Credible Environmental Disclosure and Externalities*†

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This draft: August 2024

Abstract

We study firms' private incentives to provide credible environmental disclosure through clean patent filings. We use plausibly exogenous within-firm variation in environmental regulatory risk exposure via EPA actions to investigate firms' private benefits from signaling information about their environmental capabilities. Firms file more clean patents when subject to EPA actions and make their patent applications publicly available earlier. We show that firms' credible signaling is targeted towards regulators and investors. Moreover, we find evidence of positive social benefits from such clean disclosure through technology spillovers that result in emission reductions beyond the firm. The social returns of disclosing clean technology surpass the private costs for firms, indicating a systemic under-disclosure of clean technology that may fall short of the socially optimal level.

Keywords: Environmental Disclosure; Clean Technology; Emissions; Patent Publication; Externalities

*We thank Jan Bena, Catherine Casamatta, Po-Hsuan Hsu, Kai Li, Margarita Tsoutsoura, Jan Starmans, Johan Sulaeman, Hannes Wagner, Alminas Zaldokas, Yifei Zhang, and participants at the SGFIN Sustainability Research Conference, 3^{rd} Luxembourg Conference in Sustainable Finance, HEC-HKUST Sustainable Finance Webinar, NTHU-UNSW Sustainability Symposium, University of Sydney, University of Technology Sydney, and UNSW Sydney for very helpful suggestions.

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1 Introduction

Corporations face growing pressure from investors, regulators, and other stakeholders to decrease the environmental impact of their activities. Reduction in environmental impact increasingly relies on the development of novel emission abatement processes and technologies, which can be risky, expensive, and time-consuming (IEA, 2020). Moreover, even when firms can successfully limit the environmental impact of their operations, they face the issue of credibly communicating their environmental commitment and emission abatement capabilities to stakeholders without risking disclosing sensitive information to product market rivals and competitors. As a consequence, disclosure of information about firms' environmental technologies and capabilities is limited, and even if reported, it is often inconsistent, selective, superficial, and subject to greenwashing. In recent discourse, regulators (e.g., the SEC) and investors (e.g., BlackRock, the California Public Employees' Retirement System) have expressed concerns about the failures of firms' environmental reporting, reflecting the increasing importance of firms' exposure to environmental risk in financial markets, highlighting the need to understand firms' private decision-making process and the social returns of environmental disclosure for informing policy decisions.

Against the backdrop of skepticism, many firms are confronted with the question: when faced with environmental risk, how can they effectively convey their commitment to emission reduction and demonstrate long-term pollution abatement capabilities to stakeholders? In this paper, we examine the private returns of environmental disclosure by investigating how an exogenous increase in firms' environmental risk exposure affects the provision of credible environmental information. We then derive potential policy implications by assessing the private and social returns of environmental disclosure.

The relation between credible environmental disclosure and environmental regulatory risk exposure can be exemplified by the case of Cabot Corporation, a specialty chemicals and performance materials producer. In November 2010, Cabot faced formal action by the Environmental Protection Agency (EPA) for actions leading to substantial harmful emissions, including Nitrogen Oxide (NOx) and Hydrogen Sulfide. The EPA's enforcement action posed a significant risk for Cabot: failure to address the EPA's concerns could result in large direct and indirect costs, including the withdrawal of Cabot's emission and operating licenses, and exponential increases in monetary penalties, regulatory scrutiny, reputation damage, and litigation risk (Blundell, Gowrisankaran, and Langer, 2020). In November 2011, less than a year after the EPA's enforcement action, Cabot filed an environmental ("clean") patent application (No. 9192891) for a new Nitrogen Oxide emission reduction method and apparatus, where a provisional patent was filed as early as November 12, 2010.[1] Moreover, this patent application was publicly released at Cabot's request less than 6 months after the filing, well before the U.S. Patent and Trademark Office's (USPTO) 18-month mandatory publication deadline. In July 2012, Cabot filed another clean patent application (No. 9233862) on environmental preservation, which was also publicly released earlier than mandatory in January 2013. Both these patents have been widely cited since their publication. Importantly, Cabot had not submitted a pollution abatement patent since 2004. The surge in patent applications for cutting-edge environmental technologies, coincidentally closely following the EPA's enforcement action, suggests the existence of a strategic relation between Cabot's environmental disclosure and its regulatory risk exposure.

