Innovation in Response to the Public: Endogenous Effect of Publicizing Pollution Information of Manufacturing Firms

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Abstract

While publicizing violation-related information could exert public pressure and improve compliance, its endogenous effect on innovation remains unclear. Examining the quasi-random variation in manufacturing firms' responses to the mandatory publicization of their pollutant emissions under China's 2014 pollution disclosure program, we show that the program encouraged innovation toward pollution reductions in the short run without sacrificing other innovation and led to a greater knowledge spillover effect. Firms located in cities with greater public pressure on environmental affairs have greater innovation responses to the disclosure program. However, the program appeared to also cause economic loss of the publicized firm.

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1 Introduction

Regulatory agencies face imperfect information about violations and insufficient incentives to enforce regulations (e.g., Polinsky and Shavell, 2000; Zou, 2021; Yang et al., 2024). Mandatorily publicizing violation-related information, also known as disclosure regulation, is expected to mitigate these problems by enabling the public to assist in detecting noncompliance or impose pressure on regulatory enforcement. Evidence from different countries and regulatory domains broadly supports this mechanism. For instance, in the context of the US environmental regulation, Bennear and Olmstead (2008) document that firms reduced their noncompliance behaviors due to disclosure of environmental standards. Beyond the United States, evidence from China also suggests a similar pattern: Buntaine et al. (2024) reveal that publicly available pollution data enable public and private appeals, significantly encouraging local governments to strengthen enforcement. As a result, firms under pressure reduce violations of pollution standards. In the field of occupational safety, Johnson (2020) finds that firms that are required to publicly disclose their workplace safety and health violations receive more subsequent regulatory inspections and ultimately deter violations of safety regulations of neighbor establishments[4].

While the above evidence suggests that mandatory disclosure of violation-related information can strengthen regulatory enforcement and improve the compliance of disclosed firms, research on the endogenous effect of compliant behavior from violation-related information disclosure is limited. Investigating the endoge-

[4]As stated in his paper, the author admits that no convincing evidence from his data shows that establishments mandated to publicize information reduce their violations of safety regulation.

nous effect of such disclosure regulation is important because, as Nordhaus (1994) pointed out, an optimal regulation should not only force firms to comply (as which often leads to economic loss of the regulated firms) but also encourage them to develop technology that could offset the economic loss in a longer term. However, since not all policies can endogenously facilitate innovation (Acemoglu, 2002; Acemoglu et al., 2012; Gans, 2012; Acemoglu et al., 2016; Bloom et al., 2019; Calel, 2020)[5], it remains rather as an empirical question of whether (and how) mandatorily publicizing violation-related information would endogenously induce innovation[6]. To fill the gap, we ask a simple empirical question: Does mandatorily disclosing violation-related information of a firm to the public lead to stronger regulatory enforcement against the disclosed firm and thus induce its innovation to address the resulting cost?

Empirically testing the causal effect of publicizing violation-related information on innovation is challenging for the endogeneity of firm size: First, disclosure regulations are typically non-discriminatorily applicable among firms of similar size. Yet, larger firms may face a higher level of public complaints due to a disclosure mandate and disproportionately receive greater regulatory enforcement pressure.

[5]The theories suggest that the incentives for innovation depend on not only the price of the input that is distorted by regulations but also other factors. More straightforwardly, some regulations may only encourage the adoption of existing technologies or even no change of firms' technology for production (e.g., simply pay the fines), instead of the investment in R&D.

[6]We notice that some recent empirical works have explored the effect of mandatory environmental disclosure on clean innovation, for example, Chen et al. (2023), which are relevant to our study. However, these papers have a very different institutional background from our study: The disclosed information, Greenhouse Gas (GHG) in the US, explored by these studies lack a clear connection to regulations. In particular, assesseing the Greenhouse Gas (GHG) Reporting Program in the US under the Consolidated Appropriations Act of 2008, which required large emitters to disclose their emissions data publicly, the studies find the GHG program promote the disclosed firms' low-carbon innovation. Nevertheless, in the US, there is no obvious carbon emission taxes or relevant regulations regarding carbon emissions that could influence disclosed firms' compliance with regulations.

On the other hand, R&D decisions are also highly endogenous to firm size —larger firms could have more innovation capacity in response to regulations(Thomas, 1990; Aghion et al., 2023). We overcome the difficulties of firm size by introducing a natural experiment involving the 2014 pollution disclosure program for the "National Key Monitoring Firms" (國家重點監控企業, NKMFs) in China. The policy mandated "NKMFs," identified by the plant-level pollutant emissions under an earlier regulatory program from 2008, to publicly disclose real-time pollutant emission data[7] without making changes to incumbent environmental regulations. While large manufacturing firms of similar emission normally have a similar size[8], they may own plants with different emissions. In other words, large manufacturing firms of similar size can be assigned either NKMF or non-NKMF status due to distinct plant portfolios. This nature allows us to use a difference-in-differences (DiD) design to contrast firms with quasi-random variation in their size for their innovation activities in response to the public appeals related to pollutant emissions. Specifically, we exploit the data of the listed manufacturing companies of similar size (and other observable covariates regarding innovation incentives)[9] that can be

[7]Details required to reveal in the disclosure mandate sees Appendix I.

[8]Due to data limitation on firm-level pollutant emission, we cannot directly test this assumption. Alternatively, drawing on the theory that firms with higher level pollution would have to signal their compliance publicly (Arora and Gangopadhyay, 1995), we proxy firm-level pollutant emissions using pollution-related disclosure in the firm's annual report and use this measurement to test the assumption. We find that in our data, firms of similar size are statistically indistinguishable in their pollution-related disclosure during the pre-policy period (2013), supporting the assumption that firms of similar size are also identical in their pollutant emissions. The details of how we measure the pollution-related disclosure and the relevant statistical testing are displayed in Appendix II.

[9]We apply propensity score matching to identify NKMFs and non-NKMFs of similar size and other observable heterogeneities that may influence firms' incentives for innovation redirection. Nevertheless, we acknowledge that there may be other unobserved heterogeneities in the selection of NKMF, which could blur the causal effect we claim. To address this concern, we ealso mploy a triple-difference strategy with local regulators' enforcement budgets, which is exogenous to the selection of NKMF and time invariant, as a robustness check. Details are provided in the robustness section.

linked as either NKMF or non-NKMF to run the DiD model, and test the firms' innovation response by their clean patenting activity[10], hereinafter also referred to "clean innovation."

Our main empirical finding is that publicizing violation-related information (pollutant emissions) leads to an increase in firms' clean innovation in the short run. The DiD estimates using Poisson models with pseudo-maximum likelihood (PPML) show that treated firms experience a significant increase in clean patenting, adding approximately 0.5 clean patents relative to non-treated firms within three years after the enacted of the disclosure mandate in 2014. However, this effect becomes insignificant over the longer horizon (up to 2021) in our dynamic models, indicating that the induced incentives for clean innovation wane once the firms respond to the disclosure mandate. In particular, the event-study model shows that the policy' s effect lasted until 2017, with no significant impact thereafter.

In a mechanism analysis, we confirm the role of regulatory enforcement in connecting the public pressure enabled by publicizing pollutant emissions and firms' incentive for innovation: The data of environmental administrative fines on firms exhibits that, compared to non-NKMFs of similar size, NKMFs received more environmental penalties due to the 2014 pollution disclosure program. However, the stronger environmental enforcement against the NKMFs declined over time. More specifically, we find that after 2017, the environmental enforcement between NKMFs and non-NKMFs converged again, coinciding with the time when the NKMFs' disproportionate increase in clean innovation declined.

[10]Following the IPC Green Inventory by WIPO, we classify a patent as clean if it belongs to specified green technology categories. Worth mentioning that some scholars recognized this kind of patent as "grey" patents, since they may not directly connect to clean production (Aghion et al., 2016). However, the change from "dirty" to "grey" is definitely a directed technological change toward the path met public needs because it can still reduce pollution during production.

Furthermore, we introduce a triple-difference approach to explore the underlying role of government responsiveness in the endogenous effect[11] based on the view that some governments may take stronger enforcement than others due to receiving public appeals from publicizing pollutant emissions. Specifically, using the number of public environmental appeals filed in a city to proxy for local governments' political pressure to impose environmental enforcement (Chen et al., 2016), we find that firms facing stricter enforcement due to heightened public appeals respond to the exogenous disclosure mandate by applying for approximately 4.2 additional clean patents relative to all comparison groups. This finding underscores the role of local public pressure in amplifying firms' innovation responses to the public disclosure of pollutant emissions, and confirms again that the endogenous effect of pollution publicization on NKMFs' innovation is mediated by regulatory enforcement responding to public appeals.

Finally, to understand more about the economic implications of pollution disclosure regulation, this paper runs DiD models using different dependent variables. First, we examine whether the 2014 disclosure mandate reduced the incentives of NKMFs for their non-clean innovation, a potential substitution that is thought of as a potential economic loss in endogenous innovation under regulation (e.g., Acemoglu et al., 2012; Hémous and Olsen, 2021). The data show no significant effect of the mandatory pollution disclosure on patent applications in non-clean technology, suggesting that innovation induced by a mandatory disclosure may not

[11]The triple-difference design also plays as the robustness check for the parallel trend assumption of our DiD estimate(Olden and Møen, 2022; Ortiz-Villavicencio and Sant'Anna, 2025): There may be some unobserved heterogeneities between NKMFs and non-NKMFs and lead to a pre-trend effect in the DiD model. To address this issue, as Olden and Møen (2022) suggests, interacting a third difference that is exogenous to the selection of NKMFs with the DiD estimator will cancel out the biases from the unobserved heterogeneities in the pre-trend.

substitute other innovation activities. Also, our data indicates that clean patents induced by that policy have received significantly more non-self citations per clean patent compared to those filed by non-NKMFs. This reflects that mandatory disclosure of violation-related information could not only induce the innovation of disclosed firms but also generate a relatively greater knowledge spillovers effect. Nevertheless, consistent with recent evidence(e.g., Chen et al., 2018; Kajüter et al., 2019), we also find that the 2014 disclosure program trigger an economic loss on disclosed firms: it caused the firms' value, cash flow, and liquidity to decrease simultaneously.

