}**} = \lim_{\epsilon \to 0^+} \left[\left(\frac{\exp z_{i2}(z_{i1}^{\mathbf{H}**} - \epsilon)}{1+f_i\theta} \right)^{\sigma-1} - \left(\frac{\exp z_{i2}(z_{i1}^{\mathbf{H}**} + \epsilon)}{1+\mu_i^*} \right)^{\sigma-1} \right] < 0$ represents the productivity gap between non-abating and abating firms around the abatement threshold $z_{i1}^{\mathbf{H}**}$; $\frac{\partial \mathrm{F}(\hat{z}_{i1}^{\mathbf{E}})}{\partial \delta} < 0$ and $\frac{\partial \mathrm{F}(z_{i1}^{\mathbf{H}**})}{\partial \delta} < 0$ capture the policy effect on the application and abatement threshold, respectively.

Next, we examine the effect of the HNTE policies on aggregate pollution emissions, E_2, as displayed in equation (G.11). On the one hand, as $\frac{\partial z_{i1}^{\mathbf{H}**}}{\partial \delta} > 0$, the HNTE policy induces more firms to adopt abatement and reduces pollution. On the other, the HNTE policy induces more firms to apply for HNTE certification and encourages HNTE firms (regardless of their abatement decisions) to conduct more R&D. This expands their production in the second period, leading to larger pollution emissions. Our quantitative analysis in Section 5.3 suggests that without the environmental criteria ($\lambda_d = 0$), the output expansion effect dominates the effect from an increase in abating firms, leading to a positive impact on aggregate pollution emissions.

$$\frac{\partial E_2}{\partial \delta} = \underbrace{\Delta e^{\mathbf{H}**} \frac{\partial \mathrm{F}(z_{i1}^{\mathbf{H}**})}{\partial \delta}}_{\text{More Abating Firms (-)}} + \underbrace{\Delta\hat{e}_{\mathbf{H}} \frac{\partial \mathrm{F}(\hat{z}_{i1}^{\mathbf{H}})}{\partial \delta} + \theta \int_{\hat{z}_{i1}^{\mathbf{H}}}^{z^{\mathbf{H}**}} \frac{\partial y_{i2}}{\partial \delta} \mathrm{dF}(z_{i1}) + \theta \int_{z^{\mathbf{H}**}}^{z_{\max}} (1-\xi_i^*) \frac{\partial y_{i2}}{\partial \delta} \mathrm{dF}(z_{i1})}_{\text{Output Expansion Effect (+)}} \tag{G.11}$$

where, $\Delta e^{\mathbf{H}**} = \lim_{\epsilon \to 0^+} \left[\theta y_{it}(z^{\mathbf{H}**} - \epsilon) - \theta (1-\xi_i^*) y_{it}(z^{\mathbf{H}**} + \epsilon) \right] > 0$ represents the gap in pollution emissions between non-abating and abating firms around the abatement threshold, $z_{i1}^{\mathbf{H}**}$; $\Delta\hat{e}_{\mathbf{H}} = \theta \lim_{\epsilon \to 0^+} \left[\theta y_{it}(\hat{z}_{i1}^{\mathbf{H}} - \epsilon) - \theta y_{it}(\hat{z}_{i1}^{\mathbf{H}} + \epsilon) \right] < 0$ represents the gap in pollution emissions between non-HNTE and HNTE firms around the application threshold, $\hat{z}_{i1}^{\mathbf{H}}$; $\frac{\partial y_{i2}}{\partial \delta} > 0$ reflects the expansion in output for HNTE firms due to a higher R&D expenditure.

Overall, the welfare effect of the HNTE policy is ambiguous, depending on the trade-off between the above two forces. In particular, though the HNTE policy stimulates R&D activities and boosts aggregate productivity, it also encourages firms to expand their production scale,

irrespective of their abatement decisions. Consequently, the HNTE policy helps address the potential issue of insufficient R&D investment but exacerbates environmental externalities for households. This creates a new trade-off between gains from productivity growth and losses from rising pollution emissions.

