Mandatory Environmental Information Disclosure and Directed Technological Change: Evidence from the Large Chinese Firms

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Abstract

Does mandatory environmental information disclosure redirect technological changes toward clean innovation? This study uses a difference-in-differences approach to evaluate the effects of China' s 2014 environmental disclosure program, which required large, heavy polluters to disclose their emissions publicly. Our findings reveal a disproportionate increase in clean patents among firms regulated by the program. However, the disproportionate increase was short-lived, indicating that mandatory environmental disclosure induces less incentive for lasting technological changes toward clean innovation. The regulation-induced clean patents received more non-self citations than clean patents not driven by regulation, implicating a greater knowledge spillover effect, which contributes to economic growth.

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1 Introduction

In recent decades, scholars have shown that mandatory environmental information disclosure can effectively deter pollution. A prominent example is the Toxics Release Inventory (TRI) program in the United States. By making the hazardous substance emission data publicly accessible, the program empowers citizens, NGOs, and local governments to hold polluters accountable and reduce their pollution (Konar and Cohen, 1997; Khanna et al., 1998). Recently, Yang et al. (2021) investigated a mandatory disclosure program on power plants and found that disclosure reduces their emissions. Beyond the United States, evidence from other contexts, such as China, suggests that mandatory environmental information disclosure also mitigates pollution in economies governed by different political regimes. For instance, 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, targeted firms reduce violations of pollution standards.

Although mandatory environmental information disclosure has been shown to curb pollution, limited evidence exists on whether it fosters endogenous technological change toward cleaner production. Empirically addressing this gap is important for at least two reasons. First, clarifying whether mandatory environmental information disclosure contributes to endogenously directed technological change can expand the policy toolbox for promoting green transition (Jaffe et al., 1995; Newell et al., 1999; Jaffe et al., 2002; Brunnermeier and Cohen, 2003; Fischer et al., 2003; Aghion et al., 2016; Calel and Dechezleprêtre, 2016; Bloom et al., 2019; Calel, 2020). Although mandatory disclosure is not expected to generate

enduring incentives for pollution reduction (Konar and Cohen, 1997; Sterner and Coria, 2013) nor to enhance the market's information environment (Weksler and Zik, 2023), it might still induce one-off clean innovation for the regulated firms[4]. Compared to no such inducement, the one-off clean innovation may still create more freely accessed knowledge to the market and generate positive externalities for economic growth[5]. Second, disclosure policies typically enjoy broad support from the public, who values the right to know about nearby polluters (Buntaine et al., 2024). This can lower political obstacles to policy implementation and may be particularly relevant for low- and middle-income countries, which often hesitate to adopt environmental regulations due to concerns about potential political drawbacks (Greenstone and Jack, 2015). In these contexts, mandatory disclosure policies can serve as a strategic interim step toward the cooperative global equilibrium described by Acemoglu et al. (2014), in which both the Global North and South coordinate their pollution abatement efforts and foster globally directed technological change.

To guide our empirical analysis, we outline a simple conceptual framework linking mandatory environmental information disclosure to endogenous clean innovation. In our framework, regulators face budget constraints in enforcing pol-

[4]Unlike market-based regulatory instruments (e.g., carbon taxes or marketable emission permits), which impose ongoing economic costs on firms, non-market-based regulations (e.g., mandatory disclosure policies) are expected to drive only a one-time adjustment in pollution abatement to meet the newly established standards. Market-based instruments are predicted to sustain long-term incentives for cleaner technologies (Acemoglu et al., 2012; Aghion et al., 2019), whereas non-market-based regulations may only trigger short-term investments in clean technologies.

[5]Some recent evidence has shown that clean innovation generates more knowledge spillover than dirty (non-clean) innovation (Popp and Newell, 2012; Dechezleprêtre et al., 2014; Verhoeven and Martin, 2024). Our data demonstrate the existence of the same spillover premium. Furthermore, we also show that induced clean innovation exhibits greater knowledge spillover not only compared to dirty innovation but also relative to clean innovation that is not driven by disclosure regulations.

lution penalties (Helland, 1998; Polinsky and Shavell, 2000; Telle, 2013). Making pollution data publicly available complements these limited budgets by enabling citizen engagement, as residents can file reports, complaints, or appeals regarding pollution violations once they have access to the information[6]. Regulatory agencies, in turn, respond to heightened public pressure by stepping up enforcement efforts[7]. Our framework assumes that clean technologies can fully replace more polluting alternatives, so that higher regulatory costs for polluting processes raise the relative profitability of innovations in cleaner alternatives[8]. Stronger regulatory enforcement on pollution violations increases the profitability of developing clean technologies for firms required to disclose their emissions data, compared to those not subject to such disclosure requirements. Nevertheless, once firms have developed cleaner technologies and complied with regulations, the impetus from public complaints diminishes, as noncompliance becomes less common. This mechanism implies that incentives for ongoing clean innovation may wane over time. We thus hypothesize that mandatory disclosure will generate a transitory—rather than permanent—increase in clean innovation by treated firms relative to untreated ones.

We examine the causal impact of mandatory environmental information disclosure on clean innovation by exploiting a 2014 monitoring reform in China that required certain major polluters, designated as "National Key Monitoring Firms"

[6]While we lack direct evidence on how the public leverages such data, Barwick et al. (2024) find that disclosure policies do prompt tangible reactions from Chinese citizens, suggesting similar effects may be at work here.

[7]In our data, this is evident as the 2014 reform led to an increase in environmental penalties for National Key Monitoring Firms (NKMFs) compared to their counterparts. Detailed text in the data reveals that most penalties were related to violations of emission standards.

[8]This is a common assumption in empirical studies on the directed technological change toward cleaner production (Aghion et al., 2016; Calel and Dechezleprêtre, 2016; Calel, 2020).

(NKMFs)[9], to disclose their real-time emissions data. The public gained the ability to track violations of pollution standards and report infractions to local authorities, effectively broadening the scope of environmental oversight. We implement a quasi-experimental design to identify the policy impact on NKMFs' innovation activities.

