How Transplanted Institutions Diverge: Evidence from a Per-day Penalty Pilot in China*

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Abstract

China has introduced a novel two-stage per-day penalty (PDP) policy to curb environmental violations, piloted in two cities (in 2007 and 2010) before being adopted as national law in 2015. Leveraging this unique pilot, we find that violating firms reduce pollutant emissions in response to escalated PDPs and that their responses vary: Small firms cut production, large firms increase abatement efforts, and multiplant firms shift production to facilities outside the pilot regions. We develop and calibrate a dynamic model with heterogeneous productivity and compliance costs, illustrating that had China adopted the one-stage PDP design as in the United States, compliance rates would have been much higher, albeit with slightly greater output losses.

Keywords: Two-stage per-day penalty; Inspections; Compliance; Institutional transplant

JEL Code: Q52, Q58, L51, D22

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[Laws] should be so specific to the people for whom they are made, that it is a great coincidence if those of one nation can suit another.

—Montesquieu, The Spirit of the Law, 1961

When an orange tree is planted south of the Huai River, it bears oranges, but when planted north of the Huai River, it bears bitter wild oranges (zhǐ).

—Yanzi Chunqiu, Spring and Autumn Period, China

1 Introduction

Institutional transplants across countries are common in the field of environmental protection due to the shared nature of environmental challenges.[1] In practice, however, some institutions succeed, while others fail. To truly understand the reasons for this, we must closely follow their "journey" across different jurisdictions to identify which elements remain core and stable and which are adaptable. Even minor modifications to an institution can drastically alter the incentives faced by regulated entities, leading to diverse economic outcomes. China's adoption of the environmental *per-day penalty* (PDP) policy from the U.S. and other developed economies provides a valuable opportunity to examine how transplanted environmental institutions diverge from their origins and, through a comparative lens, to assess their effectiveness in influencing firms' compliance and environmental and economic performance.

The original U.S. PDP model establishes a strict framework for violations. The Clean Air Act allows the environmental agency to impose a civil penalty of up to $37,500 per day for each violation. Violating firms can be penalized with a substantial fine according to the duration of their wrongful conduct, as each day of illegal emissions shall be treated as one separate wrongdoing.[2]

China started piloting the PDP in two cities, Chongqing (in 2007) and Shenzhen (in 2010), before extending the policy nationwide in 2015. Unlike the original U.S. model, China's penalty adopts a two-stage design. When a violation is detected in a routine inspection (the first stage), a regular one-time penalty is imposed. The government agency then conducts a follow-up second-stage inspection to verify whether the firm has rectified its misconduct. If the violation persists, an escalated penalty is imposed, calculated based on the number of days between the initial and follow-up inspections. In this paper, we refer to China's approach as the *two-stage* PDP, and the original U.S.'s approach as the *one-stage* PDP.[3]

[1] For instance, after the United States introduced the Environmental Impact Assessment through the National Environmental Policy Act in 1969, over 100 countries and regions institutionalized it, making it a standard practice.

[2] See 42 USCS § 6928(g) and 30 USCS § 1268(h). Many other developed countries have similar PDP policies.

[3] While the two-stage PDP specifically targets previous violators, this does not mean that routine inspections cannot prioritize plants with a higher likelihood of violations. Inspectors often assign plant-specific inspection probabilities based on past performance and other observed risk factors. In practice, this targeted inspection strategy can be integrated with the PDP.

To understand how the two-stage PDP operates and differs from the one-stage PDP and the standard *one-shot penalty* inspections, we first develop a simple dynamic model of heterogeneous firms to guide our analysis. The model captures the two-stage structure of China's PDP design and characterizes firms' production and compliance decisions. We show that under the standard one-shot penalty, firms found in violation tend to persist in their noncompliance, even after being fined. In contrast, the two-stage PDP creates stronger incentives for compliance. Under this penalty system and before being inspected, firms behave no differently than they would under a one-shot penalty. However, once the violation is detected, they face an escalated PDP for continued noncompliance, significantly increasing the cost of violations. The model predicts that firms respond differently when faced with the PDP: Large firms adopt abatement technologies and reduce emission intensity. Small firms reduce output to avoid penalties but continue to maintain high pollution intensity. Multiplant firms shift production away from penalized plants to other facilities, avoiding penalties while sustaining high pollution intensity.

To test the predictions above, we use a standard Difference-in-Difference (DID) design to identify the causal effects of the PDP pilot on compliance, pollution and production of firms, by comparing the changes in various outcomes before and after the pilot year across firms located inside and outside the pilot regions. We use firm-level data from the Annual Environmental Survey of Polluting Firms in China, the Annual Survey of Industrial Firms, the penalty data from the Institute of Public and Environmental Affairs, and the business registration data from the State Administration for Industry and Commerce. Our baseline regressions show that after the two-stage PDP is introduced, non-penalized firms continue to behave as they would under one-shot fines, while penalized firms significantly reduce their emissions and pollution intensity. These results are robust to parallel trend tests and other validation checks.

To uncover the underlying heterogeneity, we further divide firms into large, small, and those with affiliates. We find that when faced with the PDPs, large firms not only reduce emissions but also lower pollution intensity by adopting abatement technologies. In contrast, small firms reduce emissions only by cutting output rather than adopting clean technologies. Lastly, firms with affiliates shift production away from the pilot regions to the plants outside the regions to minimize compliance costs. This is reflected in a significant decline in sales and emissions for firms within the pilot regions while their pollution intensity remains largely unchanged. Meanwhile, their affiliates outside the pilot regions show significant increases in sales and emissions, with minimal change in emission intensity.

Thus far, the analysis clearly illustrates that the two-stage PDP impacts only the penalized firms, with varied responses depending on firm size and production network. Meanwhile, as for firms out of the pilot region, though noncompliant, remain unaffected. This raises an important question for policy evaluation: What is the overall impact of the two-stage PDP on compliance, and what about the original one-stage PDP design? To explore this, we extend the benchmark model to account for heterogeneous compliance costs across firms and conduct a quantitative comparative analysis. Regarding total emission reduction, we find that the one-stage PDP is three to five times more effective than the two-stage PDP. This increased effectiveness comes with a modest output loss, ranging from -0.07% to -0.1% under the one-stage PDP compared to a smaller output loss of -0.03% to -0.04% under the two-stage PDP (the range of output losses depends on the policy parameters). From a welfare perspective, unless maintaining output is paramount, the one-stage PDP tends to offer better overall performance. A measure for balancing output and emissions is pollution intensity—that is, the emissions per unit of output. By this metric, the one-stage PDP reduces pollution intensity by 5% to 7%, whereas the two-stage PDP achieves a reduction of less than 1.8%. These findings suggest that the relative effectiveness of each PDP regime depends on the criteria used for evaluation. More broadly, when transplanting institutions from developed countries, it is essential to carefully consider how local modifications alter the incentives these policies create. Such scrutiny ensures that adapted policies remain aligned with local realities and broader development goals.

This paper is organized as follows: The remainder of this section reviews the literature. Section 2 introduces the two-stage PDP pilot in China. Section 3 presents a theoretical model that generates testable predictions. Section 4 describes the data and empirical specifications, and Section 5 presents the empirical findings. Section 6 provides the quantitative analysis, comparing the effects of the two-stage PDP to the one-stage PDP. Finally, Section 7 concludes.

Literature review. This paper contributes to the literature on environmental regulation in developing countries. Compared with that in developed countries, the regulatory capacity in developing countries is often much more constrained (Estache and Wren-Lewis, 2009; He, Wang and Zhang, 2020), making effective monitoring and enforcement critical (Shimshack, 2014; Karplus, Zhang and Almond, 2018; Agarwal, Han, Qin and Zhu, 2023, Rodrigue, Sheng and Tan, 2024).[4] Duflo, Greenstone, Pande and Ryan (2018) examine the impact of random and intensive inspections on plant emissions in India and find that regulator discretion allows for using local information to target the most severe violators. From the perspective of authority shift, Kong and Liu (2024) document an effect of centralizing authority in the appointment of civil servants on the rise of frequency and amount of environmental penalty a firm might face and an improved environmental quality. Complementing their study, we demonstrate the effectiveness of focusing follow-up inspections on firms with past violations. This finding not only aligns with the concept of dynamic enforcement, where regulators adjust inspection frequency and sanction intensity based on firms' past behavior (see, e.g., Harford and Harrington 1991; Helland 1998; Friesen 2003), but also provides new evidence on how different inspection strategies change firms' intention of environmental compliance. After all, rather than simply punishing firms, pushing them to

[4] Even in industrialized economies, regulatory capacity remains a significant challenge (Helland, 1998; Shimshack and Ward, 2005).

correct the misbehavior and deterring them from further violations should be the ultimate goal of legal enforcement.[5] [6]

Our paper also contributes to the literature on pollution leakage effects and negative geographical spillovers. Environmental regulations can lead to unintended increases in emissions elsewhere due to firms' strategic responses, such as production reallocation, plant closures, and new plant establishments (Henderson 1996; List et al. 2003; Dean et al. 2009; Hanna 2010; Cui and Moschini, 2020). Here, we provide new evidence of policy-induced pollution leakage within the ownership networks of regulated firms in the context of localized environmental stringency. An emerging area of literature is exploring the spatial substitution of pollution within an economy. For instance, Gibson (2019) examines how multi-facility firms in the U.S. reallocate pollution across different media and locations in response to PM regulations under the Clean Air Act. Rijal and Khanna (2020) identify significant leakage within multiplant firms linked to high-priority policy violations. Similarly, Cui et al. (2023) assess carbon leakage within firms' ownership networks using data from China's regional emission trading system pilots. Our paper adds to this literature by drawing a panorama depicting varied responses of firms with different size and production networks under stricter environmental regulation: single-plant firms adopt abatement equipment and increase production, while multiplant firms reduce output in regulated plants and shift pollution to less-regulated plants rather than investing in additional abatement measures.

In a broader sense, our paper echoes the insights from the literature on institutional transplants across countries. Berkowitz et al. (2003) emphasize the importance of tailoring transplanted institutions to local environments, arguing that success depends on alignment with local conditions. Djankov et al. (2003) extend this view, showing how institutional fit can affect policy outcomes. The current paper provides a focused analysis of an environmental regulation transplant by comparing the PDP regimes in China and the U.S. along several key dimensions. Importantly, we offer a quantitative comparison, demonstrating how China's modification of the policy may (or may not) better align with its welfare goals.

2 Background and China's per-day penalty policy

Environmental regulation in China at large. In China, pollutant emission standards and the framework for environmental regulation, including fines, are primarily established by national law. While local governments can adjust some aspects of the regulations, such as fine amounts,

[5]Our paper is also related to the discussion on the impact of inspections and monitoring in environmental regulations; see, e.g., Eckert (2004); Keohane, Mansur and Voynov (2009); Hanna and Oliva (2010); Agarwal, Han, Qin and Zhu (2023); Yang, Lin and Peng (Forthcoming). It is also related to that on emissions standards; see, e.g., Li and Lu (2020), and Najjar and Cherniwchan (2021), among others.

[6]In contrast to studies on PDPs in other fields, such as environmental science and management (see, e.g., Bu and Shi 2021), we incorporate a key feature of China's PDP design—the two-stage approach—which significantly changes the incentives for firms.

these must still comply with the national guidelines and cannot contradict national law. As of 2023, China has enacted over 30 national environmental laws and more than 100 administrative regulations related to environmental protection. Enforcement of these regulations, however, is generally managed by environmental bureaus at the city and county levels. The Ministry of Ecology and Environment delegates enforcement tasks to local bureaus, which are responsible for monitoring pollution, conducting inspections, and imposing fines on noncompliant firms. This separation between national-level lawmaking and local-level enforcement encourages local authorities to pursue institutional innovations to address the practical challenges they face.

There are two recurring challenges in local regulatory enforcement. *First*, there is a significant shortage of enforcement staff, which limits the capacity for effective oversight. As a result, the routine inspection rates in China remain very low. While exact numbers are unavailable, a report by the IPE showed that in 2016, local agencies lacked standardized inspection processes and only inspected 35.5% of the violation cases that were "self-reported" by publicly listed manufacturing firms.[7] Given the capacity constraint, local enforcement agencies strive to detect violations more effectively and at the lowest possible cost.

Second, the maximum penalty per violation is often at a very low level relative to the compliance cost. As a result, many firms find it more economical to pay the penalties rather than run their pollution control equipment properly or install clean production technologies. Indeed, the tension between the limited penalties that enforcement agencies can impose and the recurring polluting behaviors of firms over decades eventually prompted a major revision of the National Environmental Protection Law in 2015, which is also the only revision since its adoption in 1979. A key institutional innovation in this revision was the implementation of the two-stage PDP policy, allowing for heavier fines for violations in follow-up inspections. This means fines are now based on the number of days of violations, creating a stronger incentive for compliance.

Pilots of China's PDP policy. The two-stage PDP policy is not an innovation by the national law, rather, the policy was first piloted in two cities: Chongqing (beginning in 2007) and Shenzhen (beginning in 2010). Chongqing is a major industrial hub in southwest China, and Shenzhen is a leading economic and technology center in southern China. The piloted PDP approach was inspired by similar regulatory frameworks in advanced economies, particularly that of the U.S. For instance, the U.S. Clean Air Act empowers agencies to impose administrative fines of up to $\$37,500$ per day for each violation of the act and its associated regulations. This structure en-

[7]The IPE report can be found at `https://wwwen.ipe.org.cn/GreenSecurities/GreenRiskDetail.aspx?id=55`, accessed on December 11, 2023. There is ample anecdotal evidence highlighting the lack of resources in environmental enforcement in China. Take Shanghai, the country's most developed region, as an example. In the Fengxian district, the environmental supervision team consists of only 25 staff members, yet they are responsible for handling over 3,000 environmental complaints annually and monitoring more than 10,000 enterprises. Similarly, in the Baoshan district, just 34 staff members manage over 2,500 environmental complaints each year and conduct inspections for more than 6,000 enterprises. Staff shortages in other regions of China are likely even more severe. In 2017, Chen Jining, then the Minister of Environmental Protection, mentioned in an interview that enforcement teams in many areas of China even faced shortages of essential resources, such as vehicles and uniforms.

sures that the longer a firm engages in wrongful conduct, the larger the cumulative fines, creating a strong incentive for timely compliance.

When Chongqing and Shenzhen introduced the PDP rule, they modified the original model. Their revised approach involved two stages.

- In the first stage, a routine inspection is conducted. If a violation of emission standards is identified, the plant is fined for a one-time infraction (the penalty is one-shot without considering the duration of the violation). Following this, the plant is informed that a follow-up targeted inspection will occur within 30 days, without prior notice.

- In the second stage, if excessive emissions are found again during this follow-up inspection, the plant will be fined for the PDP. This fine is calculated by multiplying the initial one-time fine by the number of days between the two inspections. This second-stage procedure is repeated until the plant complies with the emission standards.

In simple words, in the revised model, the PDP is applied only in the second stage. In the first stage, the plant is subjected to a one-shot penalty rather than a daily fine.[8]

The two-stage PDP policy offers local environmental agencies at least two advantages to address the challenges previously mentioned. First, it enables reinspections to target firms with past violations. Since repeat offenders are more likely to violate again, this targeted approach optimizes the use of limited enforcement resources. More importantly, the revised model imposes much harsher penalties for continuing violations, thereby preserving the strong compliance incentives inherent in the original one-stage PDP structure.

A simple before-and-after comparison shows that the rectification rate for violations significantly improved in both Chongqing and Shenzhen after the implementation of the two-stage PDP pilot. In Chongqing, only 4.8% of violations were rectified after an initial fine before the pilot. This rate increased to 69% in 2010 and further rose to 95.5% by the end of 2014. Similarly, in Shenzhen, the rectification rate following an initial fine increased by 30% from 2009 to 2010.

Despite the anecdotal evidence, a rigorous empirical evaluation is still missing. It remains unclear whether the improved rectification rates are a causal result of the two-stage PDP pilot. If they are, it is important to understand the mechanisms behind these improvements—whether firms adopted cleaner production technologies or simply reduced production, the latter of which could have greater welfare costs. More importantly, the two-stage PDP policy significantly changes the incentives faced by firms compared to the original one-stage PDP. As part of a comprehensive policy evaluation, it is essential to determine whether this modification is more effec-

[8]There are also some subtle differences between the PDP rules in Shenzhen and Chongqing. In Shenzhen, the maximum period between inspections is limited to 30 days, while Chongqing does not explicitly specify such a time restriction. Additionally, the daily fines in Shenzhen are capped at RMB 10,000 per day, whereas in Chongqing, they can range from RMB 10,000 to 100,000 per day.