Motivated by this example, we investigate the private returns of environmental disclosure by considering firms' use of environment-related ("clean") patent filings as a credible and verifiable signal to stakeholders about their environmental technological capabilities. Patents provide a unique empirical setting to investigate the private returns from signaling environmental capabilities to stakeholders, when faced with an increase in environmental regulatory risk, and the social returns from such disclosure. Patents are subject to a rigorous third-party verification process during which a USPTO patent examiner verifies the novelty and utility

[1] Patent 9192891 provides a method and apparatus for reducing NOx emissions, through a process to control temperature and the air-to-fuel ratio in a combustor in the incineration of tail gas, and a boiler design tailored to this process.

of the filing. The patenting system requires inventors to publish a detailed description of their invention, sufficient for others to reproduce the invention (see, 35 U.S.C. 112), thereby providing valuable information to key stakeholders. As implied by signaling theory (Spence, 1973), patent filings provide one of the most highly accurate, credible, and third-party verified signals about a firm's capabilities to reduce toxic emissions. In our example, Cabot may have chosen to credibly signal its emission abatement efforts to key stakeholders by filing patents for its environmental technologies, rather than keeping the technologies in-house.

Moreover, unlike other forms of disclosure, patents are intended to generate externalities beyond the boundaries of the firm, in exchange for a temporary monopoly on the patented technology. Investigating clean patent filings therefore enables us to measure the social returns from clean technology disclosure in the form of technological spillovers to other parties and the resulting reductions in emissions beyond the boundaries of the disclosing firm. We then use these features to derive the private and social returns of clean disclosure in a broader economy-level framework.

We exploit plausibly exogenous within-facility variation in firms' regulatory enforcement actions and uncertainties regarding their clean capabilities, and thereby their private incentives to disclose clean technologies, in the form of EPA enforcement actions. When faced with a shock to environmental regulatory risk exposure, firms have stronger incentives to reduce stakeholder concerns about their emission abatement capabilities. We investigate firms' filing of clean patents and the speed of the publication of the filing information (voluntary publication dates and mandatory disclosure deadlines) following increased EPA pressure, to identify voluntary early disclosure of emission abatement technologies. We then examine how investors and regulators, as key stakeholders, respond to clean patent filing signals to derive firms' private benefits of clean technology disclosure.

Based on a sample of more than 7,000 firm- and 70,000 facility-level observations, we find that an increase in regulatory risk exposure from EPA enforcement actions is positively related to a firm's clean patent filings. In a setting that includes high-dimensional fixed effects at the facility, firm, and industry-year level, we find that a facility's first formal EPA sanction is associated with 1.1 additional clean patent filings by the facility's parent firm. We then leverage the discretionary timing of early patent application publication requests to investigate firms' incentives to disclose their clean technologies, as the decision to file a patent might be closely linked to the development of clean innovation, which in itself may be influenced by EPA actions. There is arguably a negligible likelihood that the decision to develop clean technologies is correlated with the decision to make a patent application publicly available earlier than required by the USPTO. We find that EPA-actioned firms make their abatement technology patent applications public almost three month earlier than mandated by the USPTO's 18-month deadline. Moreover, we find no significant change in the filing or disclosure timing of other non-clean patents following EPA sanctions, indicating that these results are specific to environment-related technologies, rather than overall innovation.

To further investigate whether firms gain private benefits from signaling credible information about their emission abatement capabilities when faced with an increase in regulatory risk exposure, we zoom in on two key stakeholder groups. Given the large direct (i.e., monetary penalties) and indirect (i.e., likelihood of emission license withdrawals, reputation costs, litigation risk) costs associated with repeated EPA violations, a prominent intended recipient of firms' signaling is the environmental regulator, the EPA. Clean patent filings may provide information about a firm's long-term commitment towards emission abatement and pollution-related technological capability, thereby affecting the settlement probability, duration, or future sanctions imposed by the EPA. To identify EPA-oriented signaling, we exploit a difference-in-differences (DID) setting where we consider EPA sanctions in neighboring facilities as a positive shock to firms' incentives to signal environmental information to the regulator. EPA inspection schedules are partly determined by geographical proximity, such that EPA scrutiny in nearby firms increases the anticipated regulatory pressure in the focal firm (Dasgupta, Huynh, and Xia, 2023). Consistent with this notion, we find that firms file more clean patents following EPA pressure in nearby facilities. Moreover, we also find that firms' clean patents are effective in reducing the stringency and duration of EPA sanctions: firms subject to a High-Priority Violator (HPV) designation that file at least one clean patent during their designation experience a 33% (approximately 200 days) reduction in the duration of their HPV status.