We construct panel data on 271 Chinese A-share–listed firms subject to the mandatory disclosure reform (NKMFs) and 1,373 non-monitored firms (non-NKMFs) spanning 2010–2021. As the assignment to the NKMF list was not random, we use a propensity-score–matching (PSM) strategy based on pre-policy covariates to address selection biases. Our matched sample consists of 188 NKMFs and 188 non-NKMFs. We then employ a differences-in-differences (DiD) approach to estimate the policy' s effect on firms' clean innovation, measured by their green patenting activity[10]. To investigate whether the policy' s effect on clean innovation is short-lived, we adopt two complementary strategies. First, we split the sample into two periods, a shorter window (2010-2016) and the full window (2010–2021) —and compare the policy impact across these intervals. Second, we implement an event study to analyze the time dynamics of the policy' s effect. Finally, to assess whether implementing a mandatory disclosure policy generates greater positive externalities for economic growth, we examine the knowledge spillover effects of

[9]China began introducing continuous emissions monitoring systems (CEMS) for industrial firms in 2003. To encourage public participation in environmental regulation, the government launched the National Key Monitoring Firms Automatic Monitoring Information Disclosure Program in 2014, compelling NKMFs to publicize their pollution data via official websites. NKMFs are defined as those entities collectively responsible for approximately 65 percent of local emissions (air pollution, water pollution, heavy metals, and waste). This study focuses on the policy' s effect on these designated firms.

[10]Following the IPC Green Inventory by WIPO, we classify a patent as clean if it belongs to specified green technology categories. We add one to each firm' s annual patent count and take the natural logarithm.

induced clean innovation. Specifically, we compare the non-self patent citations per clean patent between NKMF and non-NKMF firms during the years when the policy induced clean patents of NKMFs.

Our main finding is that mandatory environmental information disclosure leads to a short-term increase in firms' clean innovation. The DiD estimates for 2010–2016 with both OLS and Poisson models show that treated firms experience a significant increase in clean patenting relative to non-treated firms. However, this effect dissipates over the longer horizon (through 2021), indicating that the policy mainly induces temporary innovation gains. The event-study results further confirm that the policy' s effect peaks around 2016, with no persistent impact thereafter.

The second finding is that the clean patents filed by NKMFs between 2016 and 2018 have received more non-self citations per patent compared to those filed by non-NKMFs during the same period. Yet, NKMF firms' clean patents from other periods do not demonstrate such citation premium. These findings suggest that when significantly impacted by the mandatory disclosure policy, NKMFs not only increased their production of clean patents but also generated relatively greater knowledge spillovers to other firms on average, contributing to broader economic growth (Romer, 1990).

We conduct multiple robustness checks to substantiate our main results. These include a placebo test, different standard-error specifications (firm-level clustering and bootstrap), and estimating a Poisson model on the raw patent count. We also analyze the share of clean patents as an alternative metric. Across all these checks, our core findings remain consistent.

This study makes several contributions to the literature. First, we provide the

first solid causal evidence on how mandatory environmental information disclosure —a non-market-based regulatory tool—shapes firms' incentives for clean innovation. Consistent with the notion that such disclosure does not sustain ongoing pollution abatement incentives(Konar and Cohen, 1997), our results show a short-term surge in clean patenting (as an output endogenous to pollution abatement), followed by a reversion to incumbents' baseline innovation trajectories once public pressure wanes. This corroborates theories positing that non-market-based regulations would not exert lasting effects on green transition (Acemoglu et al., 2012; Aghion et al., 2019; Hémous and Olsen, 2021).

Second, while there is only a transient boost in clean innovation from it, we evidence that implementing mandatory environmental disclosure could leverage more knowledge spillover than without such a boost. Policy-induced clean innovation inspires more subsequent innovation than non-policy-induced clean innovation. Given that free knowledge spillovers are fundamental to endogenous economic growth (Romer, 1990), our findings highlight the additional economic benefits of mandatory environmental disclosure beyond its environmental improvement. To our best knowledge, this study is also the first to reveal that regulation-induced clean innovation generates more knowledge spillover than clean innovation that is not driven by regulations.

Finally, our findings shed light on the political economy of globally coordinated environmental policies (Acemoglu et al., 2014; Greenstone and Jack, 2015). In settings where comprehensive market-based instruments face strong political barriers, mandating firms to disclose their emissions may represent a less contentious option. Although its effect on clean innovation may be only short-lived, mandatory disclosure can still yield improvements in environmental performance, benefit innovation

in the economy, and may contribute incrementally to global clean technology capital stocks—particularly if knowledge spillovers extend from the Global South to the Global North[11].

2 Related Literature

This paper aligns with the large body of literature regarding regulation-induced innovation (Nordhaus, 1994; Jaffe et al., 1995; Porter and Linde, 1995; Jaffe and Palmer, 1997; Newell et al., 1999; Popp, 2002; Brunnermeier and Cohen, 2003; Popp, 2004; Acemoglu et al., 2012; Aghion et al., 2016; Calel, 2020). The literature strand pronounces that (environmental) regulatory policies impose costs with a firm's dirty input and induce it to invest in the (substituted) clean input to offset the cost. Modern theory with this respect further suggests that optimal environmental regulatory policies must encourage economic incentives that stimulate firms to lastingly change their incumbent dirty innovation path to a cleaner one at the same time (Popp, 2004; Gans, 2012; Acemoglu et al., 2012; Aghion et al., 2019; Hémous and Olsen, 2021). This results in the focus of the following empirical studies on market-based regulatory instruments because only market-based regulations could encourage economic incentives[12]. However, few comprehensive empirical studies have been conducted to assess the effect of non-market-based regulations, such as mandatory disclosure policy, on directing firms to develop clean technologies.

The key driver for environmental regulation-induced clean innovation is the in-

[11]See Witajewski-Baltvilks and Fischer (2023) for recent evidence on cross-border technology spillovers.

[12]For example, Aghion et al. (2016); Calel and Dechezleprêtre (2016); Calel (2020).

centive at which regulated firms develop new technologies for pollution abatement (Nordhaus, 1994; Acemoglu et al., 2012). It is important to distinguish economic and non-economic incentives provided by environmental regulations, as the former would induce firms' profit-seeking (the so-called market-based) responses and the latter would not. To our best knowledge, there are no rigorous empirical papers regarding mandatory information disclosure regulations that clearly formulate hypotheses with this perspective[13]. This article, therefore, fills the gap by empirically indicating that mandatory information disclosure is indeed a non-market-based regulation(Konar and Cohen, 1997; Weksler and Zik, 2023).

3 Institutional Background

China operates the world' s largest Continuous Emissions Monitoring System (CEMS) introduced by the Ministry of Environment and Ecology (MEE) in 2004[14]. The system requires installing automatic monitoring devices at discharge points —such as flow meters and CCTV cameras—to capture real-time data on key pollutants. Local Environmental Protection Agencies (EPAs) operate monitoring centers that automatically gather real-time data on key pollutants from each installed meters. The CEMS tracks both water pollutants (e.g., Chemical Oxygen

[13]There is a literature stream discussing the incentive induced by mandatory disclosure (Greenstone et al., 2006; Doshi et al., 2013; Ernstberger et al., 2017; Grewal et al., 2019; Johnson, 2020; Chen et al., 2023). Unfortunately, these studies did not articulate whether the induced incentive in their cases is market-based or non-market-based.