This study makes several contributions to the literature. First, this paper contributes to the literature on mandatory disclosure of violation-related information (Bennear and Olmstead, 2008; Johnson, 2020; Barwick et al., 2024; Buntaine et al., 2024) by providing the first solid evidence on the policy's endogenous effect on innovation toward a path aligned with public concerns. On the other hand, consistent with evidence documented by some recent studies (e.g., Chen et al., 2018; Kajüter et al., 2019), mandatory violation-related information disclosure would lead to economic loss of firms, casting doubts on the optimum of disclosure regulation even though the endogenous effect on technology development reveals a potential path that can offset the economic loss.

Second, while a large body of literature has discussed endogenous innovation induced by regulations (Nordhaus, 1994; Jaffe et al., 1995; Porter and Linde, 1995; Jaffe and Palmer, 1997; Newell et al., 1999; Jaffe et al., 2002; Popp, 2002; Brunnermeier and Cohen, 2003; Fischer et al., 2003; Horbach, 2008; Acemoglu et al., 2012; Gans, 2012; Berrone et al., 2013; Aghion et al., 2016; Dechezleprêtre and Sato, 2017; Bloom et al., 2019; Greaker and Popp, 2023), we provide the first evidence

of the role of the public in stressing regulatory enforcement and redirecting technological change of the firms. This opens up a new direction for regulation-driven innovation studies.

Finally, while the main DiD model only tracks the endogenous effect on innovation of the firms mandated to publicize their pollutant emissions, this paper further documents that the innovation induced by the disclosure mandate may also leverage greater economic benefits through knowledge spillovers. Our data reveals that mandatory-disclosure-induced clean innovation may inspire more subsequent innovation than non-regulation-induced clean innovation. Given that free knowledge spillovers are positive for endogenous economic growth (Romer, 1990), the finding highlights the economic benefits of mandatory information disclosure beyond directing innovation. To the best of our knowledge, our study is also the first paper to provide evidence that regulation-induced clean innovation could generate more knowledge spillover than clean innovations that are not driven by regulation, extending the current understanding of the knowledge spillover effect of clean innovation(Popp and Newell, 2012; Dechezleprêtre et al., 2014; Verhoeven and Martin, 2024).

2 Theoretical Framework

To guide our empirical analysis and indicate the generalization of this study, we propose a theoretical framework of how publicizing violation-related information of the firm induces its innovation. In our framework, regulators face information and incentive problems in regulatory enforcement (e.g., Laffont and Tirole, 1993; Helland, 1998; Polinsky and Shavell, 2000). Making violation-related data (e.g.,

pollution data) publicly available alleviates the problems, as stakeholders or the public (e.g., local residents, NGOs) can help uncover undetected or hard-to-detect violations of regulations (Maniloff and Kaffine, 2021) or impose political pressure on regulatory agencies for their enforcement (Buntaine et al., 2024). Regulatory agencies, in turn, respond to the public pressure by stepping up enforcement efforts(Anderson et al., 2019; Zhang et al., 2025)[12]. To respond to the stricter regulatory enforcement triggered by public pressure, firms that are required to disclose their violation-related data alter their operations that could provoke public pressure[13]. The change, according to the factor-augmented induced hypothesis(Acemoglu, 2002), may make investment in corresponding technologies relatively more attractive. Nevertheless, once firms have technologically addressed factors in their production process that might provoke public appeals against them, the trigger of public pressure on regulatory agencies diminishes, and consequently the incentives for investing in corresponding technology.

3 Institutional Background

3.1 NKMFs and the 2014 Disclosure Program in China

In 2014, China launched a nationwide environmental disclosure program that mandated major polluters, formally designated as National Key Monitoring Firms

[12]In an environment where the public/stakeholders can observe violation-related information of a firm and appeal violations using that information without liability, regulatory enforcement may deviate from its (optimal) incumbent criteria. For example, facing a strong populism against some firms, regulators would rather over enforce regulations to show their responsiveness to the public, even though the public appeal of violations is in fact a hallucination.

[13]The operations mentioned here include not only exceeding emission standards in production but also "unusual" operations such as gaming the production timing or dodging monitoring.

(NKMFs)[14], to publicly disclose hourly emissions data of both water pollutants (e.g., Chemical Oxygen Demand and ammonia nitrogen) and air pollutants (e.g., sulfur dioxide, particulate matter, and nitrogen oxides). The emission data are posted on the website maintained by the provincial government[15], but the NKMF, as a discloser, has the responsibility to upload and renew the real-time emission data. Worth mentioning that although only NKMFs have to disclose their pollution information on the platform, the government also own similar data of the pollutant emissions of non-NKMFs, collected by its Continuous Emissions Monitoring System (CEMS) installed in both the NKMFs and non-NKMFs in 2004[16]. In other words, compared to non-NKMFs, the pollutant emission disclosed by NKMFs from 2014 did not actually provide new information for regulatory enforcement against them, as regulators already had such information beforehand. Rather, to regulators, the 2014 disclosure program merely provided information about public reaction to NKMFs' pollutant emission.

NKMFs were selected based on emissions thresholds of plants from the preceding two years in 2008, assessed by provincial and central governments[17]. The

[14]The reform was launched by the MEE in a set of guidelines— "Regulations for Corporate Self-Monitoring and Information Disclosure of NKMF" —available on the central government website, see`http://www.gov.cn/gongbao/content/2013/content_2496407.htm`

[15]The interface of the website and the pollution information disclosed there is shown in Appendix I.

[16]China operates the world' s largest CEMS for scaled polluting companies, introduced in 2004 by the Ministry of Environment and Ecology (MEE). CEMS requires installing automatic monitoring devices at discharge points, such as flow meters and CCTV cameras, to capture real-time data on water and air pollutants. Local Environmental Protection Agencies (EPAs) operate and maintain the monitoring devices. By January 2020, over 24,620 plants responsible for approximately 75% of China's industrial pollution had installed these devices(Buntaine et al., 2024).

[17]Provincial governments submitted the list of major emitters that accounted for a large share of local pollution to the central government, and the central government aggregated these lists to form a nationwide roster. The final list of NKMFs is published on the MEE website `https://www.mee.gov.cn/gkml/hbb/bgt/201312/t20131231_265877.htm`.

plant-level threshold leads to the fact of a discriminatory selection among the large firms of similar size but with multiple plants that have with different emission levels: Some of them would be selected as NKMFs and some would not, even though they are in the same industry and the same province. For example, Jiangsu Sopo Chemical Co., Ltd. and Nanjing Hongbaoli Co., Ltd. are two listed firms in Jiangsu's chemical industry with comparable sizes[18]. Yet, only Jiangsu Sopo was designated as an NKMF in 2008. Even though the exact selection criteria of the Jiangsu government remain unclear, it seems plausible that Jiangsu Sopo was included as NKMF because its production was more concentrated in some plants and reached the emission threshold of NKMF: In 2007, the benchmark year for provincial governments' NKMF selections, Jiangsu Sopo operated just two manufacutring subsidiaries, whereas Nanjing Hongbaoli managed more than four[19]. A similar pattern emerges in Tianjin's pharmaceutical industry. Tianjin Tianyao Pharmaceuticals Co., Ltd. and Tasly Pharmaceutical Group Co., Ltd. reported nearly identical total assets in 2007 (21.9422 and 22.2322, respectively), yet only Tianyao was designated as an NKMF. The contrast again appears linked to production structure: Tianyao operated a single registered subsidiary, while Tasly had six subsidiaries. Together, these two cases illustrate that among firms of similar size, NKMF designation could be fairly random, with the only difference being whether a firm's production is concentrated in a few or distributed across numerous subsidiaries, making it less likely that a single plant will exceed the threshold.

[18]According to their 2007 annual reports, the total assets (in log form) were 20.8042 for Jiangsu Sopo and 20.6582 for Nanjing Hongbaoli.

[19]Exact plant-level information is generally unavailable for Chinese listed firms. However, the number of subsidiaries disclosed in annual reports provides a reasonable proxy for production dispersion.

Since the plant targeted by the NKMF policy is typically the main manufacturing facility of a firm, it is very important for the NKMF and can determine the firm-level decision-making, such as whether to invest in abatement technology to offset the public pressure from the disclosure mandate. In this regard, we argue that firms with plants assigned as NKMFs would respond sensitively to the 2014 disclosure program.

3.2 Stronger Regulatory Enforcement against NKMFs due to the 2014 Disclosure Program

Local EPAs retain enforcement discretion under the public pressure enabled by the 2014 disclosure program. For them, in general, penalties typically require corroborating evidence beyond CEMS reports, such as on-site inspections, due to practical enforcement constraints. For example, in our interview conducted with local EPA officials in a city in Sichuan province in 2017, upon detected excessive emissions via the CEMS, the typical response of local EPA officials is to contact the firm for further information rather than implement penalties without hesitation, because the firm has the right to appeal the CEMS report[20]; administrative fines are issued only if the "authenticity" of the detected violation is verified. Indeed, many policy documents mention that environmental implementation should rely on both automatic (CEMS) and manual (on-site) environmental monitoring[21]. In addition,

[20]The right is stated in the Notice of the Ministry of Environmental Protection on Issuing the "Measures for the Operation and Management of Automatic Monitoring Facilities for Pollution Sources" (环境保护部关于印发《污染源自动监控设施运行管理办法》的通知).

[21]For example, Notice of the Ministry of Environmental Protection on the issuance of the "Measures for Self-monitoring and Information Disclosure of National Key Monitoring Enterprises (Trial)" and the "Measures for Supervisory Monitoring of Pollution Sources of National Key Monitoring Enterprises and Information Disclosure (Trial)" (环境保护部关于印发《国家重点监控企业自行监测及信息公开办法（试行）》和《国家重点监控企业污染源监督性监测及信息公开

Buntaine et al. (2024) conducted a field experiment and found that local officials typically act on CEMS-reported violations only after receiving public complaints.