The large costs of repeated EPA violations, which far exceed the direct monetary penalties, also have important consequences for the firm's investors. Firms' exposure to environmental risk has been shown to affect investors' portfolio choices and the firm's cost of capital, therefore it is reasonable that firms want to signal to investors.[2] We investor signaling through two analysis. First, we compare clean patent market values before and after EPA actions (Kogan, Papanikolaou, Seru, and Stoffman, 2017). Second, we use the heterogeniety in the investor information environment and information asymmetries. We find that clean patents' grant announcements are associated with 9.8% higher market valuations when filed in the context of EPA actions relative to patents filed in non-enforcement periods. In contrast, non-clean patents are not associated with higher market valuations, indicating stock price increases are unique to firms' clean patent filings.

We document a stronger effect of EPA enforcement actions on firms' clean patent filings for firms operating in weaker information environments (proxied by higher analyst forecast dispersion), firms with a more sophisticated investor base (proxied by higher institutional investor holdings), and CEOs whose compensation is tied more closely to the firm's stock price. Moreover, we show that firms try to draw attention to their pollution abatement technology information at the filing of the patent, through their annual reports. We consider the use of terminology related to clean patents in annual statements, 10-K, and 10-Q filings. We find that firms are more likely to refer to clean technology in the year of the clean patent

[2]The relation between ESG performance and cost of capital, both equity and debt, is widely documented. Recent work provides evidence of a pollution premium in the stock market, e.g., Starks, Venkat, and Zhu (2017), Bolton and Kacperczyk (2021), Cao, Titman, Zhan, and Zhang (2021), Ilhan, Krueger, Sautner, and Starks (2023), Hsu, Li, and Tsou (2023). Seltzer, Starks, and Zhu (2020) document higher corporate bond premia, while Delis, de Greiff, de Greiff, Iosifidi, and Ongena (2018) and Kleimeier and Viehs (2018) show higher bank loan rates for firms with poorer environmental performance. Karpoff, Lott, and Wehrly (2005) show that reputation costs of environmental violations can be substantial.

filing, further increasing in subsequent years.

We then turn to the externalities and social returns arising from regulation-induced clean technology disclosure. A key feature of our patent setting is the technological spillover effect to other parties. In contrast to technology spillovers arising from non-clean patents, clean technology spillovers may create significant social benefits by reducing emissions beyond the filing firm. For example, firms benefiting from the development of Cabot's NOx emission-reducing technology may pollute less NOx after the disclosure of Cabot's clean patent filing. We investigate the social returns from clean innovation disclosure by considering the relation between technology spillovers in the form of patent citations (Jaffe, Trajtenberg, and Henderson, 1993; Bloom, Schankerman, and Van Reenen, 2013) and reductions in emissions beyond the filing firm. We find that the level of acquired knowledge in firms citing clean patents is negatively related to citing firms' toxic emissions, which are stronger for patents filed after EPA actions.

While technology spillovers are environmentally and socially beneficial from the social planner's perspective, the firm might also face private costs from disclosing information to product market rivals. Disclosing innovation via a patent filing allows competitors to use the invention without restrictions, design around the disclosed patent, and reduce environmental regulatory costs at the expense of the disclosing firm.

We empirically derive the trade-off between the private product market rivalry costs and the social and private benefits of clean technology disclosure by measuring the valuation effects of technology spillovers to industry rivals and to the wider economy generated by a marginal increase in clean patents. Our results suggest a sub-optimal level of clean technology disclosure, as the social returns from disclosing clean patents exceed the private costs associated with product rivalry spillovers. Clean disclosure via patent filings may therefore play an important role in ensuring the propagation of clean technology knowledge spillovers, a key concern for the global reduction in carbon emissions. In a social context in which there are significant social returns from clean patent filings following the mandatory public disclosure of patents in 1999, when the American Inventor Protection Act (AIPA) was enacted, our findings imply that policies aimed at reducing barriers for the reporting and disclosure of environment-related technologies can yield significant societal benefits. Taken together, our results indicate that firms can credibly signal their environmental capabilities to stakeholders via clean patent filings, when faced with an increase in regulatory risk exposure. This innovation disclosure can generate significant social benefits beyond firm boundaries.

This paper contributes to the literature in several ways. First, it relates to the literature that investigates firm incentives to provide credible information via third-party-verified disclosure. Third-party verification is widely employed across industries to ensure firms' adherence to regulatory standards.[3] Given the wide criticism regarding the reliability and credibility of climate disclosure (e.g., Marquis, Toffel, and Zhou, 2016; Berg, Kölbel, and Rigobon, 2022), we investigate firms' economic incentives to provide a third-party verified signal regarding their environmental capabilities via clean patent filings as a credible signal to stakeholders. A unique strength of our paper is that we can trace the timing of firms' credible environmental disclosure via clean patent filings. Moreover, we study how such disclosure may lead to lower industrial pollution and higher technology spillovers.