[14]Other countries use similar systems for various regulatory purposes. For example, the United States EPA and many state governments require firms to install CEMS equipment to demonstrate compliance with permitted emission levels (United States EPA 2021). In India, specific provinces have started to require firms to install continuous monitoring equipment to support emissions trading (Greenstone et al. 2020). Likewise, the European Union has made continuous emissions monitoring support operation of its Emissions Trading Scheme (EU 2021). Yet none of these schemes have approached the scale of the CEMS in China, where it is used as a systematic regulatory tool for all key industrial polluters.

Demand [COD] and ammonia nitrogen [NH3-N]) and air pollutants (e.g., sulfur dioxide [SO2], particulate matter [PM], and nitrogen oxides [NOX]). By January 2020, this CEMS infrastructure had been installed in more than 24,620 plants, collectively responsible for over 75 percent of China' s industrial air and water pollution.

In 2014, China launched a nationwide environmental monitoring reform targeting large polluters, formally designated as National Key Monitoring Firms (NKMFs)[15]. Firms that exceeded a certain emissions threshold for any pollutant in the preceding two years were deemed NKMFs, following a selection process that involved both local and central government assessments[16]. Under the reform, NKMFs were mandated to disclose their hourly emissions via online platforms operated by provincial EPAs. Firms had to maintain this information for at least one year, including not only real-time emissions data but also basic corporate information, monitoring plans, and annual reports[17]. The standards for different emission concentrations are also available, allowing the public to check whether each plant violates the standards hour by hour. The NKMFs themselves assumed

[15]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`

[16]Although the Chinese central government did not set uniform national criteria for designating NKMFs, local governments typically submitted lists of major emitters that accounted for a large share of local pollution, 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`. Since we do not have access to historical firm-level emissions data, we cannot independently verify that local governments relied solely on emissions levels. To mitigate potential selection bias, we use a matching approach on observable covariates, which we detail later in the paper.

[17]Some recent studies identified the monitoring reform as central policies requiring local EPA to publicize in real time the hourly emissions data of every monitored plant to the public (Buntaine et al., 2024). According to the policy document, it de facto mandated the NKMFs emission disclosure. The hourly emission data of the firms should not only be transmitted to the local EPA's monitoring centers, but also to the provincial public platforms through CEMS for disclosure.

responsibility for the accuracy and reliability of the published information.

Local regulators often face incentives to avoid stringent enforcement, partly due to concerns about harming local economic growth or employment. Local EPAs have considerable discretion in determining whether and when to penalize offenders (Becker and Stigler, 1974). Indeed, Buntaine et al. (2024) find that local officials typically act on CEMS-reported violations only after receiving public complaints (in their study, these were initiated by the researchers). This finding is consistent with an interview conducted with local EPA officials in a city in Sichuan province. Upon detecting excessive emissions via the CEMS, the standard response is to contact the firm for further explanation; fines are issued only if subsequent investigations verifying the "authenticity" of the detected violation.

Requiring NKMFs to disclose real-time emissions effectively reduces the scope for regulatory forbearance, as it introduces public participation in environmental monitoring. The central government has also encouraged citizens to engage in environmental protection by mandating that local EPAs open official accounts on popular social media platforms, such as Weibo and WeChat. NGOs and individual citizens use these channels to flag apparent violations by NKMFs, generating public pressure that compels local EPAs to increase inspections and enforce penalties more rigorously. Figure 1 provides descriptive evidence of a substantial spike in pollution-related fines levied on NKMFs shortly after the policy was implemented in 2014. The increased frequency of inspections and heightened likelihood of penalties driven by emission disclosure and public participation further incentivized the monitored NKMFs to comply with emission standards and reduce pollutionBuntaine et al. (2024). To achieve these abatement goals, many firms likely invest in cleaner technologies, reflected in a surge in green patent appli-

cations. Figure 2 contrasts the trends in green patenting between NKMFs and non-NKMFs over this period, indicating a pronounced divergence that coincides with the introduction of mandatory real-time emissions disclosure.

4 Data and Empirical Strategy

4.1 Data and Variables

Our empirical analysis draws on data from official Chinese government websites, the China Stock Market and Accounting Research (CSMAR) database. To identify the treated group, we use annual NKMF rosters published on the website of the Ministry of Ecology and Environment (MEE). A firm is classified as an NKMF if it appears on the roster for at least one pollutant category in every year from 2014 onward. Because the NKMF classification occurs at the plant level, we aggregate this information to the firm level for publicly traded entities, thus designating a listed firm as NKMF if it operates at least one monitored plant. Non-NKMF firms are those not included on any NKMF lists, excluding those in finance, agriculture, or services[18]. We combine these NKMF records with patent data and firm characteristics from CSMAR. Environmental penalty data come from the Institute of Public and Environmental Affairs (IPE) website [19], a non-profit organization in China that focuses on public pollution data. Merging these sources produces a panel spanning 2010–2021 for publicly listed Chinese firms. We focus on firms already listed in 2010, resulting in an unbalanced panel of 20,748 observations for

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

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

271 NKMF firms and 1,373 non-NKMF firms.

Our key dependent variable, firms' clean innovation (Log_Green Patent), is identified by the number of Chinese green patent applications of the firm in a given year according to the IPC Green Inventory directory by WIPO[20]. We transformed the patent count data into natural logarithms by applying the natural logarithm function to the original values incremented by one (i.e., log(x + 1))[21], a widely used method to address zero values and stabilize variance in count data. We also use the Poisson model on the count of patents for robustness. We incorporate a two-year lag in the patent data to account for the time between a firm' s R&D efforts and patent applications (Hall et al., 1984). For the knowledge spillover effect, we measure the non-self citation per clean patent.

In our difference-in-differences (DiD) framework, the treatment indicator (KMF_i) equals 1 if the firm is NKMF since 2014 and 0 otherwise. A post-policy indicator ($Post_t$) equals 1 in years following the policy and 0 in earlier years. Also, we controlled for variables potentially influencing 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 (Green_Stock) in a given year by the firm's accumulated patent application[22]. To account for firms' overall innovation capability, the total knowledge stock (All_Stock) is added as well. Massive empirical studies on firms' R&D articulated the significant role of firm size (Cohen, 2010). In this paper,

[20]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.

[21]We also use count data for robustness check.

[22]Similar to 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.

we operationalize firm size with annual revenue, presented in natural logarithms (Log_Revenue). In addition, the cash flow (Cash_Flow) was used to reflect the financial constraint that may influence the R&D investment (Hall and Lerner, 2010). All the monetary variables are deflated by their appropriate deflators in each year published by the national bureau of statistics (NBS). The age of the firms (Age) is also considered (Cohen, 2010). 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 natural language processing method to clarify and calculate the annual R&D grants of each firm[23].