Requiring NKMFs to disclose real-time emissions introduces public appeals against them. Since the public appeals are observable for the upper level governments, they also bring political pressure for local EPAs' enforcement and force them to strengthen the enforcement in response to the political pressure, as suggested by Chen et al. (2016). Nevertheless, drawing on the insight from the finding of Anderson et al. (2019), to avoid further provoke the public, NKMFs may quickly adjust their operations, e.g., make their disclosed emission information less likely to be detected as violating regulations. Public oversight wanes accordingly, as the public no longer has as much violation-related information as before, and thus, they cannot stress the local EPA to enhance the enforcement against NKMFs. In this situation, for-profit NKMFs no longer have incentives to invest in abatement technology.

4 Data

Our main data come from Chinese government websites and the China Stock Market and Accounting Research (CSMAR) database. To identify the public pressure on firm, we use annual list of NKMF with water, air, and solid pollutants, published on the website of the Ministry of Ecology and Environment (MEE), to label the publicly listed manufucturing firms in CSMAR. Because the NKMF classification occurs at the plant level, we aggregate this information to the firm level, designating a publicly listed firm as NKMF if it operates at least one plant in

办法（试行）》的通知).

the NKMF list. A firm is classified as an NKMF if it appears on the list for at least one pollutant category in every year from 2014 onward. Non-NKMF firms are those listed manufacturing companies not included on any NKMF lists[22]. To measure the enforcement treatment faced by the firms when they are appealed by the public, this paper collects local public appeals from People's Daily's message board for local leaders[23]. In China, there are very limited official channels for public opinions toward government officials. Message board for local leader in People' s Daily provides a unique window in this regard because People' s Daily is a state-owned media and is directly responsible to the Central Committee of the Communist Party of China (CPC), the supreme power of China. This data also has a category of public opinions by issue (transportation, environment, public security, etc.). In particular, we classify firms by whether their prefectures have a three-year average environmental public appeals (before 2014) from People's Daily's message board for local leader that is at or above the provincial median. This classification means that firms in our data face a time invariant environmental enforcement environment between 2010 and 2017. The rationale of this measurement is that, first, more public appeals make local enforcers in China face a stronger political pressure in response to any new public appeal(Chen et al., 2016), such as the one against NKMFs. In addition, public appeals targeting at prefecture leaders are determined by complicated social-economic conditions and therefore remains unchanged over time[24]. Third, in China, regulatory enforcement within a prefecture is strongly shaped by its provincial institutional context be-

[22]To ensure consistency, we further exclude firms that were not continuously designated as NKMF throughout the study period from our sample.

[23]`https://liuyan.people.com.cn/`

[24]This design thereby satisfies the time-invariant assumption for the third difference in a DDD design(Ortiz-Villavicencio and Sant'Anna, 2025).

cause provincial governments are autonomous in environmental affairs[25]. As the results, for example, even if a prefecture in a western province in China received more appeals about local company's environmental violations than a prefecture in an eastern province, the latter usually still exhibits stronger enforcement against the appealed company because in general, the government's social responsiveness in Eastern provinces is greater than those in Western provinces[26] Therefore, this paper uses a within-province comparison to measure the difference in environmental enforcement between prefectures.

Our key dependent variable, firms' clean innovation, is measured through annual counts of clean patent applications in China, classified according to the IPC Green Inventory directory by WIPO[27]. The patent data is based on CSMAR's patent database. Also, we controlled for variables that may influence firms' innovation incentives. First, following Aghion et al. (2016), we construct variables to capture the knowledge path dependence of the firm. Specifically, we create the knowledge stock relevant to clean technologies (Clean Patent Stock) in a given year by the firm's accumulated patent applications[28]. To account for firms' overall innovation capability, the total knowledge stock (All Patent Stock) is added as well. Massive empirical studies on firms' R&D articulated the significant role of

[25]This principle is explicitly mentioned in national environmental protection law. In fact, provincial governments in China are even allowed to employ distinct regulatory standards of pollutant emissions in enforcement.

[26]Firms located in the four direct-administered municipalities, Beijing, Chongqing, Shanghai, and Tianjin, do not face obviously different enforcement environment between their districts (counterparts of prefectures in a province). Hence, we assume the firms in those cities face the same enforcement environment and all receive relatively stronger enforcement treatment if receiving public complaints than firms in prefectures with less public participation rate.

[27]https://www.wipo.int/classifications/ipc/green-inventory/home we identify the green patent according to the coverage of IPC Green Inventory except for Agriculture/Forestry as we focus on the manufacturing industries.

[28]Following Aghion et al. (2016), we introduce the annual depreciation of this knowledge capital to be 20 percent. The depreciation is applied in the total knowledge stock as well.

firm size (Cohen, 2010). In this paper, we measure firm size by annual revenue, total assets, and the number of employees, all of which are presented in natural logarithms. In addition, to reflect the financial constraint that may influence the R&D investment (Hall and Lerner, 2010), we include cash flow. We also involve firms' R&D intensity, measured by the ratio of R&D expense to revenue, and intangible assets in our econometric model as controls. The age of the firms is also considered (Cohen, 2010). Since governments play an important role in shaping firms' incentives in China (Qian and Roland, 1998), we control this effect by considering whether they are state-owned enterprises (SOE). Finally, we account for the R&D grants received by firms, as clean innovation might be influenced by the subsidies from governments (Acemoglu et al., 2012; Aghion et al., 2016). Given the subsidy details of the listed firms available in the CSMAR database, we conduct a natural language processing method to clarify and calculate the annual R&D grants of each firm[29]. Since many firms do not receive R&D grants, we plus one to the absolute value of the R&D grant gained from our algorithm and then convert them into a log form. All the monetary variables are deflated by their appropriate deflators annually published by the National Bureau of Statistics (NBS).

Our raw panel dataset covers 269 NKMF firms and 1,348 non-NKMF firms listed on China's A-share market from 2010–2017. After matching, we get a final dataset comprises 197 NKMFs and 197 non-NKMF firms across 26 industries. The

[29]The structured text data provide explanation of purposes for each record of the subsidies. Each of the authors randomly read 5,000 records and manually selected a list of keywords related to R&D and innovation. The union of the keywords was defined as the final keywords list, which was then applied to a natural language processing programming to classify the subsidy records with the purpose of promoting R&D and innovation. Based on the classification, we calculated the amount of R&D grant for each firm in each year. The text data is in Chinese. The keywords used for the classification include: 专利; 科技; 创新; 研究; 技术; 研发; 博士; 知识产权; 院士; 火炬; 领军人才; 成果转化; 高新; 高精尖; 瞪羚; 先进制造; 战略性新兴产业;863 项目.

comparison and t-test of the core dependent variable and covariates used in the matching model is presented in Table 1. The summary statistics after matching are in Table 2.

Table 1: T-test for the Difference between Groups

	"Before PSM"		"After PSM"	
	Mean Diff.	(t-stat.)	Mean Diff.	(t-stat.)
Clean Patent Count	0.374	(-0.246)	0.076	(0.846)
Clean Patent Stock	0.167	(0.503)	-0.095	(-0.514)
All Patent Stock	-31.764	(-0.68)	-40.264	(-1.474)
Revenue (million RMB)	-10877.61***	(-7.286)	420.389	(0.347)
Age	-3.609***	(-8.825)	0.355	(0.612)
Observations	1617		382	

t-statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Summary Statistics of the Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Non-NKMFs					NKMFs				
VARIABLES	N	mean	sd	min	max	N	mean	sd	min	max
Clean Patent Count (one-year-lagged)	1,500	0.239	1.697	0	31	1,540	0.251	1.567	0	28
Clean Patent Stock	1,512	0.525	1.980	0	22.33	1,543	0.649	2.620	0	46.11
All Patent Stock	1,512	32.93	138.0	0	3,926	1,543	89.12	778.7	0	20,258
ln_Revenue	1,514	21.60	1.386	15.36	25.85	1,544	21.80	1.208	11.76	25.32
ln_Employees	1,512	7.755	1.146	2.890	11.29	1,543	8.084	1.039	1.609	11.14
ln_Total Assets	1,514	22.13	1.161	18.48	26.52	1,545	22.38	1.107	17.16	26.32
Age	1,514	12.13	6.317	0	27	1,545	11.86	5.841	0	25
Cash Flow	1,514	0.199	0.684	-13.28	13.31	1,545	0.209	0.351	-2.688	5.696
ln_R&D subsidy	1,514	10.11	6.698	0	20.48	1,545	9.635	6.854	0	21.24
R&D Intensity	1,514	0.0220	0.0271	0	0.349	1,544	0.0208	0.0284	0	0.763
SOE	1,514	0.439	0.496	0	1	1,545	0.585	0.493	0	1

5 Empirical Strategy

The central purpose of our empirical analysis is to test whether firms that are required to disclose their pollution data publicly and thus face more public appeals regarding their pollution behaviors would have higher incentives for innova-

tion for pollution reduction than those firms that do not disclose. To this end, we discern firms into disclosed and non-disclosed firms through an exogenous impact of the disclosure program for NKMFs in China in 2014. We identify the impact using an interaction term between the NKMF-based binary variable $Treated_i$ (NKMFs or non-KNMFs) and a time-varying binary variable $Post_t$(before and after 2014), i.e., a differences-in-differences (DiD) design. As mentioned in the previous part of this paper, we employ propensity score matching (PSM) (Heckman et al., 1997) to address the endogeneities of firm size and other innovation-related covariates in $Treated_i$, using 2013 as the pre-policy year. Specifically, we run intra-industry Probit models that include firm-level covariates, namely, revenue, age, and patent stocks, to generate propensity scores within industry with a non-replacement nearest-neighbor approach and use the scores to resample our data[30].