Second, our study contributes to the growing literature on the financial and real effects of environmental disclosure (Jouvenot and Krueger, 2019; Krueger, Sautner, and Starks, 2020; Bolton and Kacperczyk, 2021; Ilhan et al., 2023). Our findings highlight how reporting environmental innovation provides social benefits through the mechanism of technology spillovers, and these benefits exceed firms' private disclosure costs. On a broader scale, this suggests a systemic under-disclosure of clean technologies, with the level of disclosed clean technology falling short of what would be socially optimal. Our results highlight a potential area for policy intervention, suggesting that policy-makers might need to mandate firms benefiting from federal environmental R&D tax credits and support to report and patent

[3]See, e.g., studies investigating financial accounting (Dranove and Jin, 2010), credit ratings (Bolton, Freixas, and Shapiro, 2012), food safety and healthcare (Hatanaka, Bain, and Busch, 2005; Dranove and Jin, 2010), and environmental regulation (Duflo, Greenstone, Pande, and Ryan, 2013).

all clean technology projects, motivated by the potential for knowledge and environmental outcome spillovers.

Our study also intersects with the finance literature on the impact of regulations on firms' environmental conduct. Previous work studies the determinants of firms' responses to environmental regulation, including the influence of corporate reputation (Karpoff, Lott, and Wehrly, 2005), financial limitations (Cohn and Deryugina, 2018; Goetz, 2018; Bartram, Hou, and Kim, 2022), bank lending (Kacperczyk and Peydró, 2021), supplier capability (Custódio, Ferreira, Garcia-Appendini, and Lam, 2021), ownership structure (Shive and Forster, 2020; Azar, Duro, Kadach, and Ormazabal, 2021), the role of supply chains (Schiller, 2018; Dai, Liang, and Ng, 2021), and the impact of socially responsible mutual funds (Dasgupta, Huynh, and Xia, 2023). Building on these insights, our work explores how EPA enforcement actions influence firms' disclosure of clean technology. We provide evidence that clean technology disclosure prompted by environmental regulatory risk exposure can contribute to wider social benefits beyond the boundaries of the firm through technology spillovers.

2 Data and Methods

In this section, we provide a detailed discussion of the patent data, disclosure measures, EPA data, and descriptive statistics of our sample.

2.1 Patent Data

We obtain data on firms' patent filings from Patentsview provided by the USPTO. Patentsview holds the full history of patents granted by the USPTO from 1976 and patent applications from 2001. We use patents pertaining to abatement innovation based on the environment-related technologies (ENV-TECH) identification defined by the OECD. The structured retrieval and identification methods for mapping patent documents to environment-related technologies have been developed by experienced examiners working in relevant fields in cooperation with external experts. These patent examiners are technical experts who retrieve pertinent patent information, perform prior art searches, and classify patents into Cooperative Patent Classification (CPC) and International Patent Classification (IPC) classifications based on their relevance as an environment-related technology. The ENV-TECH classification features eight environmental families, separated into three different areas: Environmental Management, Water-Related Adaptation Technologies, and Climate Change Mitigation Technologies (CCMT).[4] We focus on patents in the area of Environmental Management, as these are most closely related to emission abatement under the EPA's requirements. Work on climate change and carbon emissions uses the subset of CCMT patents.

To define clean patents, we first identify all USPTO-granted patents from 1976 to 2020 with the ENV-TECH IPC classification. To ensure a patent has a substantial focus and contribution to environmental management, we require at least 20% of their IPC/CPC classes to belong to environmental management. The 20% cutoff is arbitrary, but the results are qualitatively similar for higher cutoffs and the full sample. We identify 186,981 clean patents across all types of assignees (private, public, government, and individual assignees). Our analysis focuses on patents filed by publicly listed firms, for which we have comprehensive accounting and financial information. The subset of clean patents granted to public firms is 53,082 patents from 1976 to 2020. To analyze EPA actions and pollution related outcomes, we primarily rely on facility-level information, which starts in 1987. The sample from 1987 to 2020 includes 41,190 clean patents filed by publicly-listed firms. We report some of the most cited clean patents in Table A1 in the Appendix.