4.2 Propensity Score Matching

Because NKMF assignment is non-random, sample selection bias may arise. We therefore employ propensity score matching (PSM), following (Heckman et al., 1997). Using 2013 as the pre-policy year, we estimate a Probit model that includes firm-level covariates—namely revenue, cash flow, and patent stocks—to generate propensity scores. We then conduct non-replacement nearest-neighbor matching within industries. The matched sample comprises 376 firms (188 NKMFs and 188 non-NKMFs) spanning 27 industries. The t-test and summary statistics of the matched sample are presented in Table 1 and Table 2.

[23]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.

Insert Table 1 and Table 2 Here

4.3 Empirical Strategy

We first estimate the causal relationship between the NKMF treatment and the firms' clean innovation performance with a short time window (2010-2016). To estimate the causal effects, we apply a DiD regression to evaluate the effect of the monitoring reform related to NKMF on firms' clean innovation performance. Our DID specification implemented as a fixed effects panel regression is:

$$\Upsilon_{it+2} = \alpha_1 KMF_i \times Post_t + \alpha_2 KMF_i + \alpha_3 Post_t + \beta X_{it} + \theta_i + \zeta_t + \eta_j + \delta_k + \epsilon_{it} \quad (1)$$

Where Υ_{it+2} is the log-transformed green patent count for firm i in year t+2[24], α_1 is the DID estimate of the effect of the disclosure policy on NKMF, KMF_i is a dummy variable distinguishing the NKMF ($KMF_i = 1$) from the non-NKMF ($KMF_i = 0$), $Post_i$ is a dummy variable indicating the period after ($Post_t = 1$) and before the disclosure ($Post_i = 0$). Finally, we set X_{it} as the matrix of all control variables in the firm i and year t, θ_i as the firm fixed effect, ζ_t as the year fixed effect, η_j as the industry fixed effect, δ_k as the province fixed effect, and ϵ_{it} as the error item within the regression.

To test whether the policy effect $KMF_i \times Post_t$ continues beyond the short term, we then introduce a longer period (2010-2021) to the same DiD model. Our prediction is that the policy effect will no longer exist in the model with the longer period.

[24]We also apply the DID model to a Poisson regression on the count of patents for robustness checks.

Next, we employ the event study to visualize the effect' s trajectory between 2010 and 2021, identifying whether it diminishes, stabilizes, or escalates after the policy takes effect. To specify the dynamic effects of the disclosure policy, we estimate the following event study model:

$$\Upsilon_{it+2} = \sum_{k=-4}^{7} \gamma_k \, \text{Post}_{t+k} \cdot KMF_i + \alpha X_{it} + \theta_i + \zeta_t + \eta_j + \delta_k + \varepsilon_{it} \tag{2}$$

where: Υ_{it+2} represents the log-transformed green patent count for firm i at time $t+2$. 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. KMF_i is a dummy variable distinguishing monitored NKMFs ($KMF_i = 1$) from non-NKMFs ($KMF_i = 0$). 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. X_{it} is the matrix of control variables for firm i at time t. θ_i represents firm fixed effects to control for unobservable time-invariant characteristics at the firm level. ζ_t denotes year fixed effects to account for time-specific shocks affecting all firms. η_j represents industry fixed effects, and δ_k captures province fixed effects. ε_{it} is the error term.

Finally, to test whether the disclosure policy also brings more positive externalities on economic growth than no policy, we investigate its knowledge spillover effect by comparing the forward non-self patent citation between clean patents induced by the disclosure policy and those that are not. We quantify knowledge

spillover by a firm's non-self citations per clean patent filed in a specific year [25] and compare the knowledge spillover between NKMF and non-NKMF firms for clean patents filed between 2016 and 2018—years significantly impacted by the disclosure policy. The rationale of this estimate is that even though we cannot directly observe the exact clean patents induced by the disclosure policy, the average non-self citation of the clean patents of the NKMF firms filed in the policy-affected years, anchored by our event study, can capture (at least a part of) the citation from the induced clean patent. Hence, the difference of the average non-self citations of the clean patents between the NKMF and non-NKMF firms in the policy-affected years will reflect the gap between the policy- and non-policy-induced citations of clean patents. Based on this rationale, we predict that the knowledge spillover effect would significantly differ between NKMF and non-NKMF firms in the periods between 2016 and 2018 but does not differ in other periods that are not affected by the policy. Specifically, the three-year time window before and after the focal years, i.g, 2013-2015 and 2019-2021, is adopted to build the counterfactual sample for comparison. We estimate the knowledge spillover effect by the following model:

$$\Pi_{it} = \beta KMF_i + \alpha X_{it-2} + +\zeta_t + \eta_j + \delta_k + \varepsilon_{it} \tag{3}$$

Where Π_{it} is the non-self citations per clean patent for firm i, β is the effect of the disclosure policy on NKMF. X_{it-2} as the matrix of all control variables in the firm i lead 2 years (consider the lagged nature of patenting), ζ_t denotes year fixed effects to account for time-specific shocks, η_j as the industry fixed effect, δ_k as the province fixed effect, and ϵ_i as the error item within the regression. Note that

[25] We assign zero to the firm that has no clean patent in a given year.

in this model, we do not exclude the firm that filed zero clean patents because the probability of the firm in patenting a clean patent may not be zero (Hall et al., 1984). In turn, we use the Tobit model that censors the zero average patent citation to estimate Π_{it}.

5 Results and Implications

5.1 Impact of Mandatory Environmental Information Disclosure

First, we check whether our DiD estimator satisfies the parallel trend assumption using the matched sample. Figure 2 displays the intuitive parallel trend before the policy was issued. Also, our event study (Table 4) shows that the difference of the green patents between NKMFs and non-NKMFs is not significant in pre-event trends, which validates our estimations for the impact of the policy.

The results presented in Table 3 demonstrate the impact of mandatory environmental information disclosure on firms' clean innovation in both the short-term and longer-term periods. The difference-in-differences (DID) coefficient is positive and statistically significant in the short term (Column 1), indicating that the policy led to a 7.24% increase in clean innovation shortly after its implementation. In contrast, the coefficient in the longer-run specification (Column 2) remains positive yet fails to achieve statistical significance, suggesting that the initial boost to clean innovation does not persist. Additionally, the control variables reveal interesting dynamics: Green_Stock has statistically significant negative coefficients, implying that firms with greater existing patent stocks in green technologies may

be less responsive to the disclosure policy. One possible explanation is that firms already holding substantial patent portfolios face diminishing marginal returns to additional innovation, reducing their incentive to pursue new clean technologies.