The Impact of HNTE-env Policies In our model, the parameter λ measures the extent of environmental penalties as a criterion integrated into the HNTE policy. A higher λ implies that individual firms face a higher probability of being revoked from the R&D tax credit due to environmental penalties. Analogous to the previous analysis, we take the derivative of equation (G.8) with respect to the parameter λ. We then have

$$\frac{\partial \mathbf{U}_2}{\partial \lambda} = \eta_z \frac{\partial Z_2}{\partial \lambda} - \eta_e \frac{\partial \log E_2}{\partial \lambda} \tag{G.12}$$

The above equation provides a welfare accounting of the costs and benefits associated with the EPI scheme. We now analyze each component in detail.

The effect of the EPI scheme on aggregate productivity is ambiguous, as illustrated in equation (G.13). The first term in equation (G.13) presents the R&D reduction effect. In particular, the EPI scheme reduces firms' R&D investment, which adversely affects aggregate productivity Z_2. The second and third terms in equation (G.13) reflect the production distortion effect. On the intensive margin, the environmental criteria encourage high-productivity firms to increase their abatement intensity to avoid losing their tax credits. These firms experience a higher marginal pollution cost per unit of output, i.e., $\frac{\partial(1-\mu^{\mathbf{E}})}{\partial \lambda} < 0$. As a result, they set higher prices and reduce their outputs for the same level of input, further diminishing aggregate productivity Z_2, as reflected in the second term of (G.13). Additionally, on the extensive margin, the EPI scheme has an ambiguous impact on the abatement cutoff $z_{i1}^{\mathbf{E}**}$, as shown in Appendix A.3.

$$\begin{aligned}\frac{\partial Z_2}{\partial \lambda} = & \underbrace{\Delta\hat{\chi}_{\mathbf{E}} \frac{\partial \mathrm{F}(\hat{z}_{i1})}{\partial \lambda} + \int_{\hat{z}^{\mathbf{E}}}^{z_{\min}} \left[\left(\frac{\exp z_{it}}{1+\mu_i} \right)^{\sigma-1} \phi \frac{\partial d_{i1}}{\partial \lambda} \right] \mathrm{dF}(z_{i1})}_{\text{R\&D Reduction Effect (-)}} \\ & \underbrace{\int_{z^{\mathbf{E}**}}^{z_{\max}} \left[\left(\frac{(\exp z_{it})^{\sigma-1}}{(1+\mu_i^{\mathbf{E}})^{\sigma}} \right) \frac{\partial \mu_i^{\mathbf{E}}}{\partial \lambda} \right] \mathrm{dF}(z_{i1})}_{\text{Production Distortion Effect } (z>z^{\mathbf{E}**})(-)} + \underbrace{\Delta\chi^{\mathbf{E}**} \frac{\partial \mathrm{F}(z_{i1}^{\mathbf{E}**})}{\partial \lambda}}_{\text{Production Distortion Effect at } z^{\mathbf{E}**}(?)},\end{aligned} \tag{G.13}$$

where $\Delta\hat{\chi}_{\mathbf{E}} = \lim_{\epsilon \to 0^+} \left[\left(\frac{\exp z_{i2}(\hat{z}_{i1}^{\mathbf{E}} - \epsilon)}{1+f_i\theta} \right)^{\sigma-1} - \left(\frac{\exp z_{i2}(\hat{z}_{i1}^{\mathbf{E}} + \epsilon)}{1+f_i\theta} \right)^{\sigma-1} \right] < 0$ represents the productivity gap between non-HNTE and HNTE firms around the application threshold $\hat{z}_{i1}$; $\Delta\chi^{\mathbf{E}**} =$

$\lim_{\epsilon\to 0^+}\left[\left(\frac{\exp z_{i2}\left(z_{i1}^{\mathbf{E}**}-\epsilon\right)}{1+f_i\theta}\right)^{\sigma-1}-\left(\frac{\exp z_{i2}\left(z_{i1}^{\mathbf{E}**}+\epsilon\right)}{1+\mu_i^{\mathbf{E}}}\right)^{\sigma-1}\right]<0$ represents the productivity gap between non-abating and abating firms around the abatement threshold $z_{i1}^{\mathbf{E}**}$; $\frac{\partial \mathrm{F}(\hat{z}_{i1}^{\mathbf{E}})}{\partial\lambda}<0$ and $\frac{\partial \mathrm{F}(z_{i1}^{\mathbf{E}**})}{\partial\lambda}\lessgtr 0$ capture the policy effect on the application and abatement threshold, respectively.