We proxy the innovation in response to public appeals toward pollution-related information by clean patent applications of firm i at time t. Since there is usually a time lag between the R&D input and patenting performance(Hall et al., 1984), we take a one-year lag of the patent applications, denoted by Υ_{it+1}. Considering Υ_{it+1} is a count data with many zeros, our estimate is implemented by a Poisson

[30]As a robustness check, Supplementary Appendix C also show that the main result does not change by using samples based on different matching strategies.

model with pseudo maximum likelihood (PPML) and fixed effect[31]:

$$\Upsilon_{it+1} = \exp\left(\alpha_1 Treated_i \times Post_t + \alpha_2 Treated_i + \alpha_3 Post_t + \beta X_{it} + \theta_i + \zeta_t + \delta_k + \zeta_t \times \delta_k + \eta_j\right) \tag{1}$$

Where Υ_{it+1} is the patent count for firm i in year $t+1$, α_1 is the DiD estimate of the effect of the 2014 disclosure program on treated firms, $Treated_i$ is a dummy variable distinguishing the treated group ($Treated_i = 1$) from the control group ($Treated_i = 0$), $Post_i$ is a dummy variable indicating the period after ($Post_t = 1$) and before the disclosure ($Post_i = 0$). Finally, we account for firm heterogeneity by setting X_{it} as the matrix of all control variables in the firm i and time t, θ_i as the firm fixed effect, ζ_t as the time fixed effect, δ_k as the province fixed effect for province k, $\zeta_t \times \delta_k$ as the province-year fixed effect, capturing potential regulatory enforcement differences among provinces that vary over time, and η_j for industry fixed effect for industry j.

Since our theoretical framework predicts that the effect of pollution disclosure programs may not last for a long time, we test the persistence of the effect using an event-study model in a longer period (2010-2021), which further analyzes the dynamic effects of the disclosure policy. Specifically, we estimate the following event study model:

[31]The estimate with the Poisson model with fixed effect is expected to be more consistent than using the linear model (Hausman et al., 1984; Wooldridge, 1999; Silva and Tenreyro, 2006). And, to obtain a robust estimate and avoid statistical separation and convergence issues, we use *ppmlhdfe* in Stata (Correia et al., 2020). We cluster the standard errors at the firm level for all regression models shown in this paper, except the robustness check in Appendix A, which adopts a higher level standard errors (clustered at city level).

$$\Upsilon_{it+1} = \exp\left(\sum_{k=-4}^{7} \gamma_k \, \text{Post}_{t+k} \cdot Treated_i + \alpha X_{it} + \theta_i + \zeta_t + \delta_k + \zeta_t \times \delta_k + \eta_j\right) \quad (2)$$

where: Υ_{it+1} represents the green patent count for firm i at time $t+1$. Post_{t+k} is a series of event-time dummies, where $k = 0$ indicates the period of the event (the disclosure policy), $k < 0$ captures pre-event periods, and $k > 0$ captures post-event periods. γ_k are the coefficients of interest, measuring how the treatment effect evolves over time. In addition to offering insights into the persistence of policy impacts, this model enables us to test for pre-existing trends, thereby reinforcing the validity of the parallel trends assumption. All the others remain the same as the DiD model.

Finally, we run the following triple differences model to test the role of local public pressure on environmental enforcement in moderating the effect of publicizing violation-related information.

$$\begin{aligned}\Upsilon_{it+1} = \exp\Big(&\alpha_1 \, Treated_i \cdot Post_t \cdot LPP_c + \alpha_2 \, Treated_i \cdot LPP_c + \alpha_3 \, Post_t \cdot LPP_c \\ &+ \alpha_4 \, Treated_i \cdot Post_t + \alpha_5 \, Treated_i + \alpha_6 \, Post_t + \alpha_7 \, LPP_c \\ &+ \beta X_{it} \theta_i + \zeta_t + \delta_k + \zeta_t \times \delta_k + \eta_j + \epsilon_{it}\Big)\end{aligned} \quad (3)$$

In this model, the third difference, local public pressure $LPP_c \in \{0, 1\}$, indicates whether a firm faces relatively more stringent enforcement treatment from local enforcer because it is located in the prefecture c . The indicator equals 1 if the firm is located in the prefecture c that has a greater public appeals regarding environmental issues, as stated in the former section of this paper.

6 Empirical Results

6.1 The Effect of the 2014 Pollution Disclosure Program on Clean Innovation

First, we check whether our DiD estimator satisfies the parallel trend assumption using the matched sample. Columns 3 of Table 3, which display the results from our event-study specification, show no significant pre-policy differences in clean patenting trends between NKMF and non-NKMF firms. This absence of significant pretrends supports the validity of our DiD identification strategy. Additionally, Figure 1 visually confirms the stability of these pre-trends.

The main results presented in Table 3 demonstrate the impact of mandatory environmental information disclosure on firms' clean innovation. The DiD coefficient of the Poisson estimation involving all control variables documents an increase in the expected number of clean patents by approximately 273%. Given an average baseline of 0.14 clean patents per year for non-treated firms before policy implementation, this implies an average treatment effect of about 0.24 additional clean patents annually attributable to the mandatory disclosure policy. Further analysis using the dynamic event-study specification (Column 3) highlights that mandatory disclosure generated a substantial increase in clean patenting one year after policy enactment. Nevertheless, this effect was temporary, diminishing substantially after the fourth year post-policy. These findings corroborate the first prediction of our framework: Mandatory environmental disclosure would provide short-term incentives for clean innovation among regulated firms. On the other hand, our control variables also reveal interesting patterns: Clean patent stocks negatively

predict subsequent clean innovation, suggesting diminishing marginal returns on innovation efforts for firms already possessing extensive patent portfolios. In contrast, total patent stocks are positively associated with the clean patenting, implicating its potential complementarity to clean innovation. Finally, as expected, our data shows that firms with higher R&D intensity and more R&D grants from the government would correlate with more application of clean innovation.

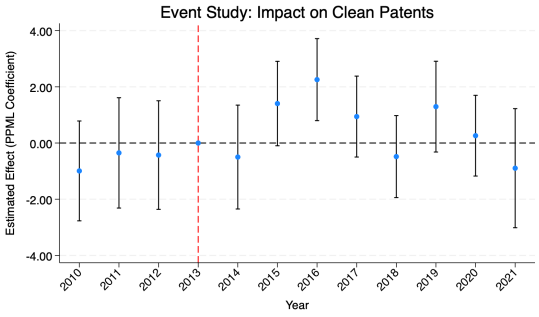


Figure 1: Difference of Clean Patent: NKMF v.s. non-NKMF

Note: This figure visualizes the dynamic pattern of the patent applications between NKMF and non-NKMF over time. The NKMFs significantly applied for more clean patents than non-NKMFs in 2016, two years after the policy was issued. The difference is not persistent, as no significant differences were found after that.

6.2 The Disclosure Program Triggered Public Appeals and Affect Firms' Innovation Via Pressure of Regulatory Enforcement

Although Huet-Vaughn et al. (2018) have documented that real-time pollution disclosure would bring more public appeals against the disclosed subject, due to data limitations, we cannot directly measure public appeals against NKMFs. Notwithstanding, this paper introduces the DDD model powered by local enforcers' responsiveness in any new environmental public appeals to validate the mechanism

that the 2014 disclosure program first triggered additional public appeals against NKMFs, then caused according local regulatory enforcement, and ultimately induced NKMFs' clean innovation. As mentioned above, we suggest that in a situation where the local regulatory agencies receive public appeals against NKMFs, the stronger local public pressure regarding environmental issues will force they to enforce the regulations against the NKMFs in a stricter way. Column 4 in Table 3 reflects that NKMFs located in the city that has a relatively stronger public pressure on its environmental enforcement applied for clean patents approximately 29 times that of their counterparts. This magnitude looks huge. However, considering the very low baseline of the comparisons in clean patenting, it can be illustrated as the average of roughly 4.2 additional clean patents applied by the NKMFs that face stricter environmental enforcement treatment in our data.

Table 3: Impact of Mandatory Pollution Disclosure on Firms' Clean Innovation

VARIABLES	(1) Clean Patent Count (DiD)	(2) Clean Patent Count (DiD)	(3) Event Study for Clean Patent Count	(4) Clean Patent Count (DDD)
Treated × Post	1.029**	1.152***		-1.654
	(0.445)	(0.441)		(1.392)
Treated × Post × Local Public Pressure				3.374**
				(1.430)
Post × Local Public Pressure				-2.709**
				(1.317)
Clean Patent Stock		-0.100***	-0.088***	-0.099***
		(0.019)	(0.014)	(0.019)
All Patent Stock		0.006*	0.004***	0.006**
		(0.003)	(0.001)	(0.003)
ln_Revenue		0.201	-0.266	0.027
		(0.618)	(0.318)	(0.632)
ln_Employees		-1.444*	-1.165**	-1.328**
		(0.838)	(0.518)	(0.663)
ln_Total Assets		1.037	1.887***	0.836
		(0.660)	(0.470)	(0.640)
Cash Flow		0.079	-0.174	0.264
		(0.351)	(0.239)	(0.399)
ln_R&D subsidy		0.038*	0.030**	0.045**
		(0.020)	(0.015)	(0.020)
R&D Intensity		32.321***	0.309	32.968***
		(10.282)	(6.886)	(10.392)
SOE		-0.198	1.044	1.363
		(1.306)	(0.734)	(1.309)
Pre_4 (2010)			-0.993	
			(0.907)	
Pre_3 (2011)			-0.351	
			(1.002)	
Pre_2 (2012)			-0.428	
			(0.986)	
Post_0 (2014)			-0.499	
			(0.943)	
Post_1 (2015)			1.405*	
			(0.767)	
Post_2 (2016)			2.257***	
			(0.745)	
Post_3 (2017)			0.942	
			(0.735)	
Post_4 (2018)			-0.483	
			(0.745)	
Post_5 (2019)			1.296	
			(0.825)	
Post_6 (2020)			0.261	
			(0.733)	
Post_7 (2021)			-0.896	
			(1.082)	
Constant	0.986***	-16.237	-52.465***	-8.377
	(0.178)	(10.906)	(9.223)	(10.741)
Observations	486	485	1,267	485
Firm FE	Yes	Yes	Yes	Yes
Povince FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province×Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

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

Note: Column 1 to 3 of the table presents the diff-in-diff and event study regression results on the lagged clean patents of firms, and column 4 shows the triple-difference result with and without control variables. All results are based on the PPML model. Standard errors are clustered at the firm level and are shown in parentheses. Variables omitted from the model do not appear.