Insert Table 3 Here

Table 4 corroborates these insights through an event study specification (Column 1) on the raw patent count of firms in leading two years. The coefficients are positive and significant since the post-treatment2, reinforcing the observation that mandatory disclosure drives a sizable increase in green patenting leading two years. By contrast, coefficients from post-treatment5 onward fail to exhibit statistical significance, indicating that the policy' s effect tapers off over time.

Insert Table 4 Here

5.2 Knowledge Spillover from the Induced Clean Innovation

In this section, we investigate the knowledge spillover effects of the induced clean innovation. The knowledge spillover in this study is proxied as the non-self citation per patent. Plotting the average non-self citation of clean patents and of dirty patents by years, we see that clean patents receive more citations than dirty patents in general, as is shown in Figure 3. In most years, one clean patent receives more than 1.5 non-self citations, while one dirty patent receives less than one non-self citation. The average citations per patent decline with years since they are lifetime citations and the more recent patents have shorter citation windows. Nonetheless, the difference between citations of clean and dirty patents is consistent over years,

which leads to the conclusion that clean innovation has more knowledge spillover effects than dirty innovation.

Insert Figure 3 Here

Next, our analysis reveals that clean patents from NKMFs during 2016 and 2018, when the clean innovation of NKMFs was induced by the disclosure policy, received more non-self citations per patent than those from non-NKMFs. As is shown in table 5, this citation advantage does not significantly exist for NKMFs' clean patents filed in other time windows before or after their clean patents are induced by the disclosure policy. The findings indicate that the policy-induced clean innovation triggers relatively more knowledge spillover.

Insert Table 5 Here

5.3 Robustness Checks

To ensure the robustness of the DiD estimates, we first conduct a placebo test using a fake timing of the policy intervention. Specifically, we assign 2013 as an artificial policy shock year and re-estimate the DiD model. This approach is grounded in the parallel trend assumption, which implies that no significant treatment effect should be observed in a period when the policy was not actually implemented. If any significant effects were detected, it would indicate the presence of confounding factors unrelated to the policy intervention. The results in table 6 show that the DiD estimator is insignificant with the fake timing, providing evidence that the original model is robust to such concerns.

Insert Table 6 Here

Next, we assess the robustness of our findings by applying alternative standard error specifications, including firm-level clustered standard errors and the bootstrap method (Bertrand et al., 2004; Angrist and Pischke, 2009). These approaches are particularly important as they account for potential serial correlation and heteroscedasticity in the error terms, which, if unaddressed, could lead to biased standard errors and unreliable inference. Specifically, for the bootstrap, we resample the data 100 times, allowing us to empirically estimate the sampling variability and generate more reliable standard errors, especially in the presence of a relatively not very big sample. The results remain unchanged with the higher standard errors, further confirming the robustness of our findings. Third, we include additional fixed effects to control unobserved confounders that vary at the industry-year and province-year level. These fixed effects capture all time-varying industry-specific or province-specific shocks or trends that affect all firms within the same industry or province in a given year. In this way, the regression yields more robust and unbiased estimation of the firm-specific policy effect. Finally, since many firms report zero green patent applications, we log-transform the patent data. While this transformation helps account for the skewness in the data, it may distort the true patenting behavior of firms and potentially affect the consistency of the estimation (Hausman et al., 1984). To address this, we re-estimate the model using a Poisson regression on the raw patent count as an alternative to the log-transformed outcome. The results remain consistent when using the raw patent count, confirming that the transformation does not bias our estimation. The table below presents the detailed results of the robustness checks.

Insert Table 7 Here

Finally, following the literature on directed technological change, which emphasizes that green innovation can be represented as a relative increase in clean technologies within the overall technological portfolio (Popp, 2002), we introduce an additional robustness check by replacing the absolute count of green patents with the green share. The green share is defined as the ratio of green patent applications to total patent applications in a given year. This alternative measure provides a relative perspective on green innovation. . This finding further reinforces the robustness of our main conclusion. The detailed results of the event study estimation on the share of green patents are shown in the table below.

Insert Table 8 Here

6 Conclusion

Over the past several decades, economists and policymakers have grappled with the challenge of balancing environmental preservation and economic growth. Regulations that steer technological trajectories toward cleaner production can exert far-reaching influences on sustainable development(Acemoglu et al., 2012). In this vein, mandatory pollution disclosure stands out as a non-market-based policy instrument that may yield short-term incentives for clean technological innovation.

Our paper investigates the impact of mandatory environmental disclosure on firms' directed technological change and the spillover effects. The main finding shows a short-lived increase in clean innovation induced by the disclosure policy. It indicates that enhanced transparency and increased public oversight can encourage firms to abate pollution with clean innovation in the short run. However, these effects do not persist in the longer term, underscoring the difficulty of sustaining

directed technological change through disclosure alone. Additionally, we observe a premium of the induced clean innovation on knowledge spillover, indicating an advantage of mandatory disclosure policies on promoting economic growth.

References

Acemoglu, D., Aghion, P., Bursztyn, L., and Hemous, D. (2012). The Environment and Directed Technical Change. *The American economic review*, 102(1):131–166.

Acemoglu, D., Aghion, P., and Hémous, D. (2014). The environment and directed technical change in a north–south model. *Oxford Review of Economic Policy*, 30(3):513–530.

Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R., and Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, 124(1):1–51.

Aghion, P., Hepburn, C., Teytelboym, A., and Zenghelis, D. (2019). Path dependence, innovation and the economics of climate change. *Handbook on green growth*, pages 67–83.

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Barwick, P. J., Li, S., Lin, L., and Zou, E. (2024). From fog to smog: The value of pollution information. *American Economic Review (Forthcoming)*.

Becker, G. S. and Stigler, G. J. (1974). Law enforcement, malfeasance, and compensation of enforcers. *The Journal of Legal Studies*, 3(1):1–18.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How Much Should We Trust Differences-In-Differences Estimates? *The Quarterly Journal of Economics*, 119(1):249–275.

Bloom, N., Van Reenen, J., and Williams, H. (2019). A toolkit of policies to promote innovation. *Journal of economic perspectives*, 33(3):163–184.

Brunnermeier, S. B. and Cohen, M. A. (2003). Determinants of environmental innovation in US manufacturing industries. *Journal of Environmental Economics and Management*, 45(2):278–293.

Buntaine, M. T., Greenstone, M., He, G., Liu, M., Wang, S., and Zhang, B. (2024). Does the squeaky wheel get more grease? the direct and indirect effects of citizen participation on environmental governance in china. *American Economic Review*, 114(3):815–850.

Calel, R. (2020). Adopt or innovate: Understanding technological responses to cap-and-trade. *American Economic Journal: Economic Policy*, 12(3):170–201.