2.1.1 Patent Disclosure Measures

To investigate firms' private incentives to provide environmental disclosure, we consider two aspects of disclosure: the extensive and intensive margin. At the extensive margin, we focus

[4]ENV-TECH classification is based on the European Patent Office's classification scheme for environment-related technologies, where relevant patent publications are classified into a separate scheme within the CPC, see `https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y.html`.

on the number of patents filed as every patent filing represents a disclosure decision. At the intensive margin, we consider the timing and speed of the patent publication by the filing firm in the spirit of Glaeser and Landsman (2021) and Hegde, Jovanovic, and Liu (2023), which capture firms' decision to voluntarily disclose clean patent applications earlier than required. By examining how fast patent applications are publicly disclosed, we reveal how firms change their information release strategies following EPA enforcement actions. This examination identifies firms that possess information on environment-related capabilities but opt to withhold it, allowing us to test the role of EPA enforcement actions through a comparative analysis between applicants who choose to disclose their information earlier versus those who delay disclosure.

Our analysis is facilitated by the enactment of the American Inventor Protection Act (AIPA) in November 1999. From November 2000, the USPTO mandates patent applications to be publicly published at three possible times: at the grant decision date, 18 months after the USPTO filing date, or 18 months after the foreign filing date (i.e., priority date) for applications seeking international protection that have not yet received a decision. If a patent has a parent application through continuations, its filing date is adjusted to match that of the parent application, in accordance with AIPA rules, which mandate that patent publication occurs 18 months from the application date of the earliest parent application.

Before the implementation of AIPA, patent applications remained confidential and hidden from the public until a patent was granted. If a patent was never granted, the application remained inaccessible to the public. After the enactment of AIPA, the "18-month publication" rule requires that patent applications are made public as published patent applications latest at 18 months after their filing date. Inventors have the option to publish before the 18-month mark or "opt out" and keep their applications confidential until the patent is granted, similar to the pre-AIPA process.[5]

[5] To opt-out, inventors must file an application for non-publication request before the decision date, see `https://www.uspto.gov/web/offices/pac/mpep/s1122.html`. Applicants with or who intend to apply for foreign filings cannot opt-out. Applicants choosing to opt-out forfeit the right to file foreign counterpart patent applications.

Our first measure of disclosure timing, *Disclosure Latency*, is based on the number of days between the clean patent priority filing date and the date of its disclosure. The disclosure date is the earliest date on which the patent is made public by the USPTO. Patents with foreign priorities are excluded from this calculation. Clean disclosure latency measures the speed at which clean technology information is made public, to address immediate concerns or comply with regulatory requirements. This measure captures not only an assignee's voluntary disclosure before the 18-month mark but also the assignee's opt-out decision to delay disclosure (disclosure latency greater than 18 months). An assignee's opt-out decision signals that the proprietary cost of early patent disclosure outweighs the benefits. To account for any variation caused by the workload in the USPTO, we also include the time from the patent filing date to the decision date as a control variable in the regression analysis.

The second measure captures clean disclosure latency as a percentage, where we normalize disclosure latency by the number of days from application filing to the patent application decision date (opt-out cases) or according to the AIPA 18 months rule for applications through continuations. Thus, *% Latency* ranges from zero to one and is increasing in the degree to which the firm delays clean disclosure. By opting out of the 18 month mark, an assignee will publicly disclose a patent application information only if and when the patent is granted, and by choosing to release early, the assignee will publicly disclose its patent application before the 18 month mark. Under the former situation, *% Latency* will be closer to one as the date of the earliest patent publication date occurs around the patent grant decision date, accounting for publication lag.

As AIPA was implemented from November 2000, our intensive margin analysis focuses on the period from January 2001 to December 2020, where 23,410 clean patents have been filed by publicly listed firms. Table 1 shows that the average *Disclosure Latency* for the period 2001 to 2020 is 462 days suggesting that clean patent filings are, on average, made publicly available 15 months after filing. This is approximately 3 months earlier than the plain vanilla mandatory disclosure USPTO requirement of 18 months. The median clean patent is published at the 18 month mark suggesting a large proportion of firms have opted out of voluntary early disclosure. This is confirmed by the mean of *% Latency* of 0.68%. Clean patents are published 32% earlier than the mandatory deadline on average.

2.2 Pollution and EPA Enforcement Action Data

We leverage within-firm and within-facility variation in environmental enforcement actions by the EPA to capture increases in firms' private incentives to provide clean disclosure. We employ facility-level data on sanctions and fines from the EPA and local environmental regulators reported through Enforcement and Compliance History Online (ECHO). Enforcement actions include both formal (e.g., fines and civil lawsuits) and informal (e.g., violation notices) actions conducted by the EPA and local regulators. We count the number of formal enforcement actions received by facility f in year t for our facility-year analysis and aggregate them across firm facilities for our firm-year level analysis, captured in *Formal Actions*.