[8]See the report from Legal Daily at `https://news.sina.com.cn/o/2015-01-13/182831394802.shtml`, accessed on December 12, 2023.

tive in curbing polluting behavior than the original U.S. approach.

3 Model

In this section, we develop a simple dynamic model with firms of heterogeneous productivity to compare the effects of different environmental penalties. To maintain consistency with our empirical tests, here, we primarily look into the regular one-shot penalty and the Chinese two-stage PDP, leaving the extension and comparison with the U.S. one-stage PDP to the quantitative analysis in Section 6.

In addition to the differences in productivity, we also consider two types of firms: those operating only one plant and those operating multiple factories. For demonstration purposes, in the latter category, we focus on firms with two factories, with one plant located in a region under the two-stage PDP and the other representing facilities located outside the pilot region.

Time is discrete and continues forever. Each firm produces a different good and faces a demand represented by a function of constant elasticity:

$$q(p) = p^{-\sigma},$$

with $\sigma > 1$. Each firm is endowed with a productivity $\psi \in (0, \infty)$ and is subject to an exogenous destruction shock, which happens each period with probability $\delta \in (0, 1)$. Here, δ can also be understood as the discount factor. Production requires labor only, and it is also accompanied by pollution. Following Shapiro and Walker (2018), we take pollution as a by-product and assume that output q is produced according to

$$q = e^{\alpha_e}(\psi l)^{\alpha_l}, \tag{1}$$

where $\alpha_e, \alpha_l > 0$ and e and l represent emission and labor, respectively. Thus, production can be equivalently interpreted as using emission and labor as inputs.[9] We allow $\alpha \equiv \alpha_e + \alpha_l < 1$, i.e., decreasing returns to scale. For dual-plant firms, Eq. (1) represents the production function at the plant level. Here, $\alpha < 1$ implies that producing in both factories is more profitable than producing in only one.

Throughout the analysis, we assume that the labor market is completely competitive, with the wage rate normalized to one. In addition, firms need to pay pollution fee $\tau > 0$ per unit of emissions. In the following, we first consider the response of single-plant firms to different penalty policies and then move on to the analysis of dual-plant firms. The proofs are provided in the appendix.

[9]See Shapiro and Walker (2018) for a micro-foundation of this function. Given that firm exit cannot be accurately tracked in the data, we omit modeling firm exit as a reaction to high penalties by removing fixed production costs from our model.

3.1 Single-plant firms: Production, abatement, and penalty

Firms can be penalized if they violate emission standards. To become compliant, firms could resort to an abatement technology at a one-time fixed cost of $f > 0$ as well as a recurring linear flow cost of $a\xi^b e$ each period with $a > 0$ and $b > \max\{1, \frac{\tau}{a}\}$. We shall refer to f as the abatement or compliance cost. The abatement technology reduces emissions by a certain fraction, denoted by ξ. We assume that firms adopting the abatement technology will comply with emission standards and, therefore, are not subject to penalties (see below).[10]

Production with the abatement technology. Suppose a firm has adopted the abatement technology. Then, in each period, it chooses emission reduction ξ together with the labor and emission to maximize flow profits:

$$\max_{e,l\geq 0,\xi\in[0,1]} \left\{pq - l - \tau(1-\xi)e - a\xi^b e\right\}.$$

The first order condition of ξ yields optimal reduction $\xi^* = \left(\frac{\tau}{ab}\right)^{\frac{1}{b-1}} \in (0,1)$. Substituting ξ^* into the objective function, the firm's problem becomes

$$\max_{e,l\geq 0} \left\{\left(e^{\alpha_e}(\psi l)^{\alpha_l}\right)^{\frac{\sigma-1}{\sigma}} - l - \tau\eta e\right\},$$

where $\eta \equiv 1 - \xi^*(1-\frac{1}{b}) \in (1-\xi^*, 1)$ is the effective reduction on emission fees. The first-order conditions with respect to l and e are

$$l = \frac{\sigma-1}{\sigma}\alpha_l pq,$$
$$e = \frac{\sigma-1}{\sigma}\frac{\alpha_e pq}{\eta\tau}.$$

Taking the ratio yields

$$\frac{e}{l} = \frac{\alpha_e}{\alpha_l}\frac{1}{\eta\tau}. \tag{2}$$

Inserting (2) into (1) and using $c(q) = \eta\tau e + l$ gives the cost function of single-plant firms, which depends on productivity ψ and output q:

$$c(q) = \Upsilon\psi^{-\frac{\alpha_l}{\alpha}}(\eta\tau)^{\frac{\alpha_e}{\alpha}}q^{\frac{1}{\alpha}},$$

where $\Upsilon \equiv \alpha\alpha_l^{-\frac{\alpha_l}{\alpha}}\alpha_e^{-\frac{\alpha_e}{\alpha}}$ is a constant. Using $c(q)$ to derive the optimal output and inserting it back into the objective yields the maximized flow profits under *clean* technologies:

$$\pi_c(\psi) = \Lambda\,(\eta)^{-\beta_\tau}\,\psi^{\beta_\psi},$$

[10] In practice, regulatory compliance requires plants to invest in acquiring and maintaining pollution control equipment. While some violations may occur sporadically, most are due to consistent neglect of existing control technologies or a failure to install the necessary equipment to meet regulatory standards (Helland 1998). In the calibration exercise of Section 6, we demonstrate that when firms adopt abatement technologies, their pollutant emissions decrease by 84.51%. See footnote 30.

where $\Lambda \equiv \frac{\sigma(1-\alpha)+\alpha}{\sigma}\left(\frac{\sigma-1}{\sigma}\right)^{\frac{(\sigma-1)\alpha}{\alpha+(1-\alpha)\sigma}}\left(\frac{1}{\alpha_l}\right)^{-\beta_\psi}\left(\frac{\tau}{\alpha_e}\right)^{-\beta_\tau}$, $\beta_\tau \equiv \frac{\alpha_e(\sigma-1)}{\sigma(1-\alpha)+\alpha}$, $\beta_\psi \equiv \frac{\alpha_l(\sigma-1)}{\alpha+(1-\alpha)\sigma}$.

Production without abatement technology. Firms are inspected by environmental authorities with probability λ. Following Fan et al. (2021) and Qi et al. (2021), we assume that if a firm does not adopt the aforementioned abatement technologies, then a proportion κ of its flow revenue will be confiscated for violating the emission standards once the firm is inspected (in an inspection, violations are detected with probability one). Each period, the firm chooses e and l to maximize flow profits:

$$\max_{e,l\geq 0} \; (1-\lambda\kappa)\left(e^{\alpha_e}(\psi l)^{\alpha_l}\right)^{\frac{\sigma-1}{\sigma}} - l - \tau e.$$

A firm utilizing polluting technologies, as opposed to one using clean technologies, incurs a higher effective penalty rate and, consequently, lower expected net revenue. Following the same procedure as above, one can derive the maximized flow profits under *dirty* technologies:

$$\pi_d(\psi, \lambda\kappa) = \Lambda\,(1-\lambda\kappa)^{\beta_\kappa}\,\psi^{\beta_\psi}.$$

where $\beta_\kappa \equiv \frac{\sigma}{\sigma(1-\alpha)+\alpha}$.

One-shot penalties and two-stage PDP. We consider two types of enforcement strategies. A standard one-shot penalty involves firms being subject to random inspections and fined for violations of emission standards. Continue to let $\lambda \in (0,1)$ be the inspection probability. Let $\kappa_0 \in (0,1)$ represent the proportional fine imposed upon detection of noncompliance. We refer to the pair (λ, κ_0) as the *type 0* inspection, which operates independently in each period, irrespective of whether the firm was previously inspected and penalized.[11]

Under the two-stage PDP, all firms initially face a *type 0* inspection. If a firm is found to be in violation, it is fined a proportion κ_0 and is subjected to another follow-up inspection within a month. If the firm still fails to rectify its misconduct during the follow-up inspection, it will be subject to a higher penalty κ_1, where $\kappa_1 > \kappa_0$. We refer to this second inspection and penalty as a *type 1* inspection. The penalty κ_1 is calculated by multiplying κ_0 by the number of days between the two inspections, which is why the penalty is called a *per-day penalty*. Let d be the expected number of days between inspections. Assuming that firms are risk neutral, it is without loss of generality to model PDP as $\kappa_1 = d \times \kappa_0$. The dynamic feature of the two-stage PDP is that if a firm is fined in the follow-up inspection, it will continue to face *type 1* inspections until its noncompliance ceases. Our model captures this essential feature.

[11] In the model, we assume that routine inspections are completely random, with all firms having the same likelihood of being inspected. However, in practice, local environmental agencies are likely to prioritize firms they know are more prone to excessive emissions, making inspection rates nonrandom. This can be modeled by allowing the inspection rate, λ, to vary as a function of firm productivity, ψ. Our conclusion remains unchanged: Under the one-shot penalty (even when inspection rates differ by firm), penalized firms will still continue their polluting behavior. Related discussions can be found in earlier studies, such as those of Landsberger and Meilijson (1982), Peltzman (1976), and Stigler (1971).

Firms' adoption decisions under the one-shot penalty. If a firm adopts pollution abatement technology, it incurs an upfront fixed compliance cost, f, and earns a flow profit of $\pi_c(\psi)$. The present discounted value of these profits is $\frac{\pi_c(\psi)}{\delta} - f$. Conversely, if the firm chooses not to comply and remains a polluter, its discounted profit value becomes $\frac{\pi_d(\psi,\lambda\kappa_0)}{\delta}$. At the margin between compliance and noncompliance, the firm has a productivity level, ψ_a, that satisfies the indifference condition:

$$\frac{\pi_a(\psi_a)}{\delta} - f = \frac{\pi_n(\psi_a, \lambda\kappa_0)}{\delta}, \tag{3}$$

which gives the threshold $\psi_a = \left(\frac{\delta f}{\Lambda(\eta^{-\beta_\tau} - (1-\lambda\kappa_0)^{\beta_\kappa})}\right)^{\frac{1}{\beta_\psi}} > 0$. Firms with $\psi \geq \psi_a$ choose to comply by adopting the abatement technology, while those with $\psi < \psi_a$ remain in violation. We assume that if a firm is indifferent, it will opt for compliance. It is important to note that the compliance decision is not influenced by whether a firm has previously been fined for a violation. Specifically, if a firm has not adopted pollution control technology (i.e., its productivity satisfies $\psi < \psi_a$), it will continue to operate in noncompliance even after an inspection has resulted in a fine.

Proposition 1 *Under the one-shot penalty, even after incurring a fine, a firm chooses to continue noncompliance in subsequent periods.*

Firms' adoption decisions under two-stage PDP. Under the two-stage PDP, a firm is subjected to either a *type 0* or a *type 1* inspection. Let $V_0(\psi)$ be the discounted value of profits when a firm with productivity ψ is under the *type 0* inspection. Let $V_1(\psi)$ be the corresponding value under the *type 1* inspection. Let $a_0(\psi), a_1(\psi) \in \{0, 1\}$ be the firm's compliance decision under *type 0* and *type 1* inspections, where $a(\psi) = 1$ indicates the firm complies with the standard and opts to install the abatement technology and $a(\psi) = 1$ indicates the firm opts for violation.

Under the *type 0* inspection, the cost is f. However, if a firm would like to install the same equipment when facing a *type 1* inspection, the cost becomes higher: $f + f_1$ with $f_1 \in \left(0, \frac{\delta f}{(1-\delta)\lambda}\right)$. The extra cost f_1 represents the higher expenses incurred during *type 1* inspections, where firms must quickly rectify violations by purchasing, installing, and operating abatement equipment within a short time frame (Helland 1998).[12]

A firm that has not previously been fined faces a *type 0* inspection and has a value of $V_0(\psi)$ given by

$$\begin{aligned} V_0(\psi) = \max_{a_0(\psi)\in\{0,1\}} \Big\{ & a_0(\psi) \left(\frac{\pi_c(\psi)}{\delta} - f \right) \\ & + \Big(1 - a_0(\psi)\Big) \Big(\pi_d(\psi, \lambda\kappa_0) + (1-\delta)[\lambda_0 V_1(\psi) + (1-\lambda_0) V_0(\psi)] \Big) \Big\}. \end{aligned}$$

The right-hand side is interpreted as follows: If a firm of ψ adopts the abatement technology

[12] Proposition 1 still holds with the extra cost f_1. Our conclusion for single-plant firms holds if $f_1 = 0$.

($a_0(\psi) = 1$), it pays the one-time fixed cost f and obtains a flow profit of $\pi_c(\psi)$ in the current and all future periods, taking into account the exogenous exit shock that happens with probability δ. If the firm does not adopt the abatement technology ($a_0(\psi) = 0$), it obtains flow profit $\pi_d(\psi, \lambda\kappa_0)$. In the next period, if the firm does not exit, it faces a *type 1* inspection with probability λ, which yields a continuation value of $V_1(\psi)$; otherwise, the continuation value remains $V_0(\psi)$.

The marginal firm that is between adopting or not adopting the abatement technology has a productivity ψ_{a0} that satisfies

$$\frac{\pi_c(\psi_{a0})}{\delta} - f = \pi_d(\psi_{a0}, \lambda\kappa_0) + (1-\delta)\Big(\lambda_0 V_1(\psi_{a0}) + (1-\lambda_0)V_0(\psi_{a0})\Big). \tag{4}$$

When facing *type 1* inspections, a firm's value $V_1(\psi)$ is given by

$$V_1(\psi) = \max_{a_1(\psi)\in\{0,1\}} \Big\{ a_1(\psi)\left(\frac{\pi_c(\psi)}{\delta} - (f + f_1)\right) + (1 - a_1(\psi))\big(\pi_d(\psi, \kappa_1) + (1-\delta)V_1(\psi)\big)\Big\}.$$

Compared to $V_0(\psi)$, the difference is that on the right-hand side, if the firm adopts the abatement technology, it faces higher cost $f + f_1$, and if the firm does not adopt, it receives lower flow profit $\pi_d(\psi, \kappa_1) < \pi_d(\psi, \lambda\kappa_0)$ in the current period and will be under a *type 1* inspection again in the next period. The marginal firm has productivity ψ_{a1}, which satisfies

$$\frac{\pi_c(\psi_{a1})}{\delta} - (f + f_1) = \pi_d(\psi_{a1}, \kappa_1) + (1-\delta)V_1(\psi_{a1}). \tag{5}$$

We derive an equilibrium condition where if $a_0(\psi) = 1$, then $a_1(\psi) = 1$. That is, if a single-plant firm adopts the abatement technology under the *type 0* inspection, it also adopts it under the *type 1* inspection. This result is intuitive because under the *type 1* inspection, the penalties are more severe, assuming the additional cost f_1 is not prohibitively large.

Given that $a_0(\psi) = a_1(\psi) = 1$, we have the following value functions:

$$V_0(\psi) = \frac{\pi_a(\psi)}{\delta} - f, \quad V_1(\psi) = \frac{\pi_a(\psi)}{\delta} - (f + f_1).$$

Inserting these expressions into Eq. (4), we derive the threshold for adopting the abatement technology under *type 0* inspection:

$$\psi_{a0} = \left(\frac{\delta f - \lambda f_1(1-\delta)}{\Lambda(\eta^{-\beta_\tau} - (1-\lambda\kappa_0)^{\beta_\kappa})}\right)^{\frac{1}{\beta_\psi}}.$$

Comparing this threshold (ψ_{a0}) to the compliance threshold (ψ_a) under the one-shot penalty, we observe that the range $[\psi_{a0}, \psi_a)$ exists only when $f_1 > 0$. Under the two-stage PDP, firms within this range choose to install abatement technologies regardless of whether they have been penalized. Firms outside this range behave in the same manner as they would under the one-shot penalty regime.

Proposition 2 *Under the two-stage PDP, firms subject to type 0 inspection exhibit identical compliance* *behavior to those under the one-shot penalty, except for firms with $\psi \in [\psi_{a0}, \psi_a)$.*

Firms with $\psi \in [\psi_{a0}, \psi_a)$ opt for violation under one-shot fines but switch to compliance under the two-stage PDP. However, considering the following empirical analysis, this range is likely to be small (and shrinks as f_1 decreases). Therefore, the two-stage PDP is expected to have a minimal impact on firms' ex ante compliance decisions—those made prior to the detection of violations.

We now turn to firms' compliance decisions after being penalized. To derive ψ_{a1}, inserting $V_1(\psi) = \frac{\pi_a(\psi)}{\delta} - (f + f_1)$ into Eq. (5) gives $\psi_{a1} = \left(\frac{\delta(f+f_1)}{\Lambda(\eta^{-\beta\tau} - (1-\kappa_1)^{\beta\kappa})}\right)^{\frac{1}{\beta_\psi}}$. To guarantee $\psi_{a1} < \psi_{a0}$, we require that f_1 not be too large.[13] Therefore, firms with $\psi \in [\psi_{a1}, \psi_{a0})$ that have been cited for violations transition to compliance in the next period by adopting abatement technology. Firms with lower productivity levels, $\psi \in (0, \psi_{a1})$, reduce both their output and emissions in response to the increased penalties they face.