Calel, R. and Dechezleprêtre, A. (2016). Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market. *Review of Economics and Statistics*, 98(1):173–191.

Chen, J., Hsieh, P.-F., and Hsu, P.-H. (2023). Mandatory carbon disclosures and the transition of corporate production technologies. *Available at SSRN 4665876*.

Cohen, W. M. (2010). Fifty years of empirical studies of innovative activity and performance. *Handbook of the Economics of Innovation*, 1:129–213.

Dechezleprêtre, A., Märtin, R.-P., and Mohnen, M. (2014). *Knowledge spillovers from clean and dirty technologies*. Centre for Economic Performance London, UK.

Doshi, A. R., Dowell, G. W., and Toffel, M. W. (2013). How firms respond to mandatory information disclosure. *Strategic Management Journal*, 34(10):1209–1231.

Ernstberger, J., Link, B., Stich, M., and Vogler, O. (2017). The real effects of mandatory quarterly reporting. *The Accounting Review*, 92(5):33–60.

Fischer, C., Parry, I. W. H., and Pizer, W. A. (2003). Instrument choice for environmental protection when technological innovation is endogenous. *Journal of Environmental Economics and Management*, 45(3):523–545.

Gans, J. S. (2012). Innovation and climate change policy. *American Economic Journal: Economic Policy*, 4(4):125–145.

Greenstone, M. and Jack, B. K. (2015). Envirodevonomics: A research agenda for an emerging field. *Journal of Economic Literature*, 53(1):5–42.

Greenstone, M., Oyer, P., and Vissing-Jorgensen, A. (2006). Mandated disclosure, stock returns, and the 1964 securities acts amendments. *The Quarterly Journal of Economics*, 121(2):399–460.

Grewal, J., Riedl, E. J., and Serafeim, G. (2019). Market reaction to mandatory nonfinancial disclosure. *Management Science*, 65(7):3061–3084.

Hall, B. H., Griliches, Z., and Hausman, J. A. (1984). Patents and r&d: Is there a lag? Technical report, National Bureau of Economic Research.

Hall, B. H. and Lerner, J. (2010). The financing of r&d and innovation. In *Handbook of the Economics of Innovation*, volume 1, pages 609–639. Elsevier.

Hausman, J. A., Hall, B. H., and Griliches, Z. (1984). Econometric models for count data with an application to the patents-r&d relationship.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *The Review of Economic Studies*, 64(4):605–654.

Helland, E. (1998). The enforcement of pollution control laws: Inspections, violations, and self-reporting. *Review of Economics and Statistics*, 80(1):141–153.

Hémous, D. and Olsen, M. (2021). Directed technical change in labor and environmental economics. *Annual Review of Economics*, 13(1):571–597.

Jaffe, A. B., Newell, R. G., and Stavins, R. N. (2002). Environmental policy and technological change. *Environmental and Resource Economics*, 22(1/2):41–70.

Jaffe, A. B. and Palmer, K. (1997). Environmental Regulation and Innovation: A Panel Data Study. *Review of Economics and Statistics*, 79(4):610–619.

Jaffe, A. B., Peterson, S. R., Portney, P. R., and Stavins, R. N. (1995). Environmental regulation and the competitiveness of us manufacturing: what does the evidence tell us? *Journal of Economic literature*, 33(1):132–163.

Johnson, M. S. (2020). Regulation by shaming: Deterrence effects of publicizing violations of workplace safety and health laws. *American economic review*, 110(6):1866–1904.

Khanna, M., Quimio, W. R. H., and Bojilova, D. (1998). Toxics release information: A policy tool for environmental protection. *Journal of environmental economics and management*, 36(3):243–266.

Konar, S. and Cohen, M. A. (1997). Information as regulation: The effect of community right to know laws on toxic emissions. *Journal of environmental Economics and Management*, 32(1):109–124.

Newell, R. G., Jaffe, A. B., and Stavins, R. N. (1999). The Induced Innovation Hypothesis and Energy-Saving Technological Change. *The Quarterly Journal of Economics*, 114(3):941–975.

Nordhaus, W. (1994). Managing the global commons: The economics of climate change.

Polinsky, A. M. and Shavell, S. (2000). The economic theory of public enforcement of law. *Journal of economic literature*, 38(1):45–76.

Popp, D. (2002). Induced Innovation and Energy Prices. *American Economic Review*, 92(1):160–180.

Popp, D. (2004). ENTICE: endogenous technological change in the DICE model of global warming. *Journal of Environmental Economics and Management*, 48(1):742–768.

Popp, D. and Newell, R. (2012). Where does energy r&d come from? examining crowding out from energy r&d. *Energy Economics*, 34(4):980–991.

Porter, M. E. and Linde, C. v. d. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of economic perspectives*, 9(4):97–118.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5, Part 2):S71–S102.

Sterner, T. and Coria, J. (2013). *Policy instruments for environmental and natural resource management*. Routledge.

Telle, K. (2013). Monitoring and enforcement of environmental regulations: Lessons from a natural field experiment in norway. *Journal of Public Economics*, 99:24–34.

Verhoeven, D. and Martin, R. (2024). Knowledge spillovers from clean innovation. a tradeoff between growth and climate?

Weksler, R. and Zik, B. (2023). Disclosure in markets for ratings. *American Economic Journal: Microeconomics*, 15(3):501–526.

Witajewski-Baltvilks, J. and Fischer, C. (2023). Green innovation and economic growth in a north–south model. *Environmental and Resource Economics*, 85(3):615–648.

Yang, L., Muller, N. Z., and Liang, P. J. (2021). The real effects of mandatory csr disclosure on emissions: Evidence from the greenhouse gas reporting program. Technical report, National Bureau of Economic Research.