We obtain facility-level data on toxic emissions from the Toxic Release Inventory (TRI) database, administered by the U.S. EPA. TRI data for each toxic chemical (level of pollutants and name of the chemical) are reported by individual industrial and federal facilities. The data covers a broad spectrum of industries, including manufacturing, mining, and electric utilities, and provides detailed information on more than 650 specified toxic chemicals. These chemicals are cataloged based on their releases into various environmental mediums — air, water, and land — in addition to other waste management activities. Facilities employing 10 or more full-time staff are obliged to submit annual reports detailing the quantities of each TRI-listed chemical that has been released or otherwise managed as waste. We use data on the following chemical releases: 1) on-site air release; 2) on-site water release; 3) on-site land fills; 4) total on-site releases, which is the sum of categories 1, 2, and 3. We include all facilities owned by publicly-listed U.S. firms for the sample period 1987 to 2020, as TRI coverage starts in 1987.

2.3 Sample

Our empirical framework for the extensive margin capitalizes on both within-firm and within-facility variation in environmental regulatory enforcement actions, necessitating the construction of a facility-year level dataset. In doing so, we can investigate firms' responses to *within-facility* variation in EPA enforcement actions, while controlling for *within-facility* variables, including toxic emissions. The sample periods for our firm and facility-level analysis are from 1976-2020 and 1987-2020, respectively. For our intensive margin analysis, the patent-level sample runs from 2001-2020, i.e., after the USPTO's mandatory disclosure rule became effective.

We match facility-level information from the TRI with accounting and financial variables sourced from the CRSP/Compustat Merged (CCM) database using parent company names. We only retain firm-year observations with positive total assets. We link patents to publicly listed firms using the Permanent Stock Identifier (PERMNO) provided by Kogan et al. (2017). The combination of these data sources yields a sample comprising 70,899 facility-year and 23,861 firm-year observations.

2.4 Summary Statistics

Summary statistics for our firm-year and facility-year panel data, as well as the patent-level data, are reported in Table 1. At the facility level, we find that facilities receive an average of 0.03 formal EPA actions a year, indicating the relative rarity of regulatory interventions. Conditional on receiving a penalty, the average facility-level penalty amounts to 183 thousand dollars, with a median of 6 thousand dollars. However, monetary penalties can reach as high as 20 million USD.

Each facility on average emits a total of 132 thousand pounds of chemicals each year. These comprise an average of 73 thousand pounds of air pollutants, 22 thousand pounds of chemicals discharged into water, and 36 thousand pounds of chemicals injected into land annually. The median facility emits just over 1,200 pounds of chemicals per year, and over half of the sample facilities do not contribute to water and land pollution. We use the natural logarithm of pollution variables for all analysis to account for the skewed distributions.

At the firm level, firms file on average 0.72 clean patents and 37 non-clean patents annually. The median number of granted patents for both categories is zero, indicating that 50% of firms in our sample are not granted patents in most years. However, several highly innovative firms, including Eastman Kodak Company, DuPont de Nemours Inc., and General Motors, consistently secure over a hundred patents each year.

2.5 Baseline Regression Specification

Our baseline estimation investigates the relation between a firm or facility's EPA enforcement actions and its disclosure measures (i.e., number of clean patent filings and disclosure latency measures). In the extensive margin analysis, we use a Poisson specification for the dependent variable – the number of clean patents filed in year t – considering its ordinal and non-negative characteristics. In doing so, we must drop all firms that do not file any clean patents over the sample period from the baseline estimation.[6]

For the firm-year level analysis, we estimate the following Poisson panel regression:

$$Patent_{i,t} = \beta_0 + \beta_1 Formal\ Action_{i,t} + \beta_2' X_{i,t}' + \lambda_i + \delta_t + \epsilon_{i,t}, \tag{1}$$

where $Patent_{i,t}$ is the number of clean (non-clean) patents filed by firm i in year t, i.e., the year of the EPA's enforcement actions. $Formal\ Action_{i,t}$ is the number of formal EPA actions toward firm i in year t scaled by the number of facilities owned by the firm i in year t to capture the average number of EPA actions per facility. $X_{i,t}'$ is a vector of firm-level control variables as described below. λ_i are firm fixed effects to account for time-

[6]Excluding these observations does not bias the estimates in a Poisson regression setting, as they contain no information about the regression coefficients with multiplicative fixed effects (Cohn, Liu, and Wardlaw, 2022). Moreover, in additional tests, we confirm that our results remain upheld in an OLS specification.

invariant unobservable heterogeneity among firms, and δ_t are year fixed effects that account for unobserved common shocks across firms.