Columns 1 and 2 present static DiD models using a sample between 2010 and 2017. The estimation shows that the mandatory disclosure policy significantly increased the clean patenting of regulated firms relative to non-regulated firms. The dynamic model (Columns 3) further documents that the policy impact was only short-lived until 2016, indicating non-persistent incentives induced by the disclosure policy. Column 4 shows the NKMFs located in city with more public appeals toward environmental affairs filed significantly more clean patents after publicizing their pollution information. The difference in the observation number between this table and the summary statistics is because the observations that could lead to statistical separation issues under high-dimensional fixed effects are removed in our model (see detailed discussion in Correia et al. (2020)).

6.3 Mechanism Analysis: the 2014 Pollution Disclosure Program Induced Regulatory Enforcement

Furthermore, Figure 2 validates the key mechanism that the 2014 disclosure program triggered additional environmental regulatory enforcement against NKMFs. Based on the data of firm-level environmental administrative fines collected from the Institute of Public and Environmental Affairs (IPE)[32], the figure shows intuitive descriptive evidence[33] about the role of regulatory enforcement in inducing firms' innovation: Although NKMFs and non-NKMFs received almost the same environmental administrative fines between 2010 and 2014, there are a significant jump for the environmental administrative fines toward NKMFs since 2015 (one year after the enacting of the disclosure program). On the other hand, NKMFs seemed quickly adjusting their operations to respond to the strengthened enforcement, which make environmental fines between NKMFs and non-NKMFs converged again after 2017, warranting the short-lived effect of the 2014 disclosure program.

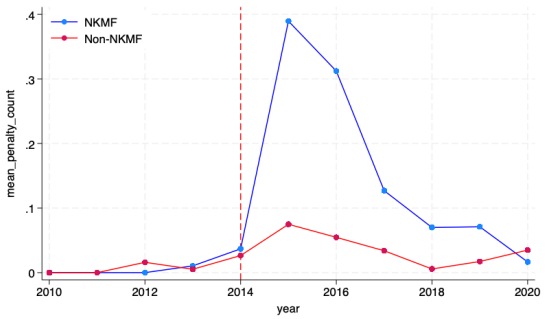


Figure 2: Average Number of Administrative Penalties: NKMF v.s. non-NKMF

[32] https://wwwen.ipe.org.cn/

[33] The formal statistical analysis of the jump in penalties and the reason of the environmental fine are in Supplementary Appendix C.

6.4 The Effect on Knowledge Spillover and Innovation Substitution

We then extend the baseline DiD specification (Equation 1) to two derivative innovation outcomes. First, we examine the firm' s average number of non-self forward citations received within a five-year window per clean patent filed in a given year,[34] which captures the extent of knowledge spillovers generated by clean innovation. Second, we analyze firms' non-clean patent applications to assess whether the disclosure mandate induces substitution between clean and conventional innovation activities.

Column (1) of Table 4 provides evidence of a significant knowledge spillover effect. Clean patents filed by regulated (NKMF) firms after the disclosure mandate receive substantially more non-self citations per patent relative to clean patents filed by firms not subject to the policy. The estimated magnitude implies that induced clean patents generate approximately three times as many external citations as those in the control group. This result suggests that clean innovation stimulated by regulatory disclosure is not merely firm-specific compliance-oriented invention, but instead embodies technological knowledge with broader applicability and diffusion potential. The implication is that regulation-induced innovation appears to redirect innovative effort toward cleaner technologies that are more easily transferable across firms and industries.

In contrast, Column (2) shows no statistically significant effect of the disclosure mandate on non-clean patenting activity. This finding indicates that the increase in clean innovation is not accompanied by a corresponding decline in conventional

[34]Firms with no clean patent filings in a given year are assigned a value of zero.

innovation, alleviating concerns that it crowds out firms' broader inventive efforts. Together, these results suggest that the policy induces additional clean innovation with meaningful spillover benefits, rather than merely reallocating innovation away from non-clean technologies.

6.5 The Effect on Firms' Economic Performance

We next examine the potential economic loss caused by the 2014 disclosure regulation. Columns (3)–(5) of Table 4 report DiD estimates for Tobin' s Q, liquidity, and cash flow, respectively, which together capture firms' market valuation and short-run financial conditions.

The results indicate that the 2014 disclosure mandate led decline in firms' economic loss in terms of their market valuation and liquidity. Specifically, NKMFs experience a 37% of reduction in Tobin' s Q following the implementation of the disclosure program. Similarly, liquidity and cash flow decline among regulated firms relative to the control group for around 6.7% and 6.4%, respectively. These findings are consistent with the evidence of short-run adjustment frictions associated with responding to environmental disclosure regulation(Chen et al., 2018; Kajüter et al., 2019). And, importantly, since these economics loss appear to coexist with the observed increase in clean innovation and knowledge spillovers, it suggests that the pollution disclosure mandate would also bring the "transition pains" that usually happen in other environmental policies.

Table 4: Impact of Mandatory Pollution Disclosure on Knowledge Spillover Effect, Non-Clean Innovation, and Economic Performance

VARIABLES	(1) Knowledge Spillover of the Induced Clean Patent	(2) Non-Clean Patent Count	(3) Tobin's Q	(4) Liquidity	(5) Cash Flow
Treated × Post	1.383**	-0.080	-0.463**	-0.069***	-0.066*
	(0.652)	(0.101)	(0.230)	(0.024)	(0.039)
Clean Patent Stock	-0.143***	-0.013	-0.000	-0.004	0.006
	(0.038)	(0.014)	(0.019)	(0.005)	(0.005)
All Patent Stock	0.042***	0.000	0.000**	0.000	0.000
	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)
ln_Revenue	-0.178	0.114	-0.517	-0.036	0.022
	(1.101)	(0.161)	(0.325)	(0.176)	(0.058)
ln_Employees	-3.207***	-0.136	-0.722***	-0.050	0.216
	(1.034)	(0.115)	(0.253)	(0.047)	(0.175)
ln_Total Assets	-0.018	0.421***	-1.102***	0.070	-0.130
	(0.990)	(0.160)	(0.188)	(0.121)	(0.080)
Cash Flow	-0.342	0.187			
	(0.871)	(0.123)			
ln_R&D subsidy	-0.024	0.020**	-0.002	0.001	-0.000
	(0.045)	(0.008)	(0.008)	(0.001)	(0.002)
R&D Intensity	48.430***	5.172**	6.809*	-5.249*	0.563
	(15.175)	(2.035)	(4.064)	(2.710)	(0.499)
SOE	1.320	0.507*	-0.515**	0.010	-0.027
	(1.204)	(0.303)	(0.235)	(0.059)	(0.074)
Constant	26.273	-6.328**	43.999***	0.220	0.109
	(19.255)	(3.063)	(8.953)	(1.522)	(1.605)
Observations	221	2,345	2,927	3,050	3,050
Firm FE	Yes	Yes	Yes	Yes	Yes
Povince FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Province×Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

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

Note: The table presents the diff-in-diff regression results of derivative analyses. Column (1) examines whether the clean innovation induced by the disclosure mandate generates downstream technological externalities. The positive and statistically significant coefficient on the DiD estimator indicates that NKMFs experience a higher level of knowledge spillovers associated with induced clean patents following the policy. Column (2) shows no significant effect on non-clean patenting activity, suggesting that the policy does not crowd out firms' conventional innovation efforts. Columns (3)–(5) explore potential economic consequences using the OLS model. We find that the mandate is associated with a modest decline in Tobin' s Q, liquidity, and cash flow in the post period, consistent with the presence of short-run adjustment or compliance costs.

Standard errors are clustered at the firm level and are shown in parentheses. Variables omitted from the model do not appear. The difference in the observation number between this table and the summary statistics is because the observations that could lead to statistical separation issues under high-dimensional fixed effects are removed in our model (see detailed discussion in Correia et al. (2020)).

6.6 Robustness Checks

We first show that even if there may be some unobserved variables in our DiD estimator, the consistent result found by our DDD estimate defends this challenge: Since SEE_i is exogenous to $Treated_i$ and time-invariant, the DDD estimator $Treated_i \cdot Post_t \cdot SEE_i$ would absorb biases in $Treated_i \cdot Post_t$ (Olden and Møen, 2022). In particular, as α_1 between equations (1) and (3) lies in the positive interval and is statistically significant, we confirm this robustness. Secondly, by replacing Υ_{it+1} with the share of clean patents in Equations (1) and (2), we test whether the main results remain consistent with an alternative measurement of clean innovation. The DDD estimate result in column 4 of the baseline table documents this robustness.

We further conduct a series of robustness checks to assess the sensitivity of our main findings to alternative outcome definitions, sample constructions, and inference procedures. First, we replace the count of clean patents with the share of clean patents to account for potential changes in firms' overall patenting activity. Table 1 in the Supplementary Appendix shows that NKMFs' clean patent share increased disproportionately relatively to non-NKMFs due to the 2014 disclosure program. The effect is also short-lived, consistent with the results using clean patent count. Next, we examine the stability of our estimates using alternative samples, including unmatched data and samples matched using the full set of control variables, and report the corresponding DiD and DDD estimates. Table 2 in the Supplementary Appendix indicates that no matter using unmatched sample or the matched sample based on a stricter condition of covariates, the results of the DDD estimates, the most robust model avoiding the unobserved variable problems,

keep consistent to our main findings. We then re-estimate the baseline specifications using standard errors clustered at a higher administrative level to address concerns related to serial correlation and unobserved spatial shocks, referred to the suggestion of Bertrand et al. (2004). Table 3 in the Supplementary Appendix documents the robustness of the main result.

Finally, we also check the robustness of the theoretical explanation surrounded with regulatory enforcement: Table 5 and 6 in the Supplementary Appendix respectively indicate that due to the 2014 disclosure program, there are no R&D compensation for NKMFs from the government nor additional ESG disclosure from the NKMFs to attract institutional investors. All of these show that subsequent regulatory enforcement is the most reasonable explanation regarding the role of public appeals in determining firms' clean innovation.