Tables

Table 1: T-test for the Difference between Groups

"Before PSM"			"After PSM"		
	Coefficient	(t-statistics)		Coefficient	(t-statistics)
Green_Stock	0.167	(0.503)	Green_Stock	-0.175	(0.502)
Total_Stock	-31.764	(-0.68)	Total_Stock	-28.288	(-0.994)
Log_Revenue	-1.24***	(-13.745)	Log_Revenue	-0.257	(-1.898)
Cash_Flow	-0.002	(-0.056)	Cash_Flow	-0.038	(-0.693)
Age	-3.609***	(-8.825)	Age	-0.011	(-0.018)
Observations	1617		Observations	376	

The coefficient presents the mean difference between non-NKMF and NKMF firms. t-statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Summary Statistics of the Variables

	(1) kmf 0	(2)	(3)	(4)	(5)	(6) kmf 1	(7)	(8)	(9)	(10)
VARIABLES	N	mean	sd	min	max	N	mean	sd	min	max
Log_Green_Patents	2,079	0.091	0.423	0	4.094	2,184	0.092	0.411	0	6.263
Green_Stock	2,073	1.117	5.267	0	67.75	2,178	1.390	14.88	0	525.0
Total_Stock	2,073	48.73	173.1	0	3,357	2,178	138.4	1,410	0	31,582
Log_Revenue	2,078	21.75	1.466	11.29	25.80	2,184	21.89	1.231	17.32	26.07
Cash Flow	2,078	0.211	0.686	-15.31	5.930	2,184	0.224	0.364	-2.688	5.696
Age	2,079	13.33	6.841	0	29	2,184	13.56	6.319	0	29
R&D Grant	2,079	8.270	7.059	0	19.82	2,184	7.980	7.088	0	20.17
Number of id	376	376	376	376	376	376	376	376	376	376

Table 3: Impact of Mandatory Environmental Information Disclosure on NKMFs' Clean Innovation

VARIABLES	(1) short-term	(2) longer-term
DID	0.073***	0.035
	(0.027)	(0.027)
Post	-0.376***	-0.434
	(0.139)	(0.332)
Green_Stock	-0.045***	-0.006***
	(0.005)	(0.001)
All_Stock	-0.000	0.000***
	(0.000)	(0.000)
Log_Revenue	0.007	-0.005
	(0.020)	(0.014)
Age	0.073***	0.043
	(0.025)	(0.032)
Cash Flow	0.023	0.006
	(0.016)	(0.013)
R&D Grant	-0.001	-0.000
	(0.001)	(0.001)
Constant	-0.303	0.136
	(0.652)	(0.482)
Observations	2,509	4,111
R-squared	0.083	0.036
Number of id	376	376
Povince FE	Yes	Yes
Industry FE	Yes	Yes
Firm FE	Yes	Yes
Firm FE	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The table presents the diff-in-diff regression results on the 2-years leaded green patents of firms in short term and long term. The results show that, during the short time period (2010–2016), the mandatory disclosure policy significantly increased the clean patenting of regulated firms relative to non-regulated firms. In contrast, during the long time period (2010-2021), the average policy effect becomes insignificant.

Table 4: Impact of Mandatory Environmental Information Disclosure: Event Study

VARIABLES	(1) log_Green_Patents (2 years leaded)
Green_Stock	-0.006***
	(0.001)
All_Stock	0.000***
	(0.000)
Log_Revenue	-0.013
	(0.013)
Age	-0.001
	(0.037)
Cash_Flow	0.003
	(0.013)
R&D Grant	-0.001
	(0.001)
Pre-treatment 4	0.072
	(0.048)
Pre-treatment 3	0.049
	(0.047)
Pre-treatment 2	0.055
	(0.047)
Treatment	0.110**
	(0.044)
Post-treatment 1	0.125**
	(0.057)
Post-treatment 2	0.108*
	(0.059)
Post-treatment 3	-0.035
	(0.053)
Post-treatment 4	0.140*
	(0.081)
Post-treatment 5	-0.046
	(0.059)
Post-treatment 6	0.058
	(0.056)
Post-treatment 7	0.064
	(0.067)
Constant	0.743
	(0.452)
Observations	4,111
Number of id	376
R-squared	0.172
Povince FE	Yes
Industry FE	Yes
Year FE	Yes
Province*Year FE	Yes
Industry*Year FE	Yes
Firm FE	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable is the log form of green patents of firm i in leading 2 years. The post-treatment coefficients indicate that the mandatory disclosure policy leads to an increase in the clean innovation of regulated firms within a short time window after policy implementation. Insignificant coefficients on the pre-treatment terms support the parallel trends assumption prior to the policy.

Table 5: Knowledge Spillover of the Induced Clean Innovation

VARIABLES	(1) Before	(2) Induced Window	(3) After
KMF	1.521	1.499***	-0.266
	(1.275)	(0.497)	(0.449)
Green_Stock_lagged	0.403***	0.090***	0.143***
	(0.136)	(0.034)	(0.042)
All_Stock_lagged	-0.004	0.001	0.000
	(0.013)	(0.002)	(0.000)
Log_Revenue_lagged	1.195*	0.328	0.256
	(0.713)	(0.222)	(0.209)
Age	-0.119	-0.036	-0.016
	(0.122)	(0.041)	(0.040)
Cash Flow_lagged	-2.473	0.739	-0.221
	(2.385)	(0.699)	(0.673)
R&D Grant_lagged	-0.126	-0.016	-0.024
	(0.099)	(0.036)	(0.032)
Constant	-90.885	-22.033	2.733
	(11,169.888)	(10,088.564)	(841.855)
Observations	1,100	1,073	990
Year FE	Yes	Yes	Yes
Povince FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province*Year FE	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: We use tobit regressoin model on different time windows to examine the knowledge spillover from the clean innovation induced by the mandatory disclosure policy on NKMFs. We find that the clean patents filed by NKMFs between 2016 and 2018 (Column 2) have received significantly more non-self citations in average, compared to those filed by non-NKMFs during the same period. Column (1) and (3) show that the NKMF clean patents from other years do not demonstrate a similar citation premium.

Table 6: Placebo Test for DID Estimation

VARIABLES	(1) log_Green_Patents	(2) log_Green_Patents	(3) log_Green_Patents
DID_2013	0.038	0.021	0.022
	(0.028)	(0.029)	(0.030)
Post_2013	0.010	-0.022	-0.351**
	(0.021)	(0.033)	(0.147)
Green_Stock		-0.045***	-0.046***
		(0.011)	(0.014)
All_Stock		-0.000***	-0.000***
		(0.000)	(0.000)
Log_Revenue		0.003	0.004
		(0.014)	(0.018)
Age		0.017**	0.074***
		(0.008)	(0.027)
Cash_Flow		0.019	0.023
		(0.014)	(0.015)
R&D Grant		-0.001	-0.001
		(0.001)	(0.001)
Constant	0.067***	-0.133	-0.265
	(0.008)	(0.278)	(0.507)
Observations	2,511	2,509	2,509
R-squared	0.003	0.056	0.080
Number of id	376	376	376
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Povince FE			Yes
Industry FE			Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The placebo test assigns 2013 as a fake policy year to test the parallel trend assumption. The insignificant DID_2013 coefficients confirm that no treatment effect is observed prior to the actual policy implementation, supporting the robustness of the original DiD results.