Next, the effect of the EPI scheme on aggregate pollution can be decomposed into three components. First, the EPI scheme has an ambiguous impact on the abatement cutoff $z_{i1}^{\mathbf{E}**}$, as shown in Appendix A.3. Second, the EPI scheme incentivizes incumbent HNTE firms to choose a higher abatement intensity to avoid being eliminated from HNTE certification, which reduces aggregate emissions. Third, the EPI scheme induces firms to become less likely to apply for the HNTE certification and prompts incumbent HNTE firms to decrease their R&D investment. This dampens firms' productivity and thereby the output level in the second period, resulting in lower aggregate pollution emissions.

$$\begin{aligned}\frac{\partial E_2}{\partial\lambda}=\;&\underbrace{\Delta e^{\mathbf{E}**}\frac{\partial \mathrm{F}(z_{i1}^{\mathbf{E}**})}{\partial\lambda}}_{\text{Num. of Abating Firms }(?)}\quad\underbrace{-\theta\int_{z^{\mathbf{E}**}}^{z_{\max}}\frac{\partial\xi_i^{\mathbf{E}}}{\partial\lambda}y_{i2}\mathrm{dF}(z_{i1})}_{\text{Increase In Abatement Intensity}(-)}\\&\underbrace{+\Delta\hat{e}_{\mathbf{E}}\frac{\partial \mathrm{F}(\hat{z}_{i1})}{\partial\lambda}+\theta\int_{\hat{z}_{i1}^{\mathbf{E}}}^{z^{\mathbf{E}**}}\frac{\partial y_{i2}}{\partial\lambda}\mathrm{dF}(z_{i1})+\theta\int_{z^{\mathbf{E}**}}^{z_{\max}}\left(1-\xi_i^{\mathbf{E}}\right)\frac{\partial y_{i2}}{\partial\lambda}\mathrm{dF}(z_{i1})}_{\text{Output Reduction Effect}(-)}\end{aligned}\tag{G.14}$$

where, $\Delta e^{\mathbf{E}**}=\lim_{\epsilon\to 0}\left[\theta y_{it}(z^{\mathbf{E}**}-\epsilon)-\theta\left(1-\xi_i^{\mathbf{E}}\right)y_{it}(z^{\mathbf{E}**}+\epsilon)\right]>0$ represents the gap in pollution emissions between non-abating and abating firms around the abatement threshold, $z_{i1}^{\mathbf{e}**}$; $\Delta\hat{e}_{\mathbf{E}}=\lim_{\epsilon\to 0}\left[\theta y_{it}(\hat{z}_{i1}^{\mathbf{E}}-\epsilon)-\theta y_{it}(\hat{z}_{i1}^{\mathbf{E}}+\epsilon)\right]<0$ represents the gap in pollution emissions between non-HNTE and HNTE firms around the application threshold, $\hat{z}_{i1}^{\mathbf{E}}$; $\frac{\partial y_{i2}}{\partial\lambda}>0$ reflects the reduction in output for incumbent HNTE firms due to a lower R&D expenditure.

Notably, the EPI scheme serves as a complementary tool for the R&D tax credit by inducing HNTE firms to adopt a higher intensity of pollution abatement. While this policy intervention mitigates the negative environmental externalities associated with industrial pollution emissions, it simultaneously introduces a trade-off by attenuating the fiscal stimulus for R&D activities.