Proposition 3 *Under the two-stage PDP, a penalized firm will reduce its emissions in the next period, either by lowering output or by adopting abatement technologies. Specifically, firms with $\psi \in [\psi_{a1}, \psi_{a0})$ adopt abatement technologies to reduce emissions, while firms with $\psi \in (0, \psi_{a1})$ reduce output.*

3.2 Dual-plant firms: Abatement and production relocation

To simplify the scenario where firms can relocate production across multiple factories to manage varying environmental penalties, we consider a firm with two plants, denoted as A and B. Both plants produce the same goods, which the firm sells at a uniform price given by $p = Q^{-\frac{1}{\sigma}}$, where Q represents the firm's total output. Although the two plants have identical productivity, they may employ different emission technologies, leading to the distinct effective emission fees τ_A and τ_B. Additionally, since the plants are located in different regions, they may be subject to different regulatory regimes, resulting in varying expected penalties, $\lambda_A\kappa_A$ and $\lambda_B\kappa_B$. As a first step for the analysis that follows, we first examine the optimal production decisions for a firm operating two plants.

The optimal production of a dual-plant firm. Each plant of the firm has a cost function that can be derived similarly to that in the single-plant case:

$$c(q_i, \tau_i) = \Upsilon \psi^{-\frac{\alpha_l}{\alpha}} \tau_i^{\frac{\alpha_e}{\alpha}} q_i^{\frac{1}{\alpha}},\ i \in \{A, B\}.$$

Then, the firm's problem is to choose a production plan for each plant:

$$\max_{q_A, q_B \geq 0} \left(q_A + q_B\right)^{-\frac{1}{\sigma}} \Big((1 - \lambda_A\kappa_A)\, q_A + (1 - \lambda_B\kappa_B)\, q_B \Big) - c(q_A, \tau_A) - c(q_B, \tau_B).$$

[13] In particular, $f_1 < \bar{f}_1$ with $\bar{f}_1 \equiv \frac{\delta f\left((1-\lambda\kappa_0)^{\beta\kappa} - (1-\kappa_1)^{\beta\kappa}\right)}{(\eta^{-\beta\tau} - (1-\lambda\kappa_0)^{\beta\kappa})\delta + \lambda(1-\delta)(\eta^{-\beta\tau} - (1-\kappa_1)^{\beta\kappa})}$. Note that $\bar{f}_1 < \frac{\delta f}{(1-\delta)\lambda}$.

Upon deriving the first-order conditions for q_A and q_B, taking the ratio, and defining the output ratio of plant A over plant B by $\gamma \equiv \frac{q_A}{q_B}$, we have

$$\frac{(\sigma + \sigma\gamma - \gamma)\frac{1-\lambda_A\kappa_A}{1-\lambda_B\kappa_B} - 1}{(\sigma + \sigma\gamma - 1) - \frac{1-\lambda_A\kappa_A}{1-\lambda_B\kappa_B}\gamma} = \left(\frac{\tau_A}{\tau_B}\right)^{\frac{\alpha_e}{\alpha}} \gamma^{\frac{1-\alpha}{\alpha}}. \tag{6}$$

A dual-plant firm optimally relocates production between plants based on differences in emission fees and penalties. For example, less production will be allocated to plant A when it faces higher expected penalty $\lambda_A\kappa_A$ or higher proportion emission fee τ_A. Moreover, the extent to which relocation is optimal is determined by α. As $\alpha \to 1$, relocation would be extreme—as long as $\lambda\kappa$ and(or) τ are different between the two plants, meaning one produces everything and the other shuts down. We obtain the following observation:

Lemma 1 *In the neighborhood of $\frac{1-\lambda_A\kappa_A}{1-\lambda_B\kappa_B} = \frac{\tau_A}{\tau_B} = 1$, the output ratio γ is strictly increasing in $\frac{1-\lambda_A\kappa_A}{1-\lambda_B\kappa_B}$ and strictly decreasing in $\frac{\tau_A}{\tau_B}$.*

Abatement and production reallocation between plants. Now, let's be more specific and suppose that plant A is located in a region subject to the two-stage PDP, whereas plant B is located in another region subject to the one-shot penalty. Throughout the analysis, we assume that plant B always produces using dirty technologies.[14] We focus on the firm's decision to adopt the abatement technology in plant A or not.

Let $\Pi(\psi, \lambda_A\kappa_A, \lambda_B\kappa_B, \tau_A, \tau_B)$ be the maximized profit of a dual-plant firm.[15] There are three scenarios where the firm obtains different flow profits. In one scenario, both plants are subject to a *type 0* inspection, and the flow profits of the firm are given by

$$\Pi_d(\psi, \lambda\kappa_0) \equiv \Pi(\psi, \lambda\kappa_0, \lambda\kappa_0, \tau, \tau).$$

In this case, the plants are symmetric, and $q_A = q_B$. In another scenario, plant A is subject to a *type 1* inspection, while plant B is (always) subject to a *type 0* inspection. Then, the flow profits are given by

$$\Pi_d(\psi, \kappa_1) \equiv \Pi(\psi, \kappa_1, \lambda\kappa_0, \tau, \tau).$$

In this case, the firm will reallocate more production to plant B. Finally, suppose plant A has adopted the abatement technology. Then, the firm's flow profits are given by

$$\Pi_c(\psi) \equiv \Pi(\psi, 0, \lambda\kappa_0, \eta\tau, \tau).$$

[14] To guarantee this result, we only need to assume that plant B's cost of abatement technology adoption is relatively higher.

[15] Solving q_A and q_B based on first-order conditions from the dual-plant firm's profit maximization and inserting them into the objective yields the maximized profits of a dual-plant firm, denoted by $\Pi(\cdot)$: $\Pi(\psi, \lambda_A\kappa_A, \lambda_B\kappa_B, \tau_A, \tau_B) = \Lambda_1(1+\gamma)^{\frac{-1}{\alpha+(1-\alpha)\sigma}}\left[\gamma(1-\lambda_A\kappa_A) + (1-\lambda_B\kappa_B)\right]^{\beta_\kappa}\left[(\gamma^{\frac{1}{\alpha}}\tau_A^{\frac{\alpha_e}{\alpha}} + \tau_B^{\frac{\alpha_e}{\alpha}})^{\frac{\alpha}{\alpha_e}}\right]^{-\beta_\tau}\psi^{\beta_\psi}$, where $\Lambda_1 = \frac{\sigma(1-\alpha)+\alpha}{\alpha(\sigma-1)}(\frac{\sigma-1}{\sigma})^{\frac{(\sigma-1)\alpha}{\alpha+(1-\alpha)\sigma}}(\frac{1}{\alpha_l})^{-\beta_\psi}(\frac{1}{\alpha_e})^{-\beta_\tau}$.

In this case, more production will be allocated to plant A since it faces no penalty.

Let $\tilde{\psi}_{a0}$ denote the threshold productivity level above which a dual-plant firm opts to adopt the abatement technology at plant A when facing a *type 0* inspection. Consider the adoption decision under the *type 1* inspection and suppose

$$\delta(f + \underline{f_1}) > \Pi_c(\tilde{\psi}_{a0}) - \Pi_d(\tilde{\psi}_{a0}, \kappa_1),$$

where the left-hand side is the cost of upgrading technologies and the right-hand side is the benefit of doing so. Then, under the *type 1* inspection, i.e., after being punished, a dual-plant firm is more profitable by reallocating production from plant A to B than by adopting the abatement technology for plant A. Intuitively, if the critical firm of $\tilde{\psi}_{a0}$ will not adopt the abatement technology under the *type 1* inspection, then none of the firms with $\psi < \tilde{\psi}_{a0}$ will adopt it. Therefore, the above condition sets a lower bound for f_1, and we denote it by $\underline{f_1}$, which is smaller than $\bar{f}_1$ in some parameter space (see the proof in Appendix A.2). Moreover, based on Proposition 2, if $f_1 < \bar{f}_1$, then there exists a range of single-plant firms that choose to adopt the abatement technology after being penalized in the first-stage inspection. Assuming $f_1 \in (\underline{f_1}, \bar{f}_1)$, we obtain the following result:

Proposition 4 *Suppose $f_1 \in [\underline{f_1}, \bar{f}_1]$ with $\bar{f}_1 > \underline{f_1} > 0$. Consider a dual-plant firm where plant A is subject to the two-stage PDP regime and plant B is subject to a one-shot penalty regime. In response to a penalty under the two-stage PDP, the noncompliant dual-plant firms opt to shift production from plant A to plant B rather than investing in abatement technologies at plant A.*

3.3 Predictions

Now, we will summarize the model's prediction to guide the empirical test that follows. Thus far, the analysis highlights that the impact of the two-stage PDP varies across single-plant and dual-plant firms. Under the two-stage PDP, single-plant firms behave the same as they would under the one-shot penalty unless they are found in violation. However, once penalized, they face escalating per-day fines, which forces them to take action to reduce emissions. Depending on their productivity, firms will either adopt pollution control technologies or scale back production to comply with the regulations. To connect to the following empirical analysis, we refer to firms with productivity lower than ψ_{a1} as *small* firms and those with productivity between ψ_{a1} and ψ_{a0} as large firms. Based on Propositions 1 to 3, we have the following prediction:

Prediction 1 *Under the one-shot penalty, firms do not alter their compliance status even after being penalized. Under the two-stage PDP, once penalized, single-plant firms reduce emissions as follows:*

(1) Large firms reduce both emissions and emission intensity by adopting abatement technologies while increasing output.

(2) *Small firms reduce emissions only by cutting output, with emission intensity remaining largely unchanged (when α is close to one).*

For dual-plant firms, resource reallocation across regions is feasible. If one plant is subject to the PDP, the firm can choose to reallocate production to the other plant that is not subjected to the PDP. Based on Proposition 4, we obtain the following prediction:

Prediction 2 *Consider a dual-plant firm where plant A is subject to the two-stage per-day penalty (PDP) and has already been penalized while plant B operates under a one-shot penalty regime. The dual-plant firm will reallocate production from plant A to plant B. Specifically:*

(1) *Plant A experiences a reduction in output and emissions, while plant B experiences an increase in both.*

(2) *The pollution intensity at both plants remains unchanged.*

4 Data and empirical specifications

We now turn to the empirical analysis, using the Chinese regional two-stage PDP pilot as a policy shock to test Predictions 1 and 2. This section outlines the data sources and the empirical setups, and the next section reports the results.

4.1 Data and key outcome variables

Data source. Our data is drawn from multiple sources. First, the firms' pollution information comes from the Annual Environmental Survey of Polluting Firms in China. This is the most comprehensive firm-level pollution dataset, offering detailed information on firm-level emissions (e.g., chemical oxygen demand [COD], nitrogen oxides, sulfur dioxide [SO_2], ammonia, dust, solid waste, and noise), abatement efforts (e.g., sewage treatment facilities or air scrubbers), and energy consumption (e.g., fresh water, recycled water, and coal).

Second, variables on firms' economic activities are obtained from the Annual Survey of Industrial Firms, maintained by the National Bureau of Statistics of China. This unbalanced panel dataset provides detailed firm-level information, including basic firm variables (e.g., name, address, industry, and products), annual sales, and variables in financial statements (e.g., balance sheet, income statement, and cash flow statement).

Third, data collected by the Institute of Public and Environmental Affairs provides comprehensive records from 2004 onward on environmental penalties imposed on firms for illegal polluting activities. It includes the nature of the violations, types of penalties, and amounts of monetary fines.

Finally, the business registration data from the State Administration for Industry and Commerce (SAIC) is used to identify firms and their affiliated firms. This dataset contains the firm name, identification number, registration date, registered capital, and legal representative. Notably, it records the shareholder structure of companies. We use this information to map the ownership between firms.

The regression dataset. We construct our regression dataset via a series of steps. To start, we generate a comprehensive nationwide dataset of manufacturing firms by merging the aforementioned datasets, using the firm name as the identifier. This merged dataset provides detailed information on both firms' polluting behaviors and their economic activities. Next, we identify whether a firm is capable of relocating production across regions. To do so, we follow the approach of Chen et al. (2021), utilizing the SAIC dataset to link each firm (referred to as the "current firm") with three types of affiliates: (1) subsidiaries owned by the current firm, (2) firms with a shareholder relationship to the current firm (considering up to two levels of shareholder linkage with an ownership threshold of 25%), and (3) parent firms, where the current firm is a wholly-owned subsidiary of the parent company. In the regression analysis, we treat all affiliated firms (subsidiaries, shareholder-linked firms, and parent firms) as "plants" within a multiplant firm.[16]

For the benchmark regression analysis, we define the treatment group as firms located in Shenzhen (starting in 2010) and Chongqing (starting in 2007), with firms located in geographically adjacent cities forming the control group.[17] Our primary dataset of empirical study consists of $3,883$ firms. Of these, 313 firms have affiliates outside the regions; thus, they have the potential to shift production across regions. These firms are classified as multiplant firms (corresponding to dual-plant firms in the model).[18] The remaining $3,570$ firms have no affiliates and are classified as single-plant firms.

We further divide single-plant firms into large and small firms based on their sales in the baseline year. For firms in Chongqing and its neighboring cities, the baseline year is 2007, while for firms in Shenzhen and neighboring cities, it is 2010. We calculate the median sales for all firms in the baseline year. Firms with sales above the median are classified as large and those below as

[16]Treating affiliates as plants captures the essence of multiplant behavior, where firms reallocate production or emissions across their network in response to regulatory changes. While it is true that these affiliates may operate independently or engage in different production processes, this approach is consistent with the standard practice in the literature on firm networks and environmental regulations (see, e.g., Chen et al. 2021; Cui et al. 2023). Given the data limitations and the absence of more granular information on the degree of operational integration or industry differences between affiliates, this assumption represents the best feasible approximation. To ensure robustness, we conduct sensitivity analyses based on ownership thresholds, confirming that our results remain consistent under alternative specifications.

[17]The control group consists of firms located in the following cities: Guangzhou, Zhuhai, Foshan, Shanwei, and Huizhou in Guangdong Province; Neijiang, Ziyang, Luzhou, Yibin, Guang'an, Suining, Nanchong, and Dazhou in Sichuan Province; Zunyi and Tongren in Guizhou Province; Xiangxi Tujia and Miao Autonomous Prefecture and Enshi Tujia and Miao Autonomous Prefecture; and Ankang in Shaanxi Province. These cities were selected due to their proximity to the pilot cities, which allows them to serve as an appropriate control group.

[18]Most multiplant firms operate more than two plants. For example, 158 multiplant firms are located in Chongqing and Shenzhen, collectively operating 1,004 affiliates in other regions.

small. Using this method, we classify 1,724 single-plant firms as large and 1,846 as small.

Key outcome variables. Of particular importance to the empirical analysis are the variables related to firm production, pollutant emissions, and abatement effort. We use the amount of COD and SO_2 to measure firms' annual emissions (in kilograms). These two variables capture the most common water and air pollutants found in firms' emissions data.

Firm output is measured by firm-level annual sales (in RMB 10,000). We divide the emissions of COD and SO_2 by the firm's annual sales, which gives two intensity variables denoted by $intensity^{COD}$ and $intensity^{SO_2}$.

For abatement efforts, we consider the number of treatment facilities operated by firms, including wastewater and waste gas treatment facilities, denoted as $facility^w$ and $facility^g$, respectively. Additionally, we measure the treatment capacities of these facilities: $ability^w$ indicates the capacity for wastewater treatment (in tons per day), and $ability^g$ represents the capacity for gas treatment (in cubic meters per day). Table 2 reports the summary statistics for these variables.

4.2 The regression specifications

We employ a standard difference-in-difference (DID) approach and specify the empirical model as follows:

$$y_{it} = \beta_1 PDP_{ct} + \beta_2 PDP_{ct} \times Punish_{it} + \beta_3 Punish_{it} + X'_{it}\gamma + \theta_t + \mu_i + \epsilon_{it}, \quad (7)$$

where y_{it} represents a set of outcome variables introduced above, including emissions, pollution intensity, adoption of abatement facilities, treatment capacity, and sales of firm i in city c in year t.[19] PDP_{ct} is a dummy variable equal to 1 if the two-stage PDP is in effect in city c from that year onward and 0 otherwise; specifically, $PDP_{ct} = 1$ for Chongqing after 2007 and for Shenzhen after 2010.$Punish_{it}$ is a dummy variable that equals 1 if firm i has been penalized by the local environmental agency in the current year or any prior year since 2004; otherwise, it equals 0. The interaction term $PDP_{ct} \times Punish_{it}$ captures whether penalized firms are subject to the two-stage PDP in year t. Next, X_{it} is a set of time-varying firm-level control variables; θ_t represents year-fixed effects, which account for time-varying factors, such as changes in other government policies, that may influence both the treatment and control groups; μ_i is the firm-fixed effects; and ϵ_{it} is the error term.