Table 7: Robustness Checks of the DID Estimation

VARIABLES	(1) Clusterd SE	(2) Bootstrap	(3) Multi Fixed Effects	(4) Poisson
DID	0.073**	0.067*	0.070**	1.248***
	(0.031)	(0.035)	(0.029)	(0.370)
Post	-0.376**	-0.050	2.483**	
	(0.149)	(0.031)	(1.175)	
Green_Stock	-0.045***	-0.044***	-0.048***	-0.061**
	(0.014)	(0.013)	(0.005)	(0.030)
All_Stock	-0.000***	-0.000	-0.000	-0.006***
	(0.000)	(0.000)	(0.000)	(0.002)
Log_Revenue	0.007	0.005	-0.004	0.071
	(0.018)	(0.014)	(0.023)	(0.353)
Age	0.073***	0.018**	-0.434**	
	(0.027)	(0.007)	(0.211)	
Cash_Flow	0.023	0.020	0.028	0.588***
	(0.015)	(0.016)	(0.017)	(0.203)
R&D Grant	-0.001	-0.001	-0.002	-0.021
	(0.001)	(0.001)	(0.002)	(0.023)
Constant	-0.303	-0.184	4.213**	0.214
	(0.503)	(0.292)	(1.877)	(7.837)
Observations	2,509	2,509	2,509	631
R-squared	0.083	0.058	0.204	
Number of id	376	376	376	
Povince FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province*Year FE			Yes	
Industry*Year FE			Yes	

Robust standard errors in parentheses

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

Note: Column (1) uses clustered standard errors to account for intra-firm correlation. Column (2) applies the bootstrap method to ensure robustness to heteroskedasticity. Column (3) and (4) use the Poisson QMLE model as an alternative specification to account for count with large zeros in patenting data. The results consistently support the main findings, indicating that mandatory environmental information disclosure significantly increases green innovation in the short term.

Table 8: Event Study on the Share of Green Patents

VARIABLES	(1) Share of Green Patents (2 years leaded)
Green_Stock	-0.001
	(0.000)
All_Stock	0.000
	(0.000)
Log_Revenue	-0.008
	(0.006)
Age	-0.001
	(0.004)
Cash Flow	0.008
	(0.006)
R&D Grant	-0.001
	(0.000)
Pre-treatment 4	0.017
	(0.024)
Pre-treatment 3	0.000
	(0.021)
Pre-treatment 2	0.014
	(0.022)
Treatment	0.025
	(0.022)
Post-treatment 1	0.048**
	(0.023)
Post-treatment 2	0.049*
	(0.025)
Post-treatment 3	0.003
	(0.021)
Post-treatment 4	0.032
	(0.026)
Post-treatment 5	-0.005
	(0.023)
Post-treatment 6	0.027
	(0.021)
Post-treatment 7	0.025
	(0.022)
Constant	0.290*
	(0.154)
Observations	4,111
Number of id	376
R-squared	0.179
Povince FE	Yes
Industry FE	Yes
Year FE	Yes
Province*Year FE	Yes
Industry*Year FE	Yes
Firm FE	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable is the share of green patents in the total patent portfolio of firm i in leading 2 years. This event study captures the dynamic effects of mandatory environmental information disclosure on firms' green innovation. The significant coefficients indicate that the disclosure policy leads to an increase in the green patent share within three to four years after policy implementation, while the positive effect does not last long. Insignificant coefficients on the pre-treatment terms suggest no anticipatory effects prior to the policy, supporting the parallel trends assumption.

Figures

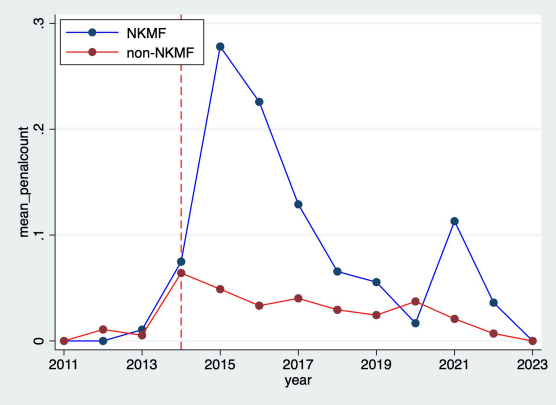


Figure 1: Count of Pollution Penalties: NKMF v.s. non-NKMF

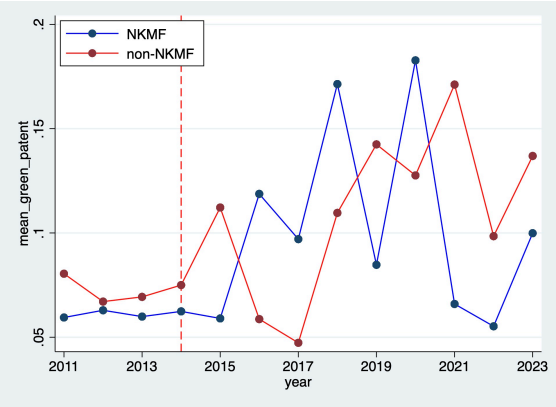


Figure 2: Green Patent (log formed): NKMF v.s. non-NKMF

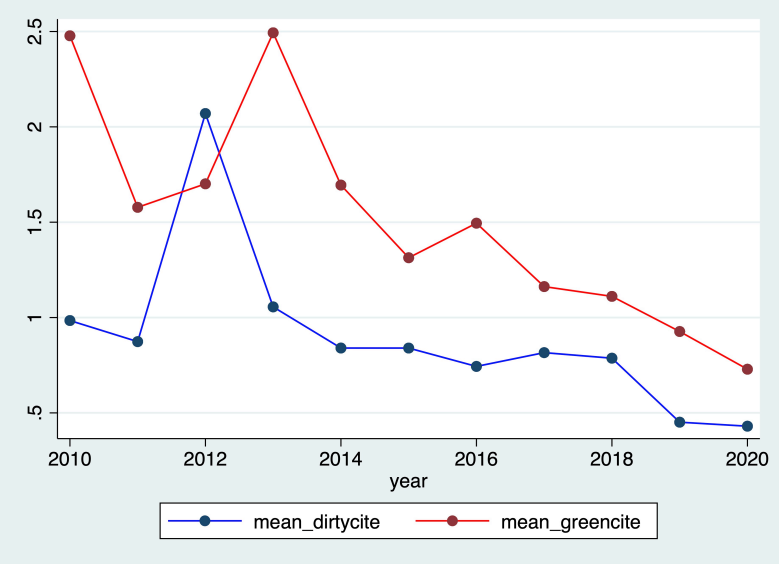


Figure 3: Average Non-self Citations of Clean Patents and Dirty Patents

Note: This figure presents the difference in the average non-self citation per patent between clean patents and dirty patents over time. In general, clean patents receive more citations than dirty patents, indicating that clean innovation has more knowledge spillover effects than dirty innovation.