For the facility-level analysis, we estimate the following Poisson panel regression:

$$Patent_{i,f,t} = \beta_0 + \beta_1 Formal\ Actions_{i,f,t} + \beta_2' X_{i,f,t}' + \lambda_f + \lambda_{ind,t} + \epsilon_{i,f,t}, \tag{2}$$

where $Patent_{i,f,t}$ is the number of clean (non-clean) patents filed by facility f's parent firm i in year t. $Formal\ Action_{i,f,t}$ measures the number of formal actions against facility f in year t. ${X'}_{f,i,t}$ is a vector of facility- and firm-level control variables. We control for the natural logarithm of the facility's parent firm's sales, Tobin's Q, cash, capital expenditures, capital intensity, R&D expenditures, product market competition, proxied by the industry-level Herfindahl-Hirschman Index (HHI), and a missing R&D indicator. λ_f are facility fixed effects to account for time-invariant unobservable heterogeneity among facilities in terms of, e.g., production processes, demographic variables, etc., and $\lambda_{ind,t}$ are Industry×Year fixed effects to account for time-varying unobservable industry effects (defined at the NAICS 6-digit level) such as pollution regulations. We also include the natural logarithm of the facility's total emissions in pounds, as a firm's incentives to develop emission-abatement technologies may be correlated with its emissions output.

3 Results

In this section, first we investigate firms' private incentives to provide environmental disclosure via clean patent filings and publication speed, when exposed to increased regulatory risk. Next we investigate two key mechanisms through which credible clean disclosure may provide private benefits to the firm, when faced with increased regulatory pressure. Specifically, we consider two stakeholder groups that are likely to respond to the firm's provision of clean technology disclosure: regulators and investors. We then investigate the private and social returns from regulation-induced disclosure in a broader economy-wide framework.

3.1 Clean Innovation Disclosure and Publication after Regulatory Pressure

We consider firms' private incentives to provide environmental disclosure by investigating firms' responses, at the extensive and intensive margin. At the extensive margin, we investigate the number of clean patents filed, while at the intensive margin we focus on the speed of publication of patent applications (timing of public disclosure) after EPA sanctions. EPA pressure amplifies firms' exposure to environmental regulatory risk, increasing the private benefits of signaling information about the firm's emission abatement capabilities to stakeholders. Thus, we anticipate there will be more clean patent filings when firms face EPA enforcement actions. In the absence of increased regulatory pressure, firms should have limited incentives to make their emission abatement technology public via a patent filing, rather choosing to keep the technology in-house or, at the very least, not choosing to make a patent filing public earlier than mandatory. Moreover, because EPA pressure should only affect the disclosure benefits of clean technologies, and not those of non-clean technologies, we can consider non-clean patent filings as a placebo test.

We estimate the effect of EPA enforcement actions on clean patent disclosure at both the firm and facility level. Consistent with the private benefits of clean disclosure, columns (1) and (2) of Panel A in Table 2 document that the number of formal actions assigned to a firm's facilities is positively related to the number of clean patents filed in the same year in both our facility- and firm-level analysis.[7] In terms of economic magnitude, a one-unit increase in formal EPA enforcement actions in a facility f is associated with a 5.34% (=$(e^{0.052} - 1) \times 100\%$) increase in clean patents filed by the facility's parent firm in the year of the enforcement action.[8] In absolute numbers, this percentage change is equivalent to approximately 1.1 more clean patents filed by a parent firm when moving from 0 to 1

[7]We consider the year of the enforcement action to fully capture the speed and timing of firms' patent filings in response to (anticipated) EPA pressure. However, to address the notion that some patent filings may occur prior to the formal EPA enforcement, we also confirm that our results hold when considering patent filings in year t+1 after the EPA's formal actions.

[8]In a Poisson model, the magnitude of a one-unit change in an independent variable (e.g., EPA enforcement action) is calculated as $e^{\beta} - 1$, which represents the percentage change in the dependent variable (e.g., clean patent count) when multiplied by 100% (Sautner, van Lent, Vilkov, and Zhang, 2020).

enforcement action in year t. These outcomes reflect economically sizable effects.