Our main parameter of interest in Eq. (7) is β_2, which estimates the impact of the two-stage PDP pilot on firm production and pollution outcomes. For example, if y represents firms' annual

[19] In our regressions, we use the natural logarithm for the following five outcome variables: COD, SO_2, $sales$, $ability^w$, and $ability^g$. The proportions of 0 values for COD, SO_2, $sales$, $ability^w$, and $ability^g$ are 2.68%, 4.03%, 0.01%, 2.44%, and 2.30%, respectively. Given the small proportion of zero values, we exclude those values from the regressions. Additionally, we conduct Poisson regressions to account for these zero values, and the results remain robust. The Poisson regression results are available upon request.

emissions of a pollutant, a significantly negative β_2 would indicate that the PDP pilot incentivizes firms to reduce emissions. Furthermore, to examine how firms with different levels of productivity reduce emissions, as outlined in Prediction 1, we estimate Eq. (7) separately for large and small firms.

To assess whether multiplant firms would relocate production to the plants that are not exposed to the PDP pilot (see Prediction 2), we use the sample of the firms located in Chongqing, Shenzhen, and their neighboring cities that have at least one affiliate outside these regions. In the language of the model, these firms are plant As, which are potentially subjected to the PDP pilot. We run regressions based on Eq. (7) on this sample to assess whether these plant As reduce production and emissions and whether they improve pollution intensity after being penalized under the two-stage PDP, as outlined in Prediction 2.

We also examine whether the affiliates located outside Chongqing and Shenzhen (referred to as plant B in the model) increase their output and emissions when their in-the-pilot-region counterpart, namely plant A, is penalized under the PDP pilot. To do this, we create a sample of plant Bs and then assess how these plants respond regarding production, emissions, and abatement efforts when their corresponding plant As are penalized. The regression specification is as follows:

$$y_{it}^{B} = \tilde{\beta}_1 PDP_{ct}^{A} + \tilde{\beta}_2 PDP_{ct}^{A} \times Punish_{it}^{A} + \tilde{\beta}_3 Punish_{it}^{A} + X_{it}^{B\prime}\tilde{\gamma} + \theta_t^{B} + \mu_i^{B} + \epsilon_{it}^{B}, \tag{8}$$

where the outcome variables (y_{it}^{B}) and control variables (X_{it}^{B}) pertain to plant B and the shock is whether plant A (the firm's corresponding affiliate in Chongqing and Shenzhen) is penalized under the PDP pilot.

5 Empirical results

We first present the results on the average effects of the PDP pilot (Section 5.1). We then proceed with a detailed analysis of firms' responses based on their size and whether they operate single or multiple plants (Sections 5.2 and 5.3).

5.1 The average effect of per-day penalty

Baseline result. Table 3 presents the baseline estimates of Eq. (7) for all firms in our sample. All regressions include year- and firm-fixed effects, and we additionally control for the interaction between year dummies and each firm's sales in the year 2004 to account for the initial differences in firm size.

In columns (1) and (2), the dependent variables are the total amounts of log COD and log SO_2, respectively. The estimates for β_2 are both negative and statistically significant at the 1% level, indicating that the two-stage PDP significantly reduces firms' emissions once a violation has been detected. Specifically, the escalated per-day fines under the two-stage regime lead to a reduction of 62.8% in *COD* emissions and 29.6% in SO_2 emissions. The coefficients for *Punish* are insignificant, suggesting that firms subjected to standard one-shot penalties do not reduce emissions, even after being punished. Similarly, the coefficients for *PDP* are insignificant, indicating that firms subject to the two-stage PDP but not penalized produce the same emissions that they would under the one-shot penalty.

Columns (3) and (4) show that firms subjected to the two-stage PDP significantly reduce their pollution intensities after inspection, suggesting that they are more likely to adopt cleaner technologies. This contrasts with firms under the one-shot penalty, where the coefficients for *Punish* remain insignificant, indicating that these firms are likely to continue using dirty technologies. Similarly, the coefficients for *PDP* are insignificant, illustrating that firms not penalized under the two-stage PDP do not alter their pollution intensity. Overall, these findings suggest that firms penalized under the two-stage PDP are more likely to reduce both emissions and emission intensity, consistent with Prediction 1.

In terms of output, column (5) indicates that the two-stage PDP has no significant effect on annual sales, whether the firm is being penalized or not. However, as we will see below, this result obscures the heterogeneous responses of firms of different sizes.

Mechanisms: Improved abatement capacities. To better understand how emission reductions are achieved, we estimate Eq. (7) using the total number of abatement facilities installed as the dependent variable. Our dataset provides detailed information on the types of abatement facilities, enabling us to distinguish between those used for water and air pollution. The interaction term coefficients in columns (6) and (7) of Table 3 show that penalized firms under the PDP pilot are more likely to install additional treatment facilities. This is further supported by the results in columns (8) and (9), where the dependent variables are the firm's daily treatment capacities for wastewater and waste gas. The significant positive coefficient on $PDP \times Punish$ indicates that penalized firms under the PDP pilot expand their capacity to treat pollutants.

Parallel trend test. A key assumption for DID identification is that firms in the treatment and control groups share common pre-pilot trends. This ensures that any differences in outcome changes over time are solely attributable to the pilot. To rule out preexisting differential trends, we modify Eq. (7) by replacing the interaction term between *Punish* and *PDP* with interactions between *Punish* and year dummies and plot the yearly estimates in Figures 1 and 2. Figure 1 presents four panels with the dependent variables of $\log COD$, $\log SO_2$, $intensity^{COD}$, and $intensity^{SO_2}$. Similarly, Figure 2 shows the results for $facilities^w$, $facilities^g$, $\log ability^w$, and $\log ability^g$. In each figure, the estimated coefficients are statistically insignificant in the pretreatment period, followed by a sharp, permanent increase after the pilot begins. These results suggest that there are no preexisting differential trends between the treatment and control groups, supporting the validity of the DID approach in identifying the effects of the PDP pilot.

Other robustness checks. To further address the concern that omitted differential trends correlated with the pilot regions might bias our estimates, we conduct a placebo test by treating firms in cities adjacent to Shenzhen and Chongqing as the false treatment group, with firms in cities adjacent to these areas serving as the control group (excluding Shenzhen and Chongqing). The rationale behind this approach is that regions sharing common borders should have sufficient similarity in terms of economic conditions. The insignificant estimates of β_2 in Table 4 indicate that our results are unlikely to be driven by other confounding factors.

Another robustness check we conduct uses firms in Ningxia as the treatment group and those in neighboring cities of Ningxia as the control group.[20] Ningxia is a provincial-level autonomous region located in western China. Although Ningxia planned to implement the two-stage PDP pilot—its legal provision was included in the amendment to the Regulation on Environmental Protection of Ningxia Hui Autonomous Region—the policy has never actually been implemented.[21]This unique situation provides an opportunity to evaluate whether the anticipation of the policy, rather than its actual implementation, could have influenced firm behavior. As shown in Table 5, the results indicate that the coefficients of the key policy-related variables are not statistically significant. This suggests that our baseline results are not driven by the potential anticipation effect, further reinforcing the robustness of our findings.[22]

5.2 The differing effects of per-day penalty on large and small firms

Based on our model, the PDP pilot should have introduced differing incentives for firms of different sizes, even though the overall effect on emissions would have been similar. For this analysis, we focus on firms without affiliates and examine how the baseline results differ between large and small firms.

In Table 6, the coefficients of the interaction term are consistently negative and statistically significant in columns (1) to (4), indicating that large firms exposed to the policy significantly reduce their emissions and pollution intensity compared to those not exposed. This is further supported by the increase in sales (column 5) and enhanced capabilities in pollution abatement facilities (columns 6 to 9). These findings align with the model's prediction that when faced with

[20]The neighboring cities we use include Yanan, Yulin, Baiyin, Qingyang, Pingliang, Alxa League, and Bayannur.

[21]Although the Regulation on Environmental Protection of Ningxia Hui Autonomous Region (amended in 2009) included provisions for a PDP, stipulating that violators who fail to rectify their illegal emissions could be fined daily, the policy was not effectively implemented. Ningxia issued its first PDP fine only in 2015 (i.e., after the PDP policy was implemented nationally), with a daily fine of RMB 18,900 imposed on Brother Caixing Chemical for 10 days of excessive emissions.

[22]Due to limited data on wastewater treatment facilities and their abatement capacity after 2010, we have restricted our analysis to wastewater and its treatment facilities for the Ningxia region placebo test.

the PDP, larger firms tend to invest in abatement technologies to meet compliance standards rather than reduce production.

In contrast, as our model predicts, small firms, which often cannot afford the high costs of pollution abatement, tend to comply by reducing output to avoid overly heavy penalties that will be imposed after reinspections. This is supported by the significantly negative coefficients of the interaction term in columns (1), (2), and (5) of Table 7.[23] Furthermore, the insignificant coefficients of the interaction term in columns (3), (4) and (6) through (9) suggest that small firms are generally reluctant to adopt abatement technologies to reduce pollution intensity.

5.3 Production shifts within multiplant firms

Our model predicts that firms with affiliates will shift production from plants subject to the PDP (located within the pilot regions) to those that are not (outside the pilot regions). In line with the model's notation, we refer to the former as Plant *As* and the latter as Plant *Bs*. To comprehensively assess this production shift, we first analyze the responses of Plant *As*, followed by those of Plant *Bs*.

Responses of the plants that are subjected to PDP (plant *As*). We begin by analyzing the sample of multiplant firms located in Chongqing, Shenzhen, and neighboring cities. We estimate Eq. (7) for nine outcome variables of the plant *As*; the results are presented in Table 8. In columns (1) and (2), the significantly negative coefficients on the interaction term $PDP \times Punish$ suggest that firms facing PDPs reduce emissions. However, columns (3) and (4) show no significant changes in pollution intensities. Despite reducing production (as shown in column 5), these firms are reluctant to expand their abatement capacities, as reflected by the insignificant coefficients of the interaction terms in columns (6) through (9).

Response of the plants whose affiliates are exposed to the PDP pilot (plant *Bs*). Next, we provide evidence that multiplant firms, with their plant *As* facing PDPs, shift production to the corresponding plant *Bs*. To examine this, we estimate Eq. (8), and the coefficient of the interaction term, $\tilde{\beta}_2$, captures the spillover effect of the PDP pilot within the multiplant firms' production networks. The results are presented in Table 9.

Columns (1) and (2) in Table 9 show that following the PDP shock (when their plant *As* are penalized and subject to PDPs), plant *Bs* experience an increase in COD and SO_2 emissions. However, there is no significant change in emission intensities, as shown in columns (3) and (4). This aligns with Prediction 2, as plant *Bs* are absorbing production shifted from their affiliated plant *As*, without burdening extra regulatory pressures. As a result, while emissions rise at

[23]The interaction term coefficient in column (2) is still at around 10% significance level.

plant Bs, emission intensities remain unaffected. This lack of change is further reflected in the insignificant coefficients of $PDP \times Punish$ for abatement facilities and capacity in columns (6) to (9). The positive coefficient of $PDP \times Punish$ in column (5) reinforces the findings from Table 8, indicating that multiplant firms have redistributed production across affiliates to minimize the compliance cost with the PDP.

6 Quantitative analysis

In this section, we extend the benchmark model of Section 3 and implement a quantitative evaluation of the PDP pilot. The aims of this exercise are two-fold. First, and most importantly, we calibrate the model and use counterfactual analysis to compare the overall effects of the Chinese two-stage PDP and the U.S. one-stage PDP. As noted in Section 2, the two approaches differ from each other in both the guiding principle and levy approach. The Chinese two-stage PDP mainly focuses on pushing violating firms, whose illegal emissions have already been detected, to rectify by imposing an inevitable and disproportionately higher new penalty if the misconduct continues. As shown both theoretically (in Section 3) and empirically (in Section 5), firms that have not been penalized under the two-stage PDP are not motivated to reduce emissions, while penalized firms are incentivized to comply. The U.S. one-stage PDP, by contrast, is designed to deter all polluters from illegal emissions with an extremely high fine at a relatively lower probability. Given the distribution of firms' productivity and compliance costs in China, our counterfactual analysis investigates which approach is more effective in reducing emissions while minimizing output losses. Second, as a by-product of this analysis, we estimate parameters of economic interest, such as the cross-firm distributions of productivity and compliance costs. The quantitative model also allows us to validate the key findings from the previous reduced-form analysis.

6.1 Parameterization

We retain most of the setup from Section 3 and parameterize the cross-firm productivity distribution as log-normal, i.e., $\log(\psi) \sim N(0, \sigma_\psi)$, with $G_\psi(\cdot)$ as the CDF. A key extension here is that we now allow for heterogeneous compliance costs f, assuming that f follows a log-normal distribution, with the mean depending on the firm's productivity (whereas in the benchmark model of Section 3, f was the same across firms). This assumption indicates two things: First, the compliance cost varies among firms with the same productivity, and second, the expected compliance cost changes with the firm's productivity. These variations can be attributed to idiosyncratic factors and differences in the technologies that firms employ and allow the model to better fit the data moments.

A tactic that we will use in calibration is that the heterogeneity in f can be equivalently expressed as the heterogeneity of the adoption threshold ψ_a, with the latter is more convenient for calibration. To see this, recall that the firm profits using clean and dirty technologies (under the one-shot penalty) are as follows:

$$\pi_c(\psi) = \eta^{-\beta_\tau}\Lambda\psi^{\beta_\psi},$$
$$\pi_d(\psi) = (1-\lambda\kappa_0)^{\beta_\kappa}\Lambda\psi^{\beta_\psi},$$

where $\beta_\kappa = \frac{\sigma}{(1-\alpha)\sigma+\alpha}$, $\beta_\tau \equiv \frac{\alpha_e(\sigma-1)}{(1-\alpha)\sigma+\alpha}$, $\beta_\psi \equiv \frac{\alpha_l(\sigma-1)}{(1-\alpha)\sigma+\alpha}$, $\Lambda = \frac{1}{\beta_\kappa}\left(\frac{\sigma-1}{\sigma}\right)^{\frac{\alpha(\sigma-1)}{(1-\alpha)\sigma+\alpha}}\left(\frac{w}{\alpha_l}\right)^{-\beta_\psi}\left(\frac{\tau}{\alpha_e}\right)^{-\beta_\tau}$. The input prices are included in Λ, with w referring to the nominal wage and τ the nominal emission fee.[24] By Eq. (3), we have

$$\log(\psi_a) = \frac{1}{\beta_\psi}\Big(\log(f) + \underbrace{\log(\delta) - \log(\Lambda) - \log[\eta^{-\beta_\tau} - (1-\lambda\kappa_0)^{\beta_\kappa}]}_{\text{constant}}\Big), \tag{9}$$

where we see that if $\log f$ follows normal distribution, which depends on ψ, so does $\log(\psi_a)$. We denote the cumulative distribution function of ψ_a by $G_a(\psi_a|\psi)$. The dependence of G_a on ψ captures the idea that the expected abatement cost varies with the firm's productivity. The variance of ψ_a is normalized to one.

Intuitively, the relationship between the expected abatement costs and a firm's productivity does not need to be monotonic. For example, low-productivity firms may need to renovate their production processes to connect to abatement equipment, resulting in decreasing adoption costs as productivity increases. However, as productivity grows further, larger-scale production may lead to higher abatement adoption costs due to the increased complexity of integrating abatement technologies into larger operations. To capture this potentially non-monotonic relationship between productivity and the (expected) abatement costs, we parameterize the mean of $\log(\psi_a)$, denoted by μ_a, as polynomial function $\mathcal{P}(\cdot)$ of $\log(\psi)$:

$$\mu_a = \mathcal{P}(\log\psi) \equiv \beta_0 + \beta_1\log\psi + \beta_2(\log\psi)^2 + \beta_3(\log\psi)^3. \tag{10}$$

We have tried higher-order polynomials, but the results do not change meaningfully. Our quantitative model can be summarized by the following data generating process:[25]

1. Consider a large number of firms. Each firm first draws a productivity level, $\log(\psi) \sim N(0,\sigma_\psi)$. Conditional on $\log(\psi)$, the firm then draws an adoption threshold, $\log(\psi_a) \sim N(\mu_a(\log\psi), 1)$.