The Impact of Separate Environmental Regulations We now turn to the separate environmental regulation policies, with the extent captured by the parameter f_i in our model. By taking derivative of equation (G.8) regarding the tax credit f_i, we have

$$\frac{\partial\mathbf{U}_2}{\partial f_i}=\eta_z\frac{\partial Z_2}{\partial f_i}-\eta_e\frac{\partial\log E_2}{\partial f_i}\tag{G.15}$$

Similarly, the above equation presents a welfare accounting of the costs and benefits of environmental regulations. We proceed to examine each component in detail and discuss how the separate regulation differs from the EPI scheme. To begin with, tighter environmental regulations affect aggregate productivity through the following channels. The first term in equation (G.16) presents the R&D reduction effect. In particular, tighter environmental regulations depress all firms' R&D investment, thereby reducing aggregate productivity Z_2. The second and third terms in equation (G.16) reflect the production distortion effect. On the extensive margin, tighter environmental regulations induce more firms to adopt abatement. For firms that switch to abate, we can demonstrate that they face lower marginal pollution costs. As a result, they can set a lower price and thereby increase their output given the same level of input. On the intensive margin, tighter environmental regulations directly increase the marginal pollution cost per unit of output, as $\frac{\partial(1-\mu_i)}{\partial f_i} > 0$ holds for all firms. Consequently, environmental regulation policies distort firms' production decisions by forcing them to set higher prices and reduce their optimal output level.

$$\begin{aligned}\frac{\partial Z_2}{\partial f_i} = & \underbrace{\Delta\hat{\chi}_{\mathbf{H}}\frac{\partial \mathrm{F}(\hat{z}_{i1})}{\partial f_i} + \int_{\hat{z}^{\mathbf{H}}}^{z_{\min}}\left[\left(\frac{\exp z_{it}}{1+\mu_i}\right)^{\sigma-1}\phi\frac{\partial d_{i1}}{\partial f_i}\right]\mathrm{d}i}_{\text{R\&D Reduction Effect (-)}} + \underbrace{\Delta\chi^{\mathbf{H}**}\frac{\partial \mathrm{F}(z_{i1}^{\mathbf{H}**})}{\partial f_i}}_{\text{Production Distortion Effect at } z^{\mathbf{H}**}(+)} \\ & \underbrace{+\theta\int_{z_{\min}}^{z^{\mathbf{H}**}}\left[\left(\frac{(\exp z_{it})^{\sigma-1}}{(1+f_i\theta)^{\sigma}}\right)\right]\mathrm{dF}(z_{i1}) + \int_{z^{\mathbf{H}**}}^{z_{\max}}\left[\left(\frac{(\exp z_{it})^{\sigma-1}}{(1+\mu_i^{\mathbf{H}})^{\sigma}}\right)\frac{\partial\mu_i^{\mathbf{H}}}{\partial f_i}\right]\mathrm{dF}(z_{i1})}_{\text{Production Distortion Effect on All Firms }(-)},\end{aligned} \tag{G.16}$$

where $\Delta\hat{\chi}_{\mathbf{H}} = \lim_{\epsilon\to 0}\left[\left(\frac{\exp z_{i2}(\hat{z}_{i1}^{\mathbf{H}}-\epsilon)}{1+f_i\theta}\right)^{\sigma-1} - \left(\frac{\exp z_{i2}(\hat{z}_{i1}^{\mathbf{H}}+\epsilon)}{1+f_i\theta}\right)^{\sigma-1}\right] < 0$ represents the productivity gap between non-HNTE and HNTE firms around the application threshold $\hat{z}_{i1}$; $\Delta\chi^{\mathbf{H}**} = \lim_{\epsilon\to 0}\left[\left(\frac{\exp z_{i2}(z_{i1}^{\mathbf{H}**}-\epsilon)}{1+f_i\theta}\right)^{\sigma-1} - \left(\frac{\exp z_{i2}(z_{i1}^{\mathbf{H}**}+\epsilon)}{1+\mu_i^{H}}\right)^{\sigma-1}\right] < 0$ represents the productivity gap between non-abating and abating firms around the abatement threshold $z_{i1}^{\mathbf{H}**}$; $\frac{\partial \mathrm{F}(\hat{z}_{i1}^{\mathbf{H}})}{\partial f_i} > 0$ and $\frac{\partial \mathrm{F}(z_{i1}^{\mathbf{H}**})}{\partial f_i} < 0$ capture the policy effect on the application and abatement threshold, respectively.