7 Conclusion

A central objective of public policy is to promote technological changes endogenously and redirect innovation toward socially desirable directions (Nordhaus, 1994; Aghion et al., 2009; Greaker and Popp, 2023). This study contributes to this objective by examining mandatory environmental disclosure as a distinct regulatory instrument and by providing empirical evidence on its innovation-inducing effects. We show that disclosure policies can redirect innovative efforts toward cleaner technologies by enabling public participation and enhancing regulatory enforcement.

Beyond documenting innovation redirection, our findings highlight an additional channel through which disclosure regulation may generate broader economic

benefits. Clean innovations induced by mandatory disclosure exhibit significantly stronger knowledge spillovers, as reflected in higher non-self citation intensity. This pattern suggests that transparency-based regulation may serve a dual role: improving regulatory compliance in the short run while fostering the diffusion of socially valuable technologies that support long-term growth (Romer, 1990). At the same time, our results indicate that these innovation gains may coexist with short-run financial adjustments. Taken together, the evidence points to an important trade-off inherent in transparency-based regulation: while disclosure can induce socially beneficial innovation and spillovers, it may also impose short-term financial frictions on regulated firms.

This study has several limitations that point to avenues for future research. From a theoretical perspective, we do not conduct a formal welfare analysis, nor do we evaluate whether mandatory disclosure alone is sufficient to achieve optimal sustainable development paths. Empirically, our analysis is conducted in the context of China, where institutional features may shape the effectiveness of disclosure policies. Future research using cross-country settings could help assess the external validity of our framework and further clarify the conditions under which transparency-based regulation most effectively redirects technological change.

APPENDIX I: Demonstration of the 2014 Disclosure Program in China

This section demonstrates the pollution information disclosed by the 2014 disclosure program against the National Key Monitoring Firms (NKMFs). The program discloses the emissions of chemical oxygen demand (COD), ammonia nitrogen (NH -N), sulfur dioxide (SO), particulate matter (PM), and nitrogen oxides (NO) on the provincial government–maintained disclosure platforms. The following screenshot, collected in 2017 by the authors of this paper[35], demonstrates an example of how an NKMF discloses its pollution on the website (in Chinese).



Figure 3: The air pollution disclosure of a NKMF in Hebei Province in 2017

The Figure provides a screenshot of the Hebei Provincial Online Disclosure Platform (河北省国家重点监控企业自行监测信息公开平台), which is one of the

[35]Although the disclosure policy remains in effect today, the interface of the disclosure website (as of 2026) has evolved a lot over the past decade, make it look substantially different from its 2017 version (the screenshot). Nevertheless, the main website structure and information disclosed on the platform have remained unchanged. See the current disclosure platform via the link: `https://wryjc.cnemc.cn/`

official government websites (each province maintains its own disclosure website). The disclosed subject in the screenshot is Huafeng Power Tangshan Fengrun Co., Ltd (华润电力唐山丰润有限公司). Each row in the table corresponds to a single monitoring record from a specific monitoring point/discharge outlet (e.g., a smokestack or wastewater outlet) of a regulated firm. For every record, the system discloses five key elements:

1. **Firm name and monitoring point** –identifying the regulated facility and the exact outlet being monitored (e.g., Stack No. 1).

2. **Monitoring time** –the precise date and time when the pollutant concentration was measured. In the screenshot, it is August 24, 2016, at 9 PM, 10 PM, and 11 PM.

3. **Pollutant type** –such as sulfur dioxide (SO), nitrogen oxides (NOx), or particulate matter.

4. **Measured concentration** –the actual emission level recorded by on-site monitoring equipment.

5. **Compliance status** –a comparison between the measured value and the standard, indicating whether the firm is in violation.

The website is publicly accessible, providing publicly observable signals and exposing firms to public scrutiny, media attention, and stakeholder pressure. This institutional setting is what underlies the disclosure-induced incentives analyzed in this paper.

APPENDIX II: Firms of Similar Size Also Have Similar Pollutant Emission in Pre-Policy Duration

In this section, we show that there are no statistically significant differences in pollutant emissions between NKMFs and non-NKMFs. Since we cannot directly measure firms' pollutant emission, a proxy based on pollution-related disclosure is created. The rationale of this proxy is that, as suggested by Arora and Gangopadhyay (1995), firms would voluntarily disclose relevant information to signal their compliance and avoid future regulatory risk. Technically, referring to the method developed by Sautner et al. (2023), we introduce a pre-trained BERT model to score the pollution-specific compliance disclosed in the firm's annual report. The pipeline of our scoring approach is as follows:

First, we derive three seed words, 工业排放 (industrial emissions), 有害垃圾 (hazardous waste), and 电子垃圾 (electronic waste), that are related to pollutant emission based on the Sino-Securities Index ESG Ratings Methodology. Second, 500 most relevant words are defined using BGE-M3[36], a popular pretrained BERT model in Chinese. Specifically, the semantic similarity derived from the language embeddings of BGE-M3 is calculated for all words occurred in the management discussion sections of the firms' annual reports. We then define the most similar 500 words as the dictionary that represents the pollution-related topic. Next, we count the keyword occurrences as a raw score of the pollution-related disclosure. Finally, we normalize the raw score by the length of the management discussion

[36] https://huggingface.co/BAAI/bge-large-zh-v1.5

and get the final score. In addition, deriving from the not-pollution-related but environmental-related keywords mentioned in the Sino-Securities Index ESG Ratings Methodology, we also create another disclosure score based on environmental-related seed words other than pollution[37].

Once gaining the pollution-related and environmental-related disclosure, we run a t-test for the scores between NKMFs and non-NKMFs of similar size in 2013 (the pre-policy year). The result (see below) shows that there are not statistically significant differences in pollutant emission between NKMFs and non-NLMFs.

Table 5: T-test for the Difference between Groups

	Mean Diff.	(t-stat.)
Pollution Disclosure Score	-0.018	(-0.869)
Environmental-Related Disclosure Score (other than pollution)	0.021	0.406
Observations	382	

t-statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[37]温室气体排放 (greenhouse gas emissions); 碳减排 (carbon emission reduction); 气候变化 (climate change); 海绵城市 (sponge city); 绿色金融 (green finance); 生物多样性 (biodiversity); 水资源 (water resources); 可再生能源 (renewable energy); 绿色建筑 (green buildings); 绿色工厂 (green factories); 可持续 (sustainability); 环保处罚 (environmental penalties)

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1 Supplementary Appendix A: More Robustness Checks

1.1 Impact on the share of clean patents

As a robustness check, we replace the count of clean patents with the share of clean patents as the dependent variable, which allows us to account for potential changes in firms' overall patenting activity. We re-estimate both the difference-in-differences and event-study specifications using this alternative measure. The results remain highly consistent with our baseline findings. In particular, NKMFs exhibit a similar post-policy increase in the intensity of clean innovation, and the dynamic estimates display comparable temporal patterns, with no evidence of differential pre-trends prior to the policy implementation. These results indicate that our main conclusions are not driven by fluctuations in total patenting volume, but instead reflect a substantive shift in the composition of firms' innovative output toward cleaner technologies.

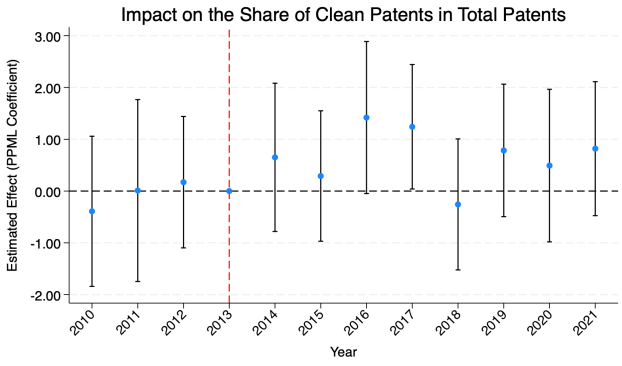


Figure 1: Difference of Clean Patent Share: NKMF v.s. non-NKMF

Note: This figure presents a visualization of Column 3 in Table 1, the share of clean patents between NKMF and non-NKMF over time. The disclosure policy effect was significant in 2017, as the share of clean patents in NKMF increased. However, consistent with the trend based on patent count, the effect declined afterward.

Table 1: Impact of Mandatory Pollution Disclosure on the Share of Clean Patents

VARIABLES	(1) DiD model	(2) DiD model	(3) Event study
Treated × Post	0.882**	1.051**	
	(0.416)	(0.434)	
Clean Patent Stock		-0.063***	-0.060***
		(0.024)	(0.015)
All Patent Stock		0.008	0.004***
		(0.007)	(0.001)
ln_Revenue		-0.952*	-0.355
		(0.503)	(0.266)
ln_Employees		-0.584*	-0.070
		(0.342)	(0.239)
ln_Total Assets		0.897	0.580*
		(0.577)	(0.321)
Cash Flow		0.306	-0.009
		(0.292)	(0.178)
ln_R&D subsidy		0.043*	0.027**
		(0.022)	(0.013)
R&D Intensity		13.065	2.037
		(8.977)	(5.586)
SOE		0.695	-0.090
		(1.299)	(0.530)
Pre_4 (2010)			-0.391
			(0.739)
Pre_3 (2011)			0.010
			(0.896)
Pre_2 (2012)			0.172
			(0.647)
Post_0 (2014)			0.652
			(0.730)
Post_1 (2015)			0.291
			(0.643)
Post_2 (2016)			1.419*
			(0.749)
Post_3 (2017)			1.241**
			(0.613)
Post_4 (2018)			-0.258
			(0.645)
Post_5 (2019)			0.785
			(0.653)
Post_6 (2020)			0.492
			(0.752)
Post_7 (2021)			0.819
			(0.660)
Constant	-1.450***	2.647	-6.603
	(0.168)	(9.194)	(5.208)
Observations	486	485	1,267
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Povince FE	Yes	Yes	Yes
Province×Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

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

Note: This table captures the static and dynamic effects of mandatory environmental information disclosure on firms' clean innovation, using the share of clean patents in a firm's total patent portfolio as an alternative dependent variable, with a one-year lagged effect of patenting. The estimated results are consistent with the baseline regressions on the count of clean patents. Columns 1 and 2 are the static DiD model without and with controls, and Column 3 presents the event study models. All results are based on the PPML model. Standard errors are clustered at the firm level and shown in parentheses.