2. Based on these draws, a firm decides on its production technology. If $\psi \geq \psi_a$, the firm adopts abatement equipment and produces using clean technologies. Otherwise, it produces using dirty technologies.

[24] Since we shall target the model moments to the data moments, we choose not to normalize $w = 1$ for this exercise.
[25] In this exercise, we treat δ as an effective discount factor and choose not to explicitly model the (exogenous) entry and exit of firms.

3. Firms are randomly inspected by the local environmental regulatory agencies with probability λ. If a dirty firm is inspected, it is fined. Under the one-shot penalty, the firm is fined a fraction, κ_0, of its revenue.

To match the sales in the data, we have to compute the counterparts in the model. Note that $R(\psi) = \beta_\kappa \pi(\psi)$. Taking logs yields

$$\log\left(R_c(\psi)\right) = C_c + \beta_\psi \log(\psi),$$
$$\log\left(R_d(\psi)\right) = C_d + \beta_\psi \log(\psi),$$

with $C_c \equiv \log(\beta_\kappa) - \beta_\tau \, log(\eta) + \log(\Lambda)$ and $C_d \equiv \log(\beta_\kappa) + \beta_\kappa \, log(1-\lambda\kappa_0) + \log(\Lambda) = C_c + \log\left(\frac{(1-\lambda\kappa_0)^{\beta_\kappa}}{\eta^{-\beta_\tau}}\right)$. We treat the ratio in the log operator as a parameter: $\zeta \equiv \frac{(1-\lambda\kappa_0)^{\beta_\kappa}}{\eta^{-\beta_\tau}}$. That is, $C_d = C_c + \log(\zeta)$. We then also take C_c as a parameter to calibrate and note that C_c encapsulates unknown nominal input prices.

6.2 Calibration

We first calibrate a subset of parameters based on the literature. We follow Chen et al. (2021) to calibrate $\sigma = 4$ and the returns of scale parameter $\alpha = 0.9$. We use the estimates from Hang et al. (2023) to calibrate $\alpha_e = 0.017$. Then, $\alpha_l = 0.9 - 0.017 = 0.883$. Based on these values, we can compute $\beta_\kappa = 3.0769, \beta_\psi = 2.0377$, and $\beta_\tau = 0.0392$. We further set β_0 such that the average firm with $\log(\psi)$ normalized to 0 has a compliance rate of 57.4%, that is, $\Phi(-\beta_0) = 0.574$, where $\Phi(\cdot)$ is the CDF of a standard normal distribution. This gives $\beta_0 = -0.1866$.[26] Finally, to calibrate ζ, we again use condition (3). Consider a firm of productivity ψ, its indifference condition between adopting and not adopting the abatement technology is

$$\zeta = \frac{(1-\lambda\kappa_0)^{\beta_\kappa}}{\eta^{-\beta_\tau}} = 1 - \beta_\kappa \frac{\delta f_a(\psi)}{R_c(\psi)}, \tag{11}$$

where $f_a(\psi)$ is the adoption cost of the indifferent firm among firms of productivity ψ. According to the model, the ratio $\frac{\delta f_a}{R_c(\psi)}$ is constant across ψ. We let $\frac{\delta f_a(\psi)}{R_c(\psi)} = 0.01$ to match that in the Chinese data, and the investment share of abatement equipment in the total output is on average 1% (Qi et al. 2021). Then, $\zeta = 1 - 3.0769 \times 0.01 = 0.9692$.

After calibration, we are left with six parameters to estimate

$$\theta = \left(C_c, \lambda, \sigma_\psi, \beta_1, \beta_2, \beta_3\right).$$

Here, C_c represents the constant terms in $\log(R_c)$; λ is the inspection probability; σ_ψ is the standard deviation of firm productivity; and β_1 to β_3 are coefficients in the polynomial (10). We

[26]The proportion of firms adopting clean technologies was calculated by Qi et al. (2021) based on China's National General Survey of Pollution Sources.

estimate θ using the simulated method of moments:

$$\hat{\theta} = \arg\min_{\theta \in \Theta} \left[m_d - m(\theta)\right]' W \left[m_d - m(\theta)\right],$$

where m_d represents the data moments, $m(\theta)$ the model-simulated moments, and W the optimal weighting matrix.[27]

The moments used in our estimation are as follows: (1) the proportion of firms that are fined; (2) the mean of $\log(\text{sales})$ for all firms in the sample; and (3) the standard deviations of $\log(\text{sales})$, as well as the 90–10 and 90–50 percentile differences of $\log(\text{sales})$, calculated separately for fined and non-fined firms. These data moments are based on our sample of firms from 2004 to 2006, which includes firms in Chongqing, Shenzhen, and the surrounding regions before the pilot took place in 2007 in Chongqing.

Although all six parameters are estimated jointly, their intuitive connections to the data moments are as follows: C_c is primarily informed by the mean of $\log(\text{sales})$, while λ is mainly determined by the proportion of firms being fined. The parameter σ_ψ is jointly driven by the standard deviations and percentile ratios of $\log(\text{sales})$. Finally, β_1 through β_3 are informed by the differences in the percentile ratios of $\log(\text{sales})$ between fined and non-fined firms.

Results. Table 10 reports the calibrated parameters, while Table 11 lists the targeted and simulated moments. In this table, we use $\mathcal{F} \in \{0, 1\}$ to indicate whether a firm has been penalized. We separately compute the moments of sales for penalized $(\mathcal{F} = 1)$ and non-penalized $(\mathcal{F} = 0)$ firms. Our model generates moments that align closely with the actual data. Specifically, it reproduces the pattern that the variations in sales are generally higher among penalized firms than non-penalized firms.

Based on the calibrated parameter values, we examine how firms' expected abatement costs and compliance rates change with productivity. Figure 3a shows the expected abatement costs (represented by μ_a) across $\log(\psi)$ (solid curve), and for comparison, we also plot a 45-degree line (red dashed). Figure 3b displays the corresponding compliance rate across $\log(\psi)$.

We observe that when ψ is low, the expected compliance cost (represented by μ_a) is high, i.e., the black curve is positioned well above the 45-degree line in Figure 3a; therefore, the compliance rate is low (slightly higher than 10%). As ψ increases, the expected compliance cost first decreases and then increases together with $\log \psi$. Consequently, the compliance rate increases rapidly and eventually stabilizes around 50% to 60%.

While conventional wisdom suggests that more productive firms would incur higher costs when adopting cleaner technologies due to their larger production scales, our findings reveal that adoption costs may actually decrease with productivity when it is in the lower range. This

[27] We use bootstrapping to calculate the variance–covariance matrix of the moments, and the weighting matrix is derived as the inverse of this variance–covariance matrix.

seemingly counterintuitive result may be due to the fact that upgrading production lines to accommodate clean technologies can be disproportionately expensive for smaller firms. For example, firms with low productivity often face significant upfront costs, such as installing pollution abatement facilities, improving infrastructure, and modernizing manufacturing equipment to connect with the piping systems necessary for emission reduction (Helland 1998).

It is worth noting that in the middle range of productivity, where μ_a is close to $\log(\psi)$, increased regulatory scrutiny and higher fines can easily reduce μ_a below $\log(\psi)$, leading to a downward shift of the solid curve in Figure 3a. Consequently, mid-productivity firms are more likely than firms in other productivity ranges to switch from noncompliance to compliance. This segment of firms thus becomes the primary target of enforcement efforts aimed at reducing discharges.

6.3 Counterfactual analysis: Comparing one- and two-stage per-day penalty

Next, we conduct a counterfactual analysis to compare compliance and production outcomes under the one-stage and two-stage PDP. We begin by simulating adoption threshold ψ_a for each firm under the one-shot penalty. Based on this, we then calculate the adoption thresholds for each firm under both the one-stage and two-stage PDP scenarios. The procedure is outlined below.

For the two-stage PDP, the initial inspection rate (λ) and fine (κ_0) are the same as the one-shot penalty. However, if a firm is penalized, it faces a follow-up inspection with a probability of one. Should the firm fail to comply, the fine escalates to $\kappa_1 = d \times \kappa_0$. In our simulations, we consider the following three values for d: 10, 20, and 30.[28] The adoption thresholds under two-stage PDP are

$$\begin{cases} \psi_a & \textit{in initial inspections} \;, \\ \psi_a^{II} & \textit{in follow-up inspections} \;, \end{cases}$$

where

$$\psi_a^{II} = \iota(d)\psi_a < \psi_a$$

and $\iota(d) \equiv \left[\frac{\eta^{-\beta\tau} - (1-\lambda\kappa_0)^{\beta\kappa}}{\eta^{-\beta\tau} - (1-d\kappa_0)^{\beta\kappa}}\right]^{\frac{1}{\beta\psi}} \in (0,1)$. The term $\iota(d)$ is strictly decreasing in d; that is, as d increases, ψ_a^{II} becomes smaller, making it more likely for firms to switch from violation to compliance. Alternatively, this can be seen as the expected threshold of compliance shifting downward: $\mu_a^{II} = \mu_a + \log[\iota(d)] < \mu_a$.

For the one-stage PDP, the inspection rate remains λ (as in routine inspections), but the fine

[28] Under China's PDP policy, the maximum number of violation days is capped at 30, and the agency has discretion over when to conduct inspections within this period. For the purposes of this quantitative analysis, we assume that dual-plant firms shift production to plants outside the pilot region (and assume $f_1 = 0$).

increases to $\kappa_1 = d\kappa_0$. The adoption threshold under the one-stage PDP becomes

$$\psi_a^I = \iota(\lambda d)\psi_a < \psi_a,$$

where $\iota(\lambda d) \equiv \left[\frac{\eta^{-\beta_\tau} - (1-\lambda\kappa_0)^{\beta_\kappa}}{\eta^{-\beta_\tau} - (1-\lambda\kappa_1)^{\beta_\kappa}}\right]^{\frac{1}{\beta_\psi}}$. The one-stage PDP can be viewed as a special case of the two-stage PDP where the follow-up inspection rate is λ instead of 1. Since $\iota(d) < \iota(\lambda d)$, the following relationship holds among the three thresholds:[29]

$$\psi_a^{II} < \psi_a^I < \psi_a.$$

6.3.1 The penalized firms under two-stage per-day penalty

To connect with the empirical findings from the previous section, we begin by examining how firms respond to the two-stage PDP policy. Specifically, we focus on firms that were found in violation during routine inspections and subsequently penalized. These firms must have $\psi < \psi_a$. Under the two-stage PDP, if these firms fail to rectify their misconduct, they are subjected to additional inspections by the environmental agency and face an escalated penalty. As shown above, they will switch to compliance if $\psi > \psi_a^{II}$.

In Figure 4, panel (a) displays the compliance rates among these firms. The rates are generally high across most productivity levels (approximately 80% for $d = 30$), with lower compliance rates observed among firms at the very low end of the productivity range due to their higher compliance costs (about 40%–50% for $d = 30$). The switch from violation to compliance is substantial because these firms all opt for violation under the one-shot penalty system.

Panels (b) and (c) show the expected changes in output and pollution intensity when firms are facing PDPs compared to when they are only subjected to the one-shot penalty. The patterns are consistent across different values of d. We observe that smaller firms (those with lower productivity) experience a larger decrease in output, while their pollution intensity decreases less. In contrast, larger firms (those with higher productivity) show a smaller reduction in output but a greater reduction in pollution intensity.

Combined with the results from panel (a), we conclude that under the two-stage PDP, penalized firms—facing escalated fines for noncompliance—reduce emissions. Larger firms tend to adopt abatement technologies, while smaller firms primarily reduce output. These results reinforce our empirical findings from Section 5, confirming that the two-stage PDP effectively drives emission reductions through differentiated firm responses.

[29] To calculate ψ_a^I and ψ_a^{II}, we use κ_0, the average penalty-to-sales ratio. This value, based on the sample of penalized firms prior to the pilot, is $\kappa_0 = 0.3467\%$.

6.3.2 The overall compliance rate

Under the one-stage PDP, the compliance rate for a firm with productivity ψ is given by

$$\Pr(\iota(\lambda d)\psi_a < \psi) = G_a\left(\frac{\psi}{\iota(\lambda d)}\right).$$

Therefore, the overall expected compliance rate (across firm productivity) can be expressed as

$$\mathbb{E}_\psi\left[G_a\left(\frac{\psi}{\iota(\lambda d)}\right)\right].$$

For the two-stage PDP, the compliance rate for a firm with productivity ψ that has been fined in the first stage is

$$\Pr(\iota(d)\psi_a < \psi) = G_a\left(\frac{\psi}{\iota(d)}\right).$$

However, because only a small fraction of violations are actually inspected and penalized (with the calibrated inspection rate in China being 4.75%), the overall compliance rate is a weighted average of the compliance rates of inspected and non-inspected firms:

$$\mathbb{E}_\psi\left[\lambda G_a\left(\frac{\psi}{\iota(d)}\right) + (1-\lambda)G_a(\psi)\right].$$

From these results, it is clear that both PDP systems yield higher compliance rates than the standard one-shot penalty and that both compliance rates increase in λ and d. However, which policy is more effective overall remains ambiguous. For instance, λ influences the compliance rate under the one-stage PDP nonlinearly, with a marginal effect of $\partial G_a\left(\frac{\psi}{\iota(\lambda d)}\right)/\partial\lambda$, while it affects the compliance rate under the two-stage PDP linearly, with a marginal effect of $G_a\left(\frac{\psi}{\iota(d)}\right)$. The ultimate impact depends on the distribution of productivity, $G(\cdot)$, and the distribution of compliance costs, $G_a(\cdot)$. Based on our calibrated distributions, we demonstrate below that the one-stage PDP consistently outperforms the two-stage PDP in terms of the overall compliance rate.

Table 12 presents compliance rates under different policy scenarios. We calculate these rates for two values of λ (the calibrated value of 0.0475 and a higher hypothetical value of 0.1) and for three values of κ_1 ($10\kappa_0, 20\kappa_0$, and $30\kappa_0$). The first row shows the compliance rates under the one-shot penalty policy, where the fine is set at a fixed level of κ_0. The second row displays the rates for the one-stage PDP, in which compliance occurs if and only if $\psi \geq \psi_a^I$. The third and fourth rows provide the compliance rates under two variations of the two-stage PDP. The "Include Leakage" scenario (third row) assumes that dual-plant firms do not comply, allowing for production shifting (leakage) to non-penalized plants. The "Exclude Leakage" scenario (fourth row) assumes that all firms operate a single plant, thereby eliminating any leakage effect. Finally, the last row presents the compliance rates for firms facing the second-stage inspection in the two-stage PDP system.

We begin by examining the results in the first three columns, from which three key observations emerge. First, although all PDP scenarios lead to an increase in compliance rates, the effect is most pronounced under the one-stage PDP. For example, when $d = 30$, the compliance rate reaches 54% under the one-stage PDP compared to a maximum of 49% under the two-stage PDP. This holds for all values of d. Second, comparing the two scenarios within the two-stage PDP, we find that eliminating production leakage does not significantly improve compliance rates. This is primarily because most firms in our sample operate only a single plant, limiting the potential for shifting production. Lastly, while compliance rates during follow-up inspections are notably higher (81.6% for $d = 30, \lambda = 0.0475$), the overall compliance rate under the two-stage PDP remains relatively low due to the low initial inspection rate.

One might expect that as the inspection probability (λ) increases, the two-stage PDP will lead to a higher compliance rate than the one-stage PDP. However, our results indicate that while compliance under the two-stage PDP does indeed rise with λ, it is still outpaced by that under the one-stage PDP. For example, in the last three columns of Table 12, where λ is increased to 0.1, in the scenario of $d = 30$, the compliance rate under the one-stage PDP reaches 59% compared to only 50% under the two-stage PDP. Our analysis concludes that the compliance rate under the two-stage PDP is relatively modest when assessed against the calibrated distribution of Chinese firms and falls short of the effectiveness observed under the one-stage PDP.

6.3.3 Output, emissions, and pollution intensity

Table 13 illustrates the percentage changes caused by three variants of the PDP policy relative to the one-shot penalty in output (panel a), emissions (panel b), and pollution intensity (panel c) across three penalty levels ($\kappa_1 = 10\kappa_0, 20\kappa_0, 30\kappa_0$) and two inspection rates ($\lambda = 0.0475, 0.1$).[30] As shown in the table, under both types of PDP policy, the emissions, pollution intensity, and total output average across firms all decline compared to those under the one-shot penalty.

There are notable differences between the one-stage and two-stage PDP policies. Both emissions and pollution intensity see more significant reductions under the former compared to the latter. For example, consider the scenario in the third column ($\lambda = 0.0475$ and $\kappa_1 = 30\kappa_0$). Under the one-stage PDP, the increased penalties lead to a reduction in emissions and pollution intensity by 7.3% and 7.2%, respectively. In contrast, under the two-stage PDP (excluding leakage effects), these reductions are only 1.77% and 1.73%, respectively. Therefore, the one-stage PDP has an effect on emissions and abatement that is 5–7 times larger than that of the two-stage PDP.