Additionally, the effect of separate environmental regulations on aggregate pollution encompasses the following aspects. The first term in equation (G.17) represents the extensive margin effect. In particular, tighter environmental regulations induce more firms to adopt abatement, as $z_{i1}^{\mathbf{H}}$ decreases with f_i. The second and third terms in equation (G.17) reflect the intensive margin effect. Tighter environmental regulations encourage incumbent abating firms to further increase their abatement intensity, leading to a decline in aggregate emissions. Moreover, tighter environmental regulations lead all firms to reduce R&D investment, lowering their

productivity and, thus, their output in the second period. The decline in output leads to less pollution emissions.

$$\frac{\partial E_2}{\partial f_i} = \underbrace{\Delta e^{\mathbf{H}**}\frac{\partial \mathrm{F}(z_{i1}^{\mathbf{H}**})}{\partial f_i}}_{\text{More Abating Firms (-)}} \quad \underbrace{-\theta\int_{z^{\mathbf{H}**}}^{z_{\max}}\frac{\partial \xi_i^*}{\partial f_i}y_{i2}\mathrm{dF}(z_{i1})}_{\text{Increase In Abatement Intensity}(-)}$$
$$+\underbrace{\Delta\hat{e}_{\mathbf{H}}\frac{\partial \mathrm{F}(\hat{z}_{i1})}{\partial f_i}+\theta\left[\int_{z\min}^{\hat{z}^{\mathbf{H}}}\frac{\partial y_{i2}}{\partial f_i}\mathrm{dF}(z_{i1})+\int_{\hat{z}_{i1}^{\mathbf{H}}}^{z^{\mathbf{H}**}}\frac{\partial y_{i2}}{\partial f_i}\mathrm{dF}(z_{i1})+\int_{z^{\mathbf{H}**}}^{z_{\max}}\left(1-\xi_i^{\mathbf{H}}\right)\frac{\partial y_{i2}}{\partial f_i}\mathrm{dF}(z_{i1})\right]}_{\text{Output Reduction Effect on All Firms}(-)} \tag{G.17}$$

where, $\Delta e^{\mathbf{H}**} = \lim_{\epsilon\to 0}\left[\theta y_{it}(z^{\mathbf{H}**}-\epsilon)-\theta\left(1-\xi_i^{\mathbf{H}}\right)y_{it}(z^{\mathbf{H}**}+\epsilon)\right] > 0$ represents the gap in pollution emissions between non-abating and abating firms around the abatement threshold, $z_{i1}^{\mathbf{H}**}$; $\Delta\hat{e}_{\mathbf{H}} = \lim_{\epsilon\to 0}\left[\theta y_{it}(\hat{z}_{i1}^{\mathbf{H}}-\epsilon)-\theta y_{it}(\hat{z}_{i1}^{\mathbf{H}}+\epsilon)\right] < 0$ represents the gap in pollution emissions between non-HNTE and HNTE firms around the application threshold, $\hat{z}_{i1}^{\mathbf{H}}$; $\frac{\partial y_{i2}}{\partial f_i} < 0$ reflects the reduction in output for HNTE firms due to a lower R&D expenditure and a tighter environmental regulation.

From the above analysis, it is straightforward to see that the separate environmental regulations also mitigate the pollution emissions, albeit at the cost of diminishing R&D investment. By comparing (G.14) and (G.17), we can observe that the separate regulations apply to all firms regardless of their firm size of HNTE status, whereas the EPI scheme specifically targets firms that apply for the tax credit. Thus, the EPI scheme leads to a lower monitoring cost compared to the uniform regulations. Further, a comparison of equations (G.13) and (G.16) reveals that the separate environmental regulations directly distort the production decisions for all firms by raising their marginal cost per unit of output. Consequently, the separate regulations result in a larger productivity loss compared to the EPI scheme. Overall, the EPI scheme is more efficient in curbing pollution emissions while causing a less adverse impact on aggregate productivity. Our numerical simulation in Section 5.5 verifies the above theoretical analysis.