1.2 Estimation based on different samples

The selection of covariates in the matching model may affect the quality of the final estimation. In this subsection, we show DiD and DDD estimations based on two alternative samples, namely unmatched data and data matched with all control variables. In particular, for each test, we present regressions with 1) DiD without control variables, 2) DiD with control variables, and 3) DDD with control variables. To make the robustness test as straightforward as possible, the time period between 2010 and 2017 is used in the regressions. The results of the triple difference models, the most robust estimation in our empirical design, show that our core argument remains unchanged across different samples. It is worth mentioning that we find the DDD estimator to be consistent between the matched and unmatched samples (i.e., the raw sample), proving the advantage of our DDD design: The exogenous difference in local agencies' enforcement strength cancels out the biases embedded in the selection of NKMFs and non-NKMFs.

Table 2: Estimation on Firms' Clean Innovation based on the Unmatched Sample

VARIABLES	(1) DiD	(2) DiD	(3) Triple Diff.
Treated × Post × Local Public Pressure			1.638***
			(0.552)
Post x Local Public Pressure			-0.785**
			(0.344)
Treated x Post	-0.314	-0.416*	-1.699***
	(0.236)	(0.250)	(0.497)
Clean Patent Stock		-0.013***	-0.013***
		(0.002)	(0.002)
All Patent Stock		0.001*	0.001
		(0.000)	(0.000)
ln_Revenue		0.895**	0.833**
		(0.350)	(0.339)
ln_Employees		-0.796***	-0.754***
		(0.212)	(0.211)
ln_Total Assets		0.174	0.181
		(0.382)	(0.379)
Cash Flow		-0.134	-0.145
		(0.176)	(0.180)
ln_R&D subsidy		-0.011	-0.013
		(0.011)	(0.011)
R&D Intensity		-1.578	-1.758
		(3.252)	(3.271)
SOE		0.255	0.147
		(0.365)	(0.342)
Constant	2.539***	-14.460***	-13.028***
	(0.046)	(4.476)	(4.544)
Observations	3114	3114	3114
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Province×Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
	*** p<0.01, ** p<0.05, * p<0.1		

Note: The table presents the results of the DiD and DDD model mentioned in the body text, using unmatched data. All results are based on the PPML model. Standard errors are clustered at the firm level and shown in parentheses. Variables omitted from the model do not show. As the most robust model, our DDD estimator (Column 3) shows that, compared to all other groups, NKMFs that faced greater public appeals and stricter enforcement environment filed more clean patents due to the 2014 disclosure program. This result is consistent with the findings of our main model.

Table 3: Estimation on Firms' Clean Innovation based on Re-Matched Sample using all control variables

VARIABLES	(1) DiD	(2) DiD	(3) Triple Diff.
Treated × Post × Local Public Pressure			3.448**
			(1.427)
Post × Local Public Pressure			-2.079
			(1.314)
Treated × Post	0.218	0.228	-2.395*
	(0.502)	(0.558)	(1.294)
Clean Patent Stock		-0.080***	-0.081***
		(0.025)	(0.025)
All Patent Stock		0.006**	0.006**
		(0.003)	(0.003)
ln_Revenue		0.442	0.099
		(0.777)	(0.782)
ln_Employees		-1.552*	-1.502**
		(0.878)	(0.728)
ln_Total Assets		0.232	0.327
		(0.679)	(0.656)
Cash Flow		0.025	0.071
		(0.484)	(0.519)
ln_R&D subsidy		0.016	0.014
		(0.028)	(0.027)
R&D Intensity		27.296***	26.516**
		(10.262)	(10.717)
SOE		-3.344**	-3.550**
		(1.443)	(1.474)
Constant	1.346***	0.119	6.465
	(0.177)	(12.794)	(12.840)
Observations	348	348	348
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Province×Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
	*** p<0.01, ** p<0.05, * p<0.1		

Note: The table presents the results of the DiD and DDD model mentioned in the body text, using the sample based on a PSM model using all control variables as covariates. All results in this table are based on the PPML model. Standard errors are clustered at the firm level and shown in parentheses. Variables omitted from the model do not show. As the most robust model, our DDD estimator (Column 3) shows that, compared to all other groups, NKMFs that faced more stringent enforcement environment filed more clean patents due to the 2014 disclosure program. This result is consistent with the findings of our main model, further warranting the robustness of our argument.

1.3 Estimates using standard errors clustered at a higher level

As suggested by Bertrand et al. (2004), a DiD estimator may be biased due to unobserved heterogeneous factors. A solution to defend against this challenge is to cluster the standard error of the estimate at a higher-level variable. In this robustness check, we introduce the PPML with standard error clustered at the prefecture level (the standard errors of the results shown in the body text are clustered at the firm level). The results are in Table 4. Our main findings remain unchanged, except for the effect of the 2014 disclosure, which becomes statistically insignificant[1].

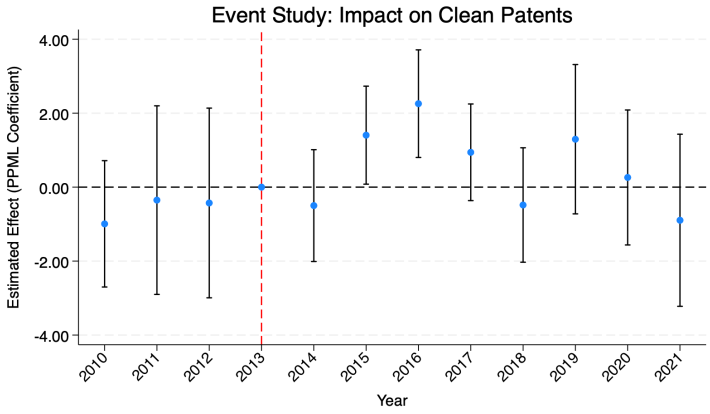


Figure 2: Difference of Clean Patent: NKMF v.s. non-NKMF using Standard Errors Clustered at Prefecture-Level

Note: This figure visualizes the dynamic pattern of the patent applications between NKMF and non-NKMF over time, applying the standard errors clustered at the prefecture level. Consistent with the main finding, the difference is not persistent, as no significant differences were found after the short-lived effect.

[1] In particular, the probability of rejecting the null hypothesis is < 0.15.

Table 4: Impact of Mandatory Environmental Information Disclosure on NKMFs' Clean Innovation with Standard Errors Clustered at the City-Level

	(1)	(2)	(3)
VARIABLES	Clean Pante Count	Clean Pante Count	Event Study for Clean Pante Count
Treated × Post	1.029**	1.152**	
	(0.484)	(0.575)	
Clean Patent Stock		-0.100***	-0.088***
		(0.025)	(0.016)
All Patent Stock		0.006*	0.004***
		(0.003)	(0.001)
ln_Revenue		0.201	-0.266
		(0.762)	(0.485)
ln_Employees		-1.444	-1.165***
		(0.943)	(0.384)
ln_Total Assets		1.037	1.887***
		(0.791)	(0.461)
Cash Flow		0.079	-0.174
		(0.542)	(0.328)
ln_R&D subsidy		0.038*	0.030*
		(0.020)	(0.018)
R&D Intensity		32.321**	0.309
		(13.616)	(9.643)
SOE		-0.198	1.044
		(1.314)	(0.723)
Pre_4 (2010)			-0.993
			(0.871)
Pre_3 (2011)			-0.351
			(1.301)
Pre_2 (2012)			-0.428
			(1.309)
Post_0 (2014)			-0.499
			(0.771)
Post_1 (2015)			1.405**
			(0.676)
Post_2 (2016)			2.257***
			(0.742)
Post_3 (2017)			0.942
			(0.667)
Post_4 (2018)			-0.483
			(0.789)
Post_5 (2019)			1.296
			(1.030)
Post_6 (2020)			0.261
			(0.931)
Post_7 (2021)			-0.896
			(1.187)
Constant	0.986***	-16.237	-52.465***
	(0.177)	(12.363)	(12.009)
Observations	486	485	1,267
Firm FE	Yes	Yes	Yes
Povince FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province×Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

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

Note: The table presents the diff-in-diff and event study regression results on the lagged clean patents of firms, with and without control variables. All results are based on the PPML model. Standard errors are clustered at the city where the firms are located and shown in parentheses. Variables omitted from the model do not show. The table presents robust and consistent results of the estimations with higher-level standard errors.

2 Supplementary Appendix B: The Defense of Potential Alternative Explanations

This section aims to address potential challenges to the mechanism claimed in this paper (i.e., the incentives for clean innovation are encouraged by regulatory enforcement enhanced by environmental disclosure mandates). We empirically document that, at least in our data, plausible non-enforcement-based mechanisms do not work.

The arrangement of this section is as follows: First, as some research argues that mandatory environmental disclosure may encourage institutional investors to stress NKMFs to invest more in their clean innovation(Berrone et al., 2013; Flammer and Kacperczyk, 2016), this appendix tests whether the 2014 disclosure program encourages firms'voluntary environmental, social, or governance (ESG) disclosure, the proxy for institutional investors' pressure. In addition, we proved that NKMFs did not receive R&D grants more than non-NKMFs due to the disclosure program, a mechanism that may bias the difference in the incentive for clean innovation between them (Acemoglu et al., 2012).