However, this stronger effect on pollution comes at the cost of a slightly higher decline in overall output. In the case where $\lambda = 0.0475$ and $d = 30$ (as seen in the third column of panel a), the total output decreases by 0.1% under the one-stage PDP compared to a 0.04% decrease under the two-stage PDP. However, if the social welfare function prioritizes output, it is possible that

[30] To compute emissions, we calibrate $b = 2.8$. Then, by definition of η, we have $\xi^* = \frac{b}{b-1}(1 - \eta) = 0.8451$. That is, emissions are reduced by 84.51% using clean technologies.

the two-stage PDP may be more favorable than the one-stage PDP despite its much weaker effect on pollution reduction.

6.3.4 Comparison across productivity

We now examine how compliance rates, output, and emissions vary across productivity. For this analysis, we set $\kappa_1 = 30\kappa_0$.

Panel (a) in Figure 5 illustrates the compliance rates across productivity under the one-shot penalty, the one-stage PDP, and the two-stage PDP. We observe that the compliance patterns for the three policies are similar. Consistent with previous results (see Table 12), the compliance rate shows a larger increase under the one-stage PDP compared to the two-stage PDP.

Panels (b) and (c) depict the changes in total output and pollution intensity under the one-stage PDP (solid black curve) and two-stage PDP (dashed red curve), relative to the one-shot penalty. Given the limited improvement in compliance with the two-stage PDP, smaller changes in these variables are expected under this approach. This is evident from the almost unchanged pollution intensity shown in panel (c) (red dashed curve), while the one-stage PDP demonstrates a more substantial effect. Specifically, under the latter, output decreases slightly by up to 0.4% across most $\log(\psi)$ values, but emissions drop by approximately 8%. Consequently, pollution intensity declines by around 8%. As illustrated in panel (c), the one-stage PDP has a more pronounced impact across the entire range of ψ than the two-stage PDP.

Lastly, under both PDP policies, the output loss is more significant for low-productivity firms, while decreases in pollution intensity are less pronounced for these firms. This suggests that heterogeneous responses exist under both policies: Smaller firms tend to lower emissions by scaling back production, whereas intermediate to large firms are more likely to adopt cleaner technologies.

7 Conclusion

We analyzed the impact of a pilot PDP policy in China on firms' production and abatement decisions. This policy is an institutional transplant from developed to developing countries, with Chinese policymakers modifying the original one-stage inspection process into a two-stage approach. While this adjustment may seem minor, we illustrate that it introduces significant changes in the incentives faced by regulated firms. Using firm-level data, we find that the Chinese PDP pilot effectively reduces pollutant emissions; however, firms' responses vary depending on firm size and production networks. Our quantitative model further shows that the U.S. one-stage PDP is more effective in encouraging compliance, resulting in greater reductions in both emissions and pollution intensity. However, this increased effectiveness comes at the expense of a higher decline in output. Lastly, we observe that both the one-stage and two-stage PDP policies have differential impacts depending on firms' productivity levels. This hints that the distribution of firm productivity within a country is a critical factor in assessing policies.

Our research has three noteworthy implications, particularly for developing countries, which often learn from the institutions created by developed countries. First, assessing whether the original or a modified institution is more effective can be challenging, as even minor adjustments can significantly alter compliance incentives. In the case of the two-stage PDP, by contrast to the original one-stage policy format, delaying the escalated PDPs to the second stage weakens such incentives unless firms are inspected. But this could be a fair choice for developing countries as it requires much less implementing costs.

Second, the evaluation criteria are crucial. While the original one-stage PDP achieves greater reductions in emissions and pollution intensity, it also leads to higher output losses. For developing countries prioritizing economic growth, the two-stage PDP may be more suitable, as it places less strain on output. Conversely, if equal emphasis is placed on reducing emissions and maintaining output, the one-stage PDP might be more effective, offering stronger emissions control with only a modest output decline. Overall, the adaptation of institutions from developed countries should align with broader development goals.

Finally, our analysis also highlights the importance of firms' productivity distribution in evaluating different environmental penalty systems. Developing countries, often characterized by a large number of small firms at the lower end of the productivity scale, may not experience the same effects as developed countries. Therefore, the economic structure should be a crucial consideration when adapting institutional frameworks.

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Tables and Figures

Table 1: Summary of zero values in key outcome variables

Variable	Zero values	Total observations	Proportion (%)
COD	957	35,653	2.68
SO_2	1,211	30,057	4.03
Sales	4	41,913	0.01
$ability^w$	704	28,860	2.44
$ability^g$	384	16,707	2.30

Notes: COD and SO_2 represent the chemical oxygen demand and sulfur dioxide emissions, respectively, measured in kilograms. "Sales" refers to the firm's annual sales revenue (in RMB 10,000); $ability^w$ denotes the firm's wastewater treatment capacity (tons/day), and $ability^g$ represents the gas treatment capacity (m^3/hour).

Table 2: Summary statistics

	N	mean	sd	min	max
$\log COD$	35000	7.940	3.158	-2.303	16.470
$\log SO_2$	29000	7.968	3.765	-2.645	18.440
$intensity^{COD}$	36000	0.620	2.686	0	33.690
$intensity^{SO_2}$	30000	0.891	3.418	0	44.770
$facility^{w}$	32000	1.306	4.305	0	720.000
$facility^{g}$	17000	2.728	6.858	0	165.000
$\log ability^{w}$	28000	5.757	1.981	-3.912	14.930
$\log ability^{g}$	16000	7.236	4.215	0	19.480
$\log sales$	42000	11.430	1.556	0	19.320
$Punish$	42000	0.148	0.355	0	1
$Large$	42000	0.755	0.430	0	1

Notes: This table presents the variables used in the empirical analysis. The data is sourced from the Annual Survey of Industrial Firms, the Annual Environmental Survey of Polluting Firms, and the Institute of Public and Environmental Affairs (IPEA). The definitions of these variables are given here. $\mathbf{\log COD}$ and $\mathbf{\log SO_2}$: The natural logarithms of chemical oxygen demand and sulfur dioxide emissions, respectively, both measured in kilograms (kg). These are key environmental pollution indicators derived from firms' reported pollutant emissions. $\boldsymbol{intensity^{COD}}$ and $\boldsymbol{intensity^{SO_2}}$: The pollution intensity of COD and SO_2, calculated by dividing the emissions of each pollutant by the firm's sales. $\boldsymbol{facilities^{w}}$ and $\boldsymbol{facilities^{g}}$: The stock of wastewater (w) and gas (g) treatment facilities held by firms, representing accumulated technological upgrades. $\boldsymbol{ability^{w}}$: The wastewater treatment capacity of firms, measured in tons per day ($tons/day$) before taking the logarithm. $\boldsymbol{ability^{g}}$: The gas treatment capacity of firms, measured in cubic meters per hour ($m^3/hour$) before taking the logarithm. $\mathbf{\log}\, \boldsymbol{sales}$: The natural logarithm of firm sales, with sales measured in RMB 10,000 before taking the logarithm. **Punish**: A binary variable that equals one if a firm has been penalized by environmental agencies in the current year or any prior year since 2004; otherwise, it equals zero. **Large**: A binary variable that equals one if a firm is categorized as large when above the median level of sales in the baseline year and zero otherwise.

Table 3: The average effects of PDP on firm emissions, emission intensities, sales, and adoption of abatement facilities

	(1) $\log COD$	(2) $\log SO2$	(3) $intensity^{COD}$	(4) $intensity^{SO2}$	(5) $\log sales$	(6) $facilities^{w}$	(7) $facilities^{g}$	(8) $\log ability^{w}$	(9) $\log ability^{g}$
PDP	0.139	0.282	0.152	-0.471	-0.130	-0.004	0.002	0.024	-0.329
	(0.94)	(1.49)	(0.95)	(-1.41)	(-1.64)	(-0.10)	(0.01)	(0.23)	(-1.53)
$Punish$	0.018	-0.122	-0.249	-0.274	0.123***	0.226***	0.966	0.211**	0.322
	(0.16)	(-1.22)	(-0.91)	(-1.22)	(3.75)	(3.36)	(1.72)	(2.37)	(0.93)
$PDP \times Punish$	-0.988***	-0.351***	-0.755*	-1.106***	-0.136	0.360***	2.525**	0.589***	0.703**
	(-3.58)	(-3.13)	(-1.81)	(-3.91)	(-0.94)	(3.25)	(2.33)	(2.93)	(2.46)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.765	0.859	0.609	0.677	0.919	0.693	0.867	0.849	0.804
$Obs.$	19004	17621	19113	17676	21682	18439	6097	15770	5862

Notes: The significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are shown in parentheses and are clustered by city to account for within-group correlation. The sample includes firms from Chongqing, Shenzhen, and their neighboring cities, covering 2004 to 2013. PDP_{ct} is a dummy variable equal to 1 if the two-stage PDP is in effect in city c from that year t onward, and 0 otherwise. Specifically, $PDP_{ct} = 1$ for Chongqing from 2007 onward and for Shenzhen from 2010 onward. $Punish_{it}$ is a dummy variable that equals one if firm i has been penalized by the local environmental agency in the current year or any prior year since 2004; otherwise, it equals 0. The interaction term $PDP_{ct} \times Punish_{it}$ captures whether penalized firms are subject to the two-stage PDP in year t. Control variables include interactions between year dummies and each firm's sales in 2004 to account for initial differences in firm size.

Table 4: The placebo test of firms' emission to the per-day penalty fine

	(1) $\log COD$	(2) $\log SO_2$	(3) $intensity^{COD}$	(4) $intensity^{SO_2}$	(5) $\log sales$	(6) $facilities^w$	(7) $facilities^g$	(8) $\log ability^w$	(9) $\log ability^g$
PDP^p	0.312	0.188	-0.354***	-0.155	0.517***	0.059	0.297	0.169	0.899***
	(1.17)	(1.16)	(-4.79)	(-0.83)	(7.04)	(0.73)	(1.00)	(1.67)	(5.17)
$Punish$	-0.081	-0.458**	-0.091	-0.928***	0.241***	-0.009	1.902***	0.506***	0.778**
	(-1.37)	(-2.69)	(-1.64)	(-3.57)	(3.04)	(-0.11)	(3.05)	(3.73)	(2.70)
$PDP^p \times Punish$	0.136	0.265	-0.143	0.354	0.058	0.287	0.868	0.131	0.406
	(0.62)	(0.88)	(-1.35)	(0.88)	(0.67)	(1.52)	(1.04)	(0.80)	(1.08)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.790	0.840	0.677	0.754	0.884	0.442	0.847	0.868	0.764
$Obs.$	29433	28102	31887	31019	36448	30670	22641	25821	18167

Notes: The significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are shown in parentheses and are clustered by city to account for within-group correlation. The placebo sample includes firms in cities surrounding Chongqing and Shenzhen, as well as in cities directly bordering these regions, excluding Chongqing and Shenzhen themselves. PDP^p equals 1 starting from 2007 for cities near Chongqing and from 2010 for cities near Shenzhen, and 0 otherwise. All regressions include year- and firm-fixed effects, and additionally control for the interaction between year dummies and each firm's sales in 2004 to account for initial firm size differences.

Table 5: Anticipation effects using firms in Ningxia Hui Autonomous Region

	(1) $\log COD$	(2) $\log SO_2$	(3) $intensity^{COD}$	(4) $intensity^{SO_2}$	(5) $\log sales$	(6) $facilities^w$	(7) $\log ability^w$
PDP^p	-0.770*	0.405	-0.007	2.990*	-0.162	0.077	-0.119
	(-1.80)	(0.97)	(-0.01)	(1.84)	(-1.44)	(0.15)	(-0.31)
$Punish$	0.441	0.142	1.325	1.281	-0.041	0.246	0.085
	(1.03)	(0.67)	(0.63)	(0.83)	(-0.37)	(0.79)	(0.37)
$PDP^p \times Punish$	0.268	-0.085	-1.635	-1.027	-0.023	-0.441	0.069
	(0.77)	(-0.50)	(-1.09)	(-0.94)	(-0.16)	(-1.08)	(0.15)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.755	0.765	0.771	0.674	0.908	0.682	0.811
$Obs.$	1252	2681	1795	2765	2920	1664	1186

Notes: The significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are shown in parentheses and are clustered by city to account for within-group correlation. The sample consists of firms located in Ningxia and its neighboring cities from 2004 to 2013. To assess the effect of anticipation, we assume Ningxia implemented a hypothetical per-day penalty policy starting in 2010. PDP^p equals 1 if the firm-year observation is located in Ningxia and occurs from 2010 onward, and 0 otherwise. All regressions include year- and firm-fixed effects, and additionally control for the interaction between year dummies and each firm sales in 2004 to account for initial firm size differences.

Table 6: The effects of PDP on large firms (without affiliates)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\log COD$	$\log SO_2$	$intensity^{COD}$	$intensity^{SO_2}$	$\log sales$	$facilities^{w}$	$facilities^{g}$	$\log ability^{w}$	$\log ability^{g}$
PDP	0.115	0.463	0.104	-0.573	-0.096	-0.028	-0.127	0.024	-0.123
	(0.84)	(1.61)	(0.65)	(-1.65)	(-0.89)	(-0.41)	(-0.18)	(0.18)	(-0.39)
$Punish$	0.081	-0.337**	-0.173	-0.434	0.008	0.375***	2.270*	0.318**	0.277
	(0.62)	(-2.64)	(-0.48)	(-1.67)	(0.26)	(3.49)	(2.00)	(2.70)	(0.61)
$PDP \times Punish$	-1.108***	-0.244**	-0.834*	-1.548***	0.216***	0.607***	3.724***	0.969***	0.982**
	(-3.52)	(-2.21)	(-1.90)	(-4.01)	(3.21)	(6.75)	(3.40)	(6.48)	(2.49)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.762	0.850	0.503	0.725	0.877	0.700	0.883	0.846	0.809
$Obs.$	9445	8236	9485	8266	10313	9224	2326	8299	2243

Notes: Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are shown in parentheses and are clustered by city to account for within-group correlation. The regression sample consists of all firms located in Chongqing, Shenzhen, and the surrounding cities, categorized as large firms. All regressions include year- and firm-fixed effects, and additionally control for the interaction between year dummies and each firm sales in 2004 to account for initial firm size differences.

Table 7: The Effects of PDP on small firms (without affiliates)

	(1) $\log COD$	(2) $\log SO_2$	(3) $intensity^{COD}$	(4) $intensity^{SO_2}$	(5) $\log sales$	(6) $facilities^{w}$	(7) $facilities^{g}$	(8) $\log ability^{w}$	(9) $\log ability^{g}$
PDP	0.226	0.134	0.217	-0.624	-0.188*	0.053	0.032	0.076	-0.493**
	(0.74)	(1.19)	(0.90)	(-1.68)	(-1.81)	(1.13)	(0.16)	(0.62)	(-2.23)
$Punish$	-0.041	0.135	-0.389	-0.311*	0.276***	-0.017	0.493	0.058	0.282
	(-0.24)	(1.34)	(-1.62)	(-1.76)	(4.38)	(-0.25)	(1.37)	(0.97)	(0.84)
$PDP \times Punish$	-0.570**	-0.559	-0.387	-0.414	-0.551***	-0.022	0.418	0.100	0.614
	(-2.33)	(-1.70)	(-0.96)	(-1.36)	(-4.69)	(-0.28)	(0.72)	(1.14)	(1.38)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.763	0.877	0.668	0.645	0.779	0.561	0.744	0.841	0.793
$Obs.$	7773	7725	7829	7738	9265	7392	3332	5834	3198

Notes: The significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are shown in parentheses and are clustered by city to account for within-group correlation. The regression sample consists of all firms located in Chongqing, Shenzhen, and the surrounding cities, categorized as small firms. All regressions include year- and firm-fixed effects, and additionally control for the interaction between year dummies and each firm sales in 2004 to account for initial firm size differences.

Table 8: The effects of the pilot on the plants of multi-plant firms located within the pilot regions

	(1) $\log COD$	(2) $\log SO_2$	(3) $intensity^{COD}$	(4) $intensity^{SO_2}$	(5) $\log sales$	(6) $facilities^{w}$	(7) $facilities^{g}$	(8) $\log ability^{w}$	(9) $\log ability^{g}$
PDP	-0.234	0.252	0.277	1.380*	-0.056	-0.035	0.501	-0.063	0.174
	(-0.57)	(0.77)	(1.37)	(2.05)	(-0.55)	(-0.35)	(0.56)	(-0.37)	(0.34)
$Punish$	-0.057	0.366	-0.325	0.564	0.400***	0.161	-0.795	0.141	1.327
	(-0.12)	(1.14)	(-0.68)	(0.91)	(4.59)	(0.78)	(-0.52)	(0.81)	(1.36)
$PDP \times Punish$	-1.442*	-0.701*	-1.629	-1.387	-0.929***	-0.081	0.724	-0.703	-1.849
	(-1.75)	(-2.06)	(-1.29)	(-1.62)	(-5.23)	(-0.22)	(0.51)	(-1.34)	(-1.72)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.708	0.824	0.470	0.633	0.930	0.769	0.871	0.839	0.842
Obs.	1786	1660	1799	1672	2104	1823	439	1637	421

Notes: The significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are shown in parentheses and are clustered by city to account for within-group correlation. The regression sample consists of all firms located in Chongqing, Shenzhen, and the surrounding cities and have at least one affiliate outside the above regions. All regressions include year- and firm-fixed effects, with additional controls for the interaction between year dummies and each firm's sales in 2004 to account for differences in firm size at the outset.

Table 9: The effects of the pilot on the plants of multi-plant firms located outside the pilot regions

	(1) $\log COD$	(2) $\log SO_2$	(3) $intensity^{COD}$	(4) $intensity^{SO_2}$	(5) $\log sales$	(6) $facilities^{w}$	(7) $facilities^{g}$	(8) $\log ability^{w}$	(9) $\log ability^{g}$
PDP^A	0.009	-0.465***	1.738***	0.457***	-0.690***	-0.097	0.652	-0.008	0.094
	(0.10)	(-3.18)	(4.09)	(3.31)	(-5.55)	(-0.83)	(0.94)	(-0.13)	(0.82)
$Punish^A$	-0.706***	-0.114	0.142	0.180	-0.178	-0.270	-1.951	-0.031	0.110
	(-4.48)	(-0.80)	(0.15)	(0.29)	(-1.40)	(-0.97)	(-1.55)	(-0.23)	(0.25)
$PDP^A \times Punish^A$	0.739***	0.389*	-0.798	0.045	0.330*	0.223	0.609	-0.047	-0.232
	(4.14)	(1.91)	(-0.71)	(0.08)	(1.72)	(0.67)	(0.47)	(-0.32)	(-0.48)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.788	0.674	0.582	0.658	0.801	0.885	0.947	0.858	0.752
$Obs.$	6325	6372	6690	6750	6970	6632	5151	6104	4660

Notes: The significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are shown in parentheses and are clustered by city to account for within-group correlation. The regression sample includes firms with affiliates located in Chongqing and Shenzhen. PDP^A is a binary variable equal to one if the city where the affiliate is located has implemented the per-day penalty in that year, and $Punish^A$ is a binary variable equal to one if the affiliate of the firm (located in Shenzhen and Chongqing) has been penalized in that year or a prior year (since 2004). All regressions include year- and firm-fixed effects, and additionally control for the interaction between year dummies and each firm's sales in 2004 to account for initial firm size differences.

Table 10: Structural model parameters.

Parameter	Value	Targets/Sources
1. Fixed Values		
Elasticity of substitution, σ	4.00	Melitz and Redding (2015)
Returns to scale, α	0.90	Chen et al. (2021)
Emission elasticity, α_e	0.017	Hang et al. (2023)
Constant term in μ_a, β_0	-0.1866	Average adoption rate
Dirty-to-clean profit ratio, ζ	0.9692	Average share of abatement investment in total output
Abatement cost function parameter, b	2.8	Annicchiarico and Di Dio (2015)
2. Method of Moments Estimation		
Revenue constant, C_c	10.8688	Average log(sales)
Inspection rate, λ	0.0475	Share of firms being fined in the sample
Standard deviation of $\log(\psi)$, σ_ψ	0.723	Standard deviation of log(sales)
1st-order coefficient in μ_a, β_1	1.1789	Percentile ratio differences
2nd-order coefficient in μ_a, β_2	0.7041	Same as above
3rd-order coefficient in μ_a, β_3	-0.6657	Same as above
3. Policy Parameters		
One-shot fine, κ	0.3467%	Average fine as a percentage of sales in the sample
Number of violation days, d	10/20/30	-

Table 11: Data targets and simulation results.

Moment	Data	Model
$mean(\mathcal{F})$	0.0250074	0.02529
$mean(\log(sales))$	10.8199	10.8576
$\mathcal{F} = 1$ $std(\log(sales))$	1.67967	1.56493
$\mathcal{F} = 1$ $\log(sales)$ 90-10	4.38365	4.04939
$\mathcal{F} = 1$ $\log(sales)$ 90-50	2.39449	1.83001
$\mathcal{F} = 0$ $std(\log(sales))$	1.50141	1.47371
$\mathcal{F} = 0$ $\log(sales)$ 90-10	3.79873	3.78071
$\mathcal{F} = 0$ $\log(sales)$ 90-50	2.13573	1.8873

Notes: This table presents the moments targeted in calibration. $\mathcal{F}$ is a dummy variable set to one if a firm is penalized, so $mean(\mathcal{F})$ represents the proportion of penalized firms. Other moments include the mean of log(sales) for all firms, the standard deviation of log(sales) as well as the 90–10 and 90–50 percentile differences in log(sales), calculated separately for fined and non-fined firms. Data moments are based on our 2004–2006 sample of firms in Chongqing, Shenzhen, and nearby regions, prior to the 2007 pilot in Chongqing.

Table 12: Compliance rates under alternative policies.

Policy	$\lambda = 0.0475$			$\lambda = 0.1$		
	$10\kappa_0$	$20\kappa_0$	$30\kappa_0$	$10\kappa_0$	$20\kappa_0$	$30\kappa_0$
One-shot policy	0.4737	-	-	0.4767	-	-
One-stage PDP	0.4976	0.52	0.5402	0.5224	0.562	0.5929
Two-stage PDP (include leakage)	0.4846	0.4876	0.4893	0.4991	0.5056	0.509
Two-stage PDP (exclude leakage)	0.4854	0.4885	0.4904	0.5008	0.5077	0.5114
Post-check adoption	0.7114	0.7808	0.816	0.7114	0.7808	0.816

Table 13: Percentage change in output, emissions, and intensities relative to the one-shot penalty.

(a) Percentage change in output

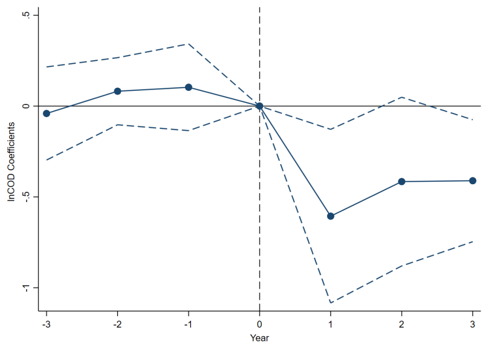
Policy	$\lambda = 0.0475$			$\lambda = 0.1$		
	$10\kappa_0$	$20\kappa_0$	$30\kappa_0$	$10\kappa_0$	$20\kappa_0$	$30\kappa_0$
One-stage PDP	-0.03%	-0.07%	-0.1%	-0.07%	-0.13%	-0.19%
Two-stage PDP (include leakage)	-0.02%	-0.03%	-0.04%	-0.04%	-0.05%	-0.07%
Two-stage PDP (exclude leakage)	-0.02%	-0.03%	-0.04%	-0.04%	-0.06%	-0.07%

(b) Percentage change in emissions

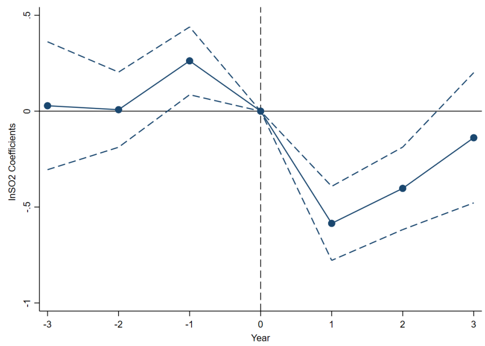
Policy	$\lambda = 0.0475$			$\lambda = 0.1$		
	$10\kappa_0$	$20\kappa_0$	$30\kappa_0$	$10\kappa_0$	$20\kappa_0$	$30\kappa_0$
One-stage PDP	-2.59%	-5.11%	-7.3%	-5.07%	-9.35%	-12.58%
Two-stage PDP (include leakage)	-1.2%	-1.52%	-1.67%	-2.31%	-2.96%	-3.24%
Two-stage PDP (exclude leakage)	-1.28%	-1.61%	-1.77%	-2.47%	-3.15%	-3.47%

(c) Percentage change in pollution intensity

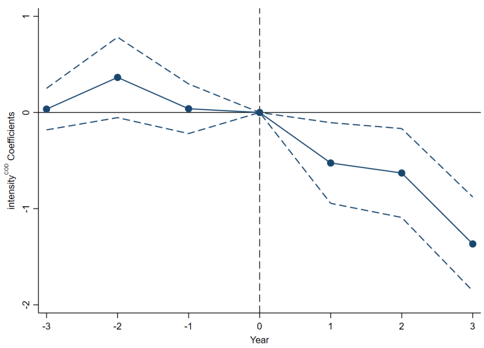
Policy	$\lambda = 0.0475$			$\lambda = 0.1$		
	$10\kappa_0$	$20\kappa_0$	$30\kappa_0$	$10\kappa_0$	$20\kappa_0$	$30\kappa_0$
One-stage PDP	-2.56%	-5.05%	-7.2%	-5.01%	-9.23%	-12.42%
Two-stage PDP (include leakage)	-1.18%	-1.49%	-1.63%	-2.27%	-2.9%	-3.18%
Two-stage PDP (exclude leakage)	-1.26%	-1.58%	-1.73%	-2.43%	-3.1%	-3.39%



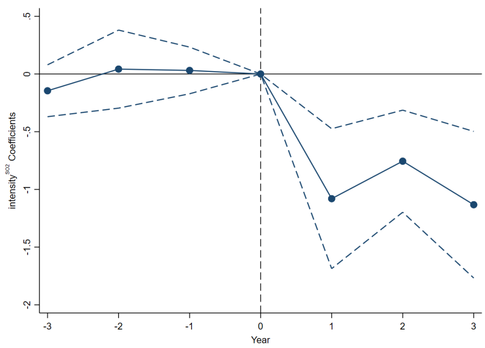
(a) $\log COD$



(b) $\log SO_2$



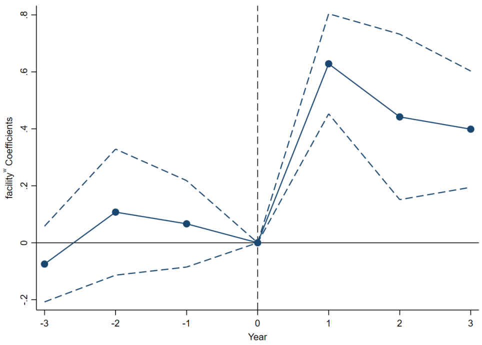
(c) $intensity^{COD}$



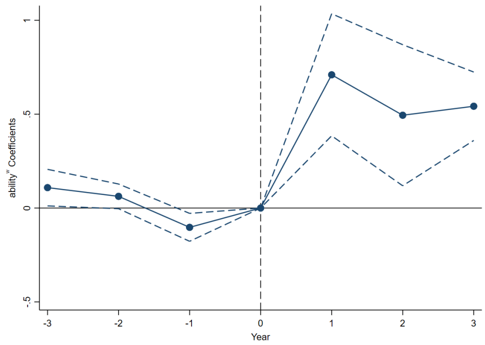
(d) $intensity^{SO_2}$

Figure 1: Parallel trends test for emissions and intensity.

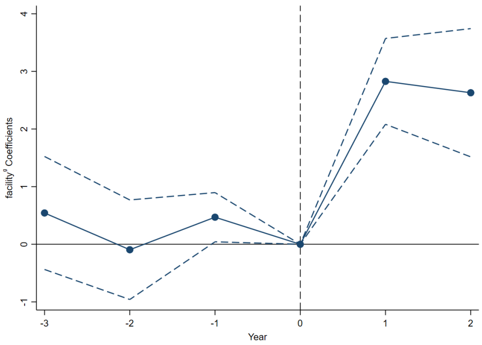
Notes: This figure displays the estimated coefficients for *Punish* and year dummies across the following four outcome variables: $\log COD$, $\log SO_2$, $intensity^{COD}$, and $intensity^{SO_2}$. The solid line represents the point estimates, while the dashed line shows the 95% confidence intervals.



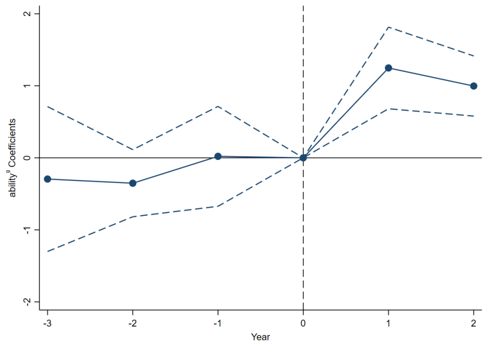
(a) $facilities^w$



(b) $ability^w$



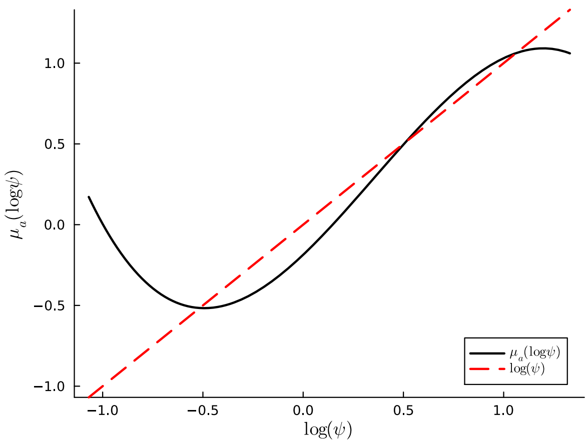
(c) $facilities^g$



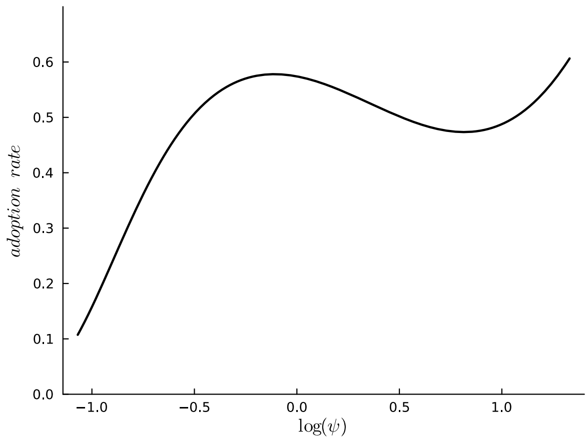
(d) $ability^g$

Figure 2: Parallel trends test for facilities and ability.

Notes: This figure displays the estimated coefficients for *Punish* and year dummies across the following four outcome variables: $facilities^w$,$ability^w$, $facilities^g$, and $ability^g$. The solid line represents the point estimates, while the dashed line shows the 95% confidence intervals.

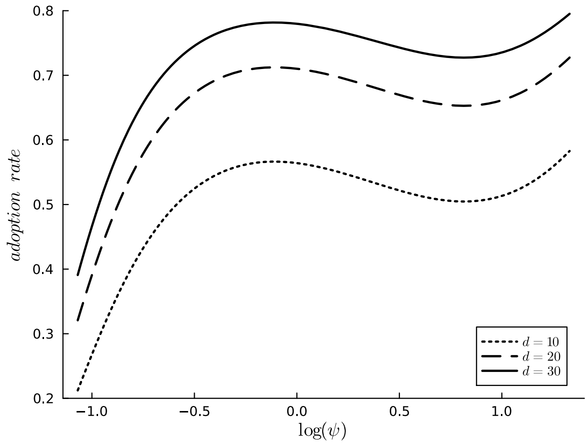


(a) The expected adoption threshold μ_a as a function of $\log\psi$: $\mathcal{P}(\log\psi)$.

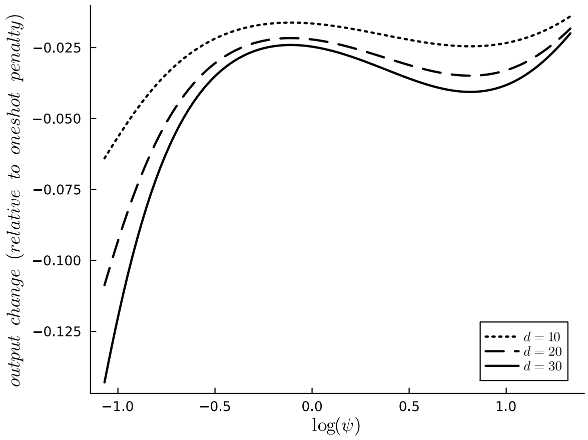


(b) The compliance rate as a function of $\log(\psi)$.