2.1 Alternative mechanism 1: induced voluntary ESG disclosure

Some studies in management argue that disclosure mandates would encourage firms' voluntary disclosure of environmental, social, and governance (ESG) information and thus attract institutional investors who value firms' environmental information to support their innovation(Berrone et al., 2013; Flammer and Kacperczyk, 2016). We defend this argument by raising the DiD model with firms' aggregate ESG and environmental-related disclosure, from the Sino-Securities Index of ESG Rating, as dependent variables. Table 2 documents the

result. Again, we do not find evidence to support this alternative explanation. These findings is consistent with the economic perspective of ESG disclosure suggested by Kitzmueller and Shimshack (2012), in which ESG disclosure is not related to induced innovation. Also, the negative coefficients of the DiD estimator on ESG scores are also consistent with the findings of the strategic substitution between mandatory and voluntary disclosure documented by recent studies (Noh et al., 2019; Heinle et al., 2023).

Table 5: Impact of Mandatory Environmental Information Disclosure on NKMFs' ESG Disclosure

VARIABLES	(1) ESG score	(2) ESG score	(3) E Score	(4) ESG score (ordinal logit model)
Treated × Post	-0.099	-0.092	0.035	-0.078
	(0.081)	(0.080)	(0.067)	(0.220)
Post	0.064	-1.495	-0.104	-0.302*
	(0.302)	(2.257)	(1.551)	(0.167)
Clean Patent Stock		0.020*	0.017	0.072*
		(0.012)	(0.014)	(0.040)
All Patent Stock		0.000***	0.000	0.000***
		(0.000)	(0.000)	(0.000)
ln_Revenue		0.015	0.029	0.027
		(0.058)	(0.049)	(0.143)
ln_Employees		0.031	-0.030	0.178
		(0.054)	(0.043)	(0.145)
ln_Total Assets		0.138*	0.046	0.400**
		(0.072)	(0.058)	(0.182)
Age		0.198	0.067	-0.066*
		(0.320)	(0.220)	(0.036)
Cash Flow		0.044*	0.048**	0.218*
		(0.024)	(0.024)	(0.112)
ln_R&D subsidy		1.692	-0.211	0.240
		(1.171)	(1.123)	(2.340)
R&D Intensity		-0.004	-0.003	-0.009
		(0.003)	(0.003)	(0.008)
SOE		-0.094	0.162	-0.030
		(0.162)	(0.126)	(0.401)
Constant	4.108***	-1.342	-0.580	
	(0.345)	(2.890)	(2.049)	
Observations	3,037	3,028	3,028	3028
Firm FE	Yes	Yes	Yes	Yes
Povince FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	No
Province×Year FE	Yes	Yes	Yes	No
Industry FE	Yes	Yes	Yes	No

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

Note: The table presents the diff-in-diff regression results on firms' ESG disclosure scores. The dependent variables in Columns 1, 2, and 4 are the scores aggregated by three dimensions (environmental, social, and governance). The dependent variable in Column 3 is the score of environmental disclosure of the firm. Columns 1, 2, and 3 are based on the OLS model, and Column 4 is an ordinal logic model(Baetschmann et al., 2020), given that the ESG scores are a rating rather than a continuous variable. Standard errors are clustered at the firm level and shown in parentheses. Variables omitted from the model do not show.

2.2 Alternative mechanism 2: more R&D subsidies

Governments may use various transfers to compensate regulated firms, to balance the economic loss from regulations and development (Laffont and Tirole, 1993; Laffont, 2005). Recent studies have also suggested that the optimal policy for directed technological change toward cleaner production would combine environmental regulations and subsidies (Acemoglu et al., 2012). Specific to the case of clean innovation affected by regulatory enforcement policies (in this paper, the 2014 disclosure program), this implies an alternative explanation that the regulated firms receive R&D funding from governments and increase their incentives for clean innovation. In other words, they conducted clean innovation because they received extra R&D subsidies instead of responding to the enhanced enforcement.

We reject this alternative explanation by empirically testing the impact of the 2014 disclosure program on the amount of R&D grants received from governments. More specifically, we run the DiD model stated in Equation (1) in the body text using the R&D grants that the firm i received in time t. The result is below. We do not find evidence to support this pattern, reinforcing the core argument that the increased clean innovation of NKMFs due to the 2014 disclosure program is driven by strengthened regulatory enforcement rather than by more R&D grants.

Table 6: Impact of Mandatory Environmental Information Disclosure on Received R&D Grants

VARIABLES	(1) DiD OLS	(2) DiD OLS	(3) DiD PPML
Treated × Post	-0.749	-0.679	-0.062
	(0.517)	(0.519)	(0.038)
Post	-2.833	20.026	
	(2.190)	(28.382)	
Clean Patent Stock		0.078	0.007
		(0.076)	(0.006)
All Patent Stock		0.000	0.000
		(0.000)	(0.000)
ln_Revenue		0.415	0.040
		(0.478)	(0.048)
ln_Employees		0.042	0.010
		(0.350)	(0.036)
ln_Total Assets		0.292	0.029
		(0.534)	(0.049)
Age		-3.355	
		(4.043)	
Cash Flow		-0.041	-0.009
		(0.206)	(0.019)
R&D Intensity		4.210	-0.199
		(7.457)	(0.619)
SOE		-0.274	-0.004
		(0.870)	(0.088)
Constant	9.739*	21.909	0.892
	(5.712)	(35.233)	(0.876)
Observations	3059	3050	2845
Firm FE	Yes	Yes	Yes
Povince FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province×Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

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

Note: The table presents the diff-in-diff regression results on firms' R&D grant. All results are based on OLS model. Standard errors are clustered at the firm level and shown in parentheses. Variables omitted from the model do not show. Our data does not find a positive role of the 2014 disclosure program in R&D grants received by the firm.

3 Supplementary Appendix C: Mechanism Analysis on Regulatory Enforcement

3.1 Statistical Analysis of Regulatory Enforcement between NKMFs and non-NKMFs

Some may question the credibility of the descriptive summary shown in Figure 1 in the body text because it is not based on statistical analysis. This section presents a formal statistical analysis to defend this concern: Table 7 shows that, based on different models, using the DiD approach, the NKMFs received significantly more administrative penalties than non-NKMFs due to the 2014 pollution disclosure program.

Table 7: Impact of Mandatory Environmental Information Disclosure on NKMFs' Received Penalties

	(1)	(2)	(3)	(4)
VARIABLES	Zero-inflated model	Zero-inflated negative binomial	Poisson model	Poisson Pseudo Maximum Likelihood
Treated × Post	2.407**	2.090**	2.323***	2.323**
	(0.966)	(0.980)	(0.858)	(0.973)
post	1.818***	2.081***	1.893***	1.893***
	(0.602)	(0.617)	(0.480)	(0.628)
Treated	-2.136**	-1.661*	-1.075	-1.075
	(0.961)	(0.994)	(0.838)	(0.888)
lnSale	-1.142***	-0.819***	-0.719***	-0.719***
	(0.149)	(0.301)	(0.081)	(0.213)
lnEMP	-0.305*	0.487*	0.305***	0.305*
	(0.157)	(0.293)	(0.115)	(0.173)
lnTA	1.434***	0.595*	0.787***	0.787**
	(0.140)	(0.307)	(0.091)	(0.352)
SOE	0.538***	0.586*	0.714***	0.714**
	(0.199)	(0.345)	(0.163)	(0.333)
Constant	-6.507***	-4.150	-9.828***	-9.828**
	(1.814)	(3.671)	(1.512)	(4.672)
Observations	3054	3054	3054	3054

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

Note: The table presents the DiD regression results on the count of the administrative penalties received by the firm, using the time period between 2010 and 2017. Since there are many zeros for administrative penalties, we employ a zero-inflated, zero-inflated negative binomial, Poisson, and PPML model, respectively, to run the regression. Control variables that could influence being penalized are added. All models show that the mandatory disclosure policy significantly increased the administrative penalties on NKMFs relative to non-NKMFs.

3.2 Context of the Environmental Administrative Penalties to the NKMFs after 2014 (text analysis)

As shown in Figure 1 of the introduction, penalties imposed on NKMFs rose sharply following the rollout of the mandatory disclosure reform in 2014, reaching a peak in 2016. To better understand this pattern, we examine the underlying reasons for these penalties. Using text mining on the detailed penalty records disclosed by local Environmental Protection Agencies (EPAs), we find that the few penalties issued prior to 2014 were largely driven by top-down inspections conducted by higher-level EPAs. In contrast, many penalties issued after 2014 appear to have been triggered by the mandatory disclosure program and the accompanying intensification of regulatory enforcement. The penalty descriptions frequently reference onsite investigations and verification procedures—typically initiated by public complaints or citizen appeals—that confirm NKMFs' air or water pollution exceeded regulatory emission standards. Below are several example statements extracted from the penalty records:

"Following investigation and verification, in the third quarter of 2014, the Municipal Environmental Protection Bureau conducted supervisory monitoring of the wastewater discharge from your company's Energy Plant. The monitoring report shows that the zinc concentration in the wastewater discharged from Outlet 101 of the Energy Plant (WS-011218) was 75.3 mg/L—36.65 times higher than the limit of 2 mg/L prescribed by the Emission Standard of Water Pollutants for the Iron and Steel Industry (GB13456–2012)."

"On December 24, 2015, environmental enforcement officers conducted an onsite inspection at Dalian Thermal Power Co., Ltd. (Donghai Thermal Power Plant), located at No. 6 Changjiang Road, Zhongshan District, to investigate excessive pollutant emissions. According to the onsite findings and the Daily Report of Hourly Average Values of Continuous Flue Gas Emission Monitoring

issued by the Dalian Environmental Monitoring Center, Boilers #3, #5, and #6 of the facility exceeded emission standards on December 3, 2015."

"According to the onsite investigation conducted by the Municipal Environmental Enforcement Brigade, your company committed the following environmental violation: At around 19:00 on December 2, your company disposed of gas-making wastewater from the gas holder, causing a large amount of such wastewater to overflow from the circulating water tank into the stormwater ditch and then enter the Yangtze River via the mountain flood channel. Sampling and analysis show that the discharged wastewater exhibited a COD concentration of 3,470 mg/L, ammonia-nitrogen concentration of 1,124 mg/L, and total phosphorus concentration of 4.62 mg/L—constituting excessive discharge of water pollutants."

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