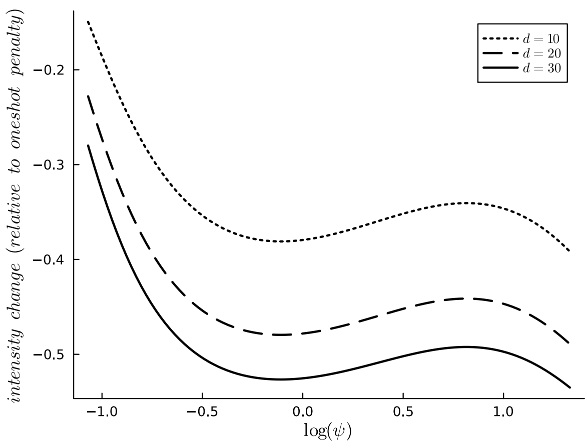
Figure 3: The estimated adoption threshold and compliance rate as functions of $\log(\psi)$ under the one-shot penalty.



(a) The compliance rate



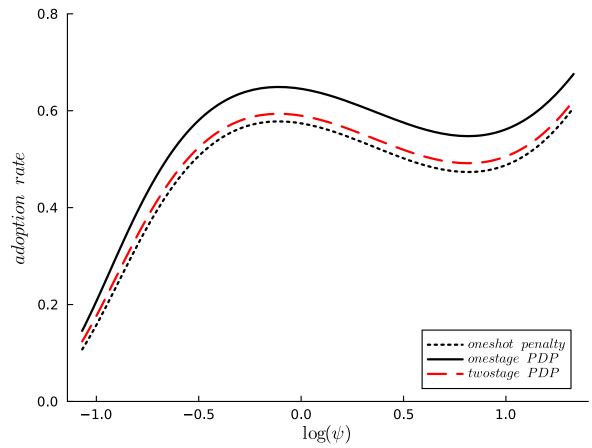
(b) Output changes



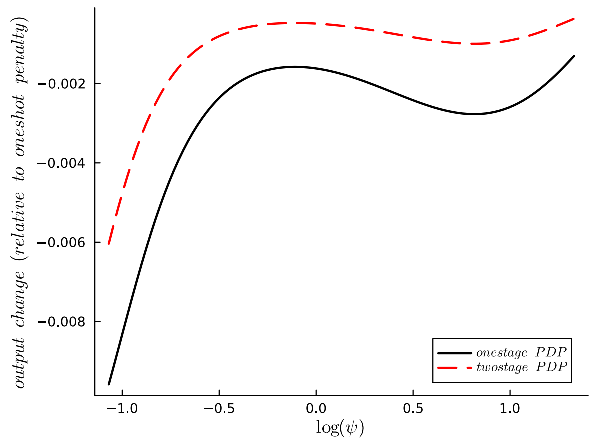
(c) Intensity changes

Figure 4: The impact on the inspected firms under two-stage per-day penalty (PDP).

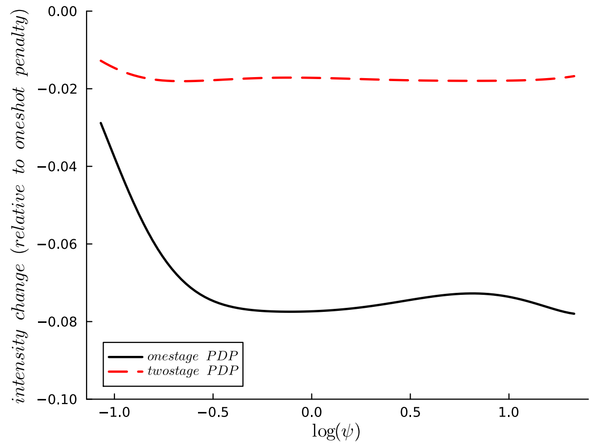
Note: We consider the subset of firms that do not adopt clean technologies under the one-shot penalty, resulting in a zero compliance rate. Panel (a) illustrates the compliance rate when these firms face follow-up inspections under the two-stage PDP, with three levels of expected violation days. Panels (b) and (c) depict the percentage changes in output and intensity experienced by these firms when they undergo follow-up inspections under the two-stage PDP compared to a one-shot penalty.



(a) The compliance rate



(b) Output changes



(c) Intensity changes

Figure 5: The compliance rate, output, emission, and intensity under alternative policies.

Note: Panel (a) compares the compliance rate of the one-shot penalty (dotted curve), one-stage per-day penalty (PDP) (solid curve), and two-stage PDP (red dashed curve). Panels (b) and (c) display the percentage changes in output and intensity of firms across productivity under the one-stage PDP (black solid curve) and two-stage PDP (red dashed curve) relative to under the one-shot penalty.

A Proofs and derivations

A.1 Proof of Lemma 1

Take $\frac{1-\lambda_A\kappa_A}{1-\lambda_B\kappa_B}$ as a variable and solve for γ from (6); then, taking derivative w.r.t. γ at $\frac{\tau_A}{\tau_B}=\gamma=1$, we have $\frac{d\left(\frac{1-\lambda_A\kappa_A}{1-\lambda_B\kappa_B}\right)}{d\gamma}|_{\frac{\tau_A}{\tau_B}=\gamma=1}=\frac{(\sigma-1)(1-\alpha)}{\alpha\sigma}>0$. Similarly, we have $\frac{d\left(\frac{\tau_A}{\tau_B}\right)}{d\gamma}|_{\frac{1-\lambda_A\kappa_A}{1-\lambda_B\kappa_B}=\gamma=1}=-(1-\alpha)/\alpha<0$. ■

A.2 Proof of Proposition 4

A dual-plant firm facing a *type 0* inspection has a value $V_0(\psi)$ that satisfies

$$V_0(\psi)=\max_{a_0(\psi)\in\{0,1\}}\left\{a_0(\psi)\left(\frac{\Pi_c(\psi)}{\delta}-f\right)\right.$$
$$\left.+(1-a_0(\psi))\left(\Pi_d(\psi,\lambda\kappa_0)+(1-\delta)[\lambda_0V_1(\psi)+(1-\lambda_0)V_0(\psi)]\right)\right\}.$$

When factory A faces a *type 1* inspection, the firm's value denoted by $V_1(\psi)$ satisfies

$$V_1(\psi)=\max_{a_1(\psi)\in\{0,1\}}\left\{a_1(\psi)\left(\frac{\Pi_c(\psi)}{\delta}-(f+f_1)\right)+(1-a_1(\psi))\left(\left(\Pi_d(\psi,\kappa_1)\right)+(1-\delta)V_1(\psi)\right)\right\}.$$

We first derive $\tilde{\psi}_{a0}$ and then derive a condition under which a dual-plant firm with $\psi=\tilde{\psi}_{a0}$ does not adopt after being punished. Since a dual-plant firm with $\psi=\tilde{\psi}_{a0}$ finds it optimal to adopt abatement technology ex ante $a_0(\tilde{\psi}_{a0})=1$ and not adopt ex post $a_1(\tilde{\psi}_{a0})=0$ in the proposed equilibrium, its values can be simplified to

$$\tilde{V}_0(\tilde{\psi}_{a0})=\frac{\Pi_c(\tilde{\psi}_{a0})}{\delta}-f,$$
$$\tilde{V}_1(\tilde{\psi}_{a0})=\frac{\Pi_d(\tilde{\psi}_{a0},\kappa_1)}{\delta}.$$

The threshold productivity $\tilde{\psi}_{a0}$ is determined by the following indifference condition:

$$\Pi_c(\tilde{\psi}_{a0})-\left[\frac{\delta}{\delta+\lambda(1-\delta)}\Pi_d(\tilde{\psi}_{a0},\lambda\kappa_0)+\frac{\lambda(1-\delta)}{\delta+\lambda(1-\delta)}\Pi_d(\tilde{\psi}_{a0},\kappa_1)\right]=\delta f. \tag{12}$$

Moreover, the lower bound $\underline{f_1}$ should satisfy $\Pi_c(\tilde{\psi}_{a0})-\Pi_d(\tilde{\psi}_{a0},\kappa_1)=\delta(f+\underline{f_1})$. Inserting into (12) yields

$$\underline{f_1}=\frac{1}{\delta+\lambda(1-\delta)}(\Pi_d(\tilde{\psi}_{a0},\lambda\kappa_0)-\Pi_d(\tilde{\psi}_{a0},\kappa_1)). \tag{13}$$

Next, the upper bound of f_1, i.e., $\bar{f}_1$, is determined by $\delta(f+\bar{f}_1)=\pi_a(\psi_{a0})-\pi_n(\psi_{a0},\kappa_1)$. After some tedious manipulation, we have $\bar{f}_1\equiv\frac{\delta f\left((1-\lambda\kappa_0)^{\beta_\kappa}-(1-\kappa_1)^{\beta_\kappa}\right)}{(\eta^{-\beta_\tau}-(1-\lambda\kappa_0)^{\beta_\kappa})\delta+\lambda(1-\delta)(\eta^{-\beta_\tau}-(1-\kappa_1)^{\beta_\kappa})}$. Finally, since for $\alpha\to 1$, $\underline{f_1}\to 0$, and $\bar{f}_1$ is always positive, we have $\bar{f}_1>\underline{f_1}$ for at least some parameter space, e.g., when α is sufficiently large. ■

A.3 Derivations of Predictions 1 and 2

CONSIDER A SINGLE-PLANT FIRM. If the firm produces using dirty technologies, it solves the following problem under a *type 0* inspection:

$$\max_{q\geq 0}\left\{(1-\lambda\kappa_0)q^{\frac{\sigma-1}{\sigma}}-\Upsilon\psi^{-\frac{\alpha_l}{\alpha}}\tau^{\frac{\alpha_e}{\alpha}}q^{\frac{1}{\alpha}}\right\},$$

with $\lambda\kappa_0$ being replaced by κ_1 if the firm is facing a *type 1* inspection. Let the optimal production under a *type 0* inspection be q_{n0}, which satisfies

$$q_{n0}^{\frac{(1-\alpha)\sigma+\alpha}{\alpha\sigma}} = \frac{\sigma-1}{\sigma}\frac{\alpha(1-\lambda\kappa_0)}{\Upsilon\psi^{-\frac{\alpha_l}{\alpha}}\tau^{\frac{\alpha_e}{\alpha}}}.$$

Similarly, when the firm faces a *type 1* inspection, its optimal output is

$$q_{n1}^{\frac{(1-\alpha)\sigma+\alpha}{\alpha\sigma}} = \frac{\sigma-1}{\sigma}\frac{\alpha(1-\kappa_1)}{\Upsilon\psi^{-\frac{\alpha_l}{\alpha}}\tau^{\frac{\alpha_e}{\alpha}}}.$$

The emissions as a function of q are given by

$$e(q) = q^{\frac{1}{\alpha}}\left(\tau\psi\frac{\alpha_l}{\alpha_e}\right)^{-\frac{\alpha_l}{\alpha}}.$$

If the firm has adopted the abatement technology, it solves the problem of

$$\max_{q\geq 0}\left\{q^{\frac{\sigma-1}{\sigma}} - \Upsilon\psi^{-\frac{\alpha_l}{\alpha}}(\eta\tau)^{\frac{\alpha_e}{\alpha}}q^{\frac{1}{\alpha}}\right\}.$$

The optimal production is given by

$$q_a^{\frac{(1-\alpha)\sigma+\alpha}{\alpha\sigma}} = \frac{\sigma-1}{\sigma}\frac{\alpha}{\Upsilon\psi^{-\frac{\alpha_l}{\alpha}}(\eta\tau)^{\frac{\alpha_e}{\alpha}}}.$$

The emissions as a function of q are given by

$$e_a(q) = \frac{1-\xi^*}{\left(1-\xi^*+\frac{1}{b}\xi^*\right)^{\frac{\alpha_l}{\alpha}}}q^{\frac{1}{\alpha}}\left(\tau\psi\frac{\alpha_l}{\alpha_e}\right)^{-\frac{\alpha_l}{\alpha}}.$$

Note that for a given q, abatement directly reduces emissions since $\frac{1-\xi^*}{\left(1-\xi^*+\frac{1}{b}\xi^*\right)^{\frac{\alpha_l}{\alpha}}} < 1$.

⊙ Case 1: Firms with productivity $\psi \in [\psi_{a1}, \psi_{a0})$ adopt the abatement technology upon being punished. There is an increase in total output:

$$\log q_a - \log q_{n0} = -\frac{\sigma\alpha}{\sigma(1-\alpha)+\alpha}\log(1-\kappa_0\lambda) - \frac{\sigma\alpha_e}{\alpha+\sigma(1-\alpha)}\log\eta > 0.$$

The change in emissions is

$$\log e_a - \log e_{n0} = \log\left(\frac{1-\xi^*}{(1-\xi^*+\frac{1}{b}\xi^*)^{\frac{\alpha_l}{\alpha}}}\right) + \frac{1}{\alpha}\left(\log q_a - \log q_{n0}\right),$$

where the first term is a direct effect of abatement and the second term is the increased optimal output due to lower effective emission fees. The net effect can be positive or negative. Inserting q_a and q_{n0}, we have that the reduction in emissions $\log e_a - \log e_{n0} < 0$ if and only if

$$(1-\lambda\kappa_0)^{-\frac{\sigma}{\alpha+(1-\alpha)\sigma}} < \frac{\eta^{\frac{\alpha_l}{\alpha}+\frac{\alpha_e}{\alpha}\frac{\sigma}{\alpha+(1-\alpha)\sigma}}}{1-\xi^*}. \tag{14}$$

Note that if b is sufficiently small, then ξ^* is large (e.g., close to one, and η remains much larger than zero), and condition (14) is satisfied. In other words, if the abatement technology is sufficiently efficient, the emissions decrease. Finally, if (14) is satisfied, the pollution intensity, given by $\log\frac{e_a}{q_a} - \log\frac{e_{n0}}{q_{n0}}$ must decrease.

⊙ Case 2: Firms with productivity $\psi \in [0, \psi_{a1})$ do not update technologies. Their output, emissions, and emission intensity will change upon being punished by

$$
\begin{aligned}
\log q_{n1} - \log q_{n0} &= \frac{\sigma\alpha}{\sigma(1-\alpha)+\alpha}\left(\log(1-\kappa_1) - \log(1-\kappa_0\lambda)\right) < 0, \\
\log e_{n1} - log e_{n0} &= \frac{1}{\alpha}\left(\log q_{n1} - \log q_{n0}\right) < 0, \\
\log \frac{e_{n1}}{q_{n1}} - \log \frac{e_{n0}}{q_{n0}} &= \frac{1-\alpha}{\alpha}\left(\log q_{n1} - \log q_{n0}\right) < 0.
\end{aligned}
$$

In particular, for a large value of α, the change of pollution intensity tends to be small and approaches 0 as $\alpha \to 1$.

CONSIDER A DUAL-PLANT FIRM. The firm has productivity $\psi < \tilde{\psi}_{a0}$, and it has two plants where factory A (B) is subject to the PDP (the one-shot penalty). The profit-maximizing output ratio between the two plants satisfies (6). Suppose factory A has been fined and is now facing a *type 1* inspection. According to Lemma 1, the ratio $\gamma = q_A/q_B$ must be lower. This means $\Delta q_A \equiv q'_A - q_A < 0$, and $\Delta q_B \equiv q'_B - q_B > 0$.

To understand this, consider a proof by contradiction. Suppose q_A increases after factory A is fined. In that case, the firm will choose q_B to maximize the part of profits related to the quantity produced at factory B: $(q_A + q_B)^{-\frac{1}{\sigma}}(1-\lambda\kappa_0)q_B - c(q_B, \tau)$. Given that q_A is higher, the marginal benefit of producing q_B is lower due to the downward-sloping demand, meaning q_B must be lower. This contradicts the fact that γ should be decreasing. Similarly, if q_A decreases after factory A is fined, q_B must increase. This aligns with the fact that γ should be lower when factory A faces stricter penalties.

Using $e(q)$, we have that $\Delta \log e_A = \frac{1}{\alpha}\log(q'_A/q_A) < 0$, $\Delta \log e_B = \frac{1}{\alpha}\log(q'_B/q_B) > 0$. Finally, the changes in pollution intensity satisfy $\Delta \log e/q = \frac{1-\alpha}{\alpha}\log(q'/q)$, which approaches 0 as $\alpha \to 1$. ■