Although the Poisson estimations control for unobserved heterogeneity through fixed effects at the firm and/or facility and industry-by-year level, there may still be some concern if the regulatory pressure faced by a facility is correlated with omitted variables that also determine the clean patents filed by its parent firm. For such a bias to explain our results, any potential omitted variable that correlates positively with regulatory pressure by the EPA should also correlate positively with a firm's clean patent filings. We note that many potential determinants of EPA sanctions and fines, such as a facility's historical emissions or a firm's overall environmental performance, tend to correlate negatively with clean patent filings and therefore are unlikely to explain our findings.

Nevertheless, our results so far also rely on the notion that firms' clean patent filings reflect a short-term response to EPA pressure in which firms signal credible and verified information about emission abatement efforts to stakeholders by disclosing clean technologies. We further investigate this short-term response by considering the latency of clean patent filings' public disclosure. In doing so, we investigate not only firms' decisions to signal information via the filing of clean patents (i.e., the extensive margin), but also the speed by which they make the filing information publicly available (i.e., the intensive margin).

If EPA enforcement actions increase the private benefits of disclosure, firms may accelerate the public disclosure of their clean innovation before the patents are granted. In columns (3) and (4) of Panel A of Table 2, we investigate the timing of firms' clean disclosure following an increase in EPA pressure. We conduct this analysis at the patent application level and include firm and year fixed effects, enabling us to investigate the intensive margin of disclosure by comparing successful clean patent applications by the same firm that differ in how fast they were publicly disclosed. We control for potential omitted variables that may drive the overall decision to file a clean patent and the success of the patent application.

We investigate two measures of disclosure timing, disclosure latency and its percentage counterpart. In column (3) of Table 2, we find that a one-unit increase in formal actions by the EPA is associated with a 3.3% decrease in the time until disclosure $(e^{-0.033} - 1) \times 100\%$, which is equivalent to roughly 15 days earlier disclosure when the patent is filed during EPA actions. In column (4), we show that an additional EPA enforcement action is associated with an 11.5% decrease in disclosure latency, equivalent to 87 days (approximately 3 months) earlier disclosure. These results suggest firms not only disclose more clean technologies, they also choose to make their clean technologies public faster when regulatory pressure increases the private benefits from signaling credible information to stakeholders.

Given the proprietary costs associated with disclosing information via patent filings and the lack of private signaling benefits, an increase in firms' exposure to environmental regulatory risk should *not* increase firms' disclosure of non-clean technologies. Non-clean patent filings provide a natural placebo test for our results. In contrast to clean patent filings, we do not find evidence of an increase in non-clean patent filings following EPA enforcement actions at the firm- and facility-level in columns (1) and (2) of Panel B. Firms only increase the disclosure of their clean technology investments, implying that the increased disclosure is not due to a change in the innovation disclosure strategy by the firm, but is strictly related to clean innovation in response to an increase in EPA pressure. Moreover, we also find no reduction in the time to disclosure for non-clean patents following EPA enforcement actions in columns (3) and (4), consistent with EPA actions only affecting firms' clean disclosure decisions.

The disclosure timing analysis is conducted at the patent level. The publication speed and choice may very by technological area of the innovation (patent class). Therefore, the publication differences may be driven by the IPC patent class. To control for differences across patent classes, we conduct robustness analysis including IPC $\times$ time fixed effects in Table B2. These results remain qualitative similar to the above analysis.

Collectively, these findings indicate the existence of private benefits from disclosing clean technology when faced with increased environmental regulatory pressure. They reveal that firms targeted by EPA actions are notably more likely to (1) increase their clean patent filings and (2) release clean patent information earlier than needed or mandated by regulations.

3.2 Credible Signaling to Regulators

3.2.1 Anticipated Regulatory Costs: Enforcement Actions in Nearby Facilities

Repeated environmental violations incur large direct and indirect costs by exponentially increasing monetary penalties and the likelihood of emission license withdrawals, reputation costs, and litigation risk. Thus, it is not unlikely that firms' signaling of clean innovation is directed towards the environmental regulator, the EPA. The filing of a clean patent provides a credible and verifiable signal about a firm's long-term commitment towards emission abatement, and may thereby affect the settlement probability, duration to settlement, and strictness of future sanctions imposed by the EPA.[9]

To identify such signaling, we first exploit a difference-in-differences (DID) estimation where we consider EPA enforcement actions in neighboring facilities as a positive shock to firms' exposure to environmental regulatory risk. EPA inspection schedules are at least partly determined by geographical proximity, and firms respond to EPA pressure in nearby firms even if they are not inspected themselves (Dasgupta, Huynh, and Xia, 2023). The likelihood of a facility being inspected and, consequently, receiving fines and sanctions, is therefore higher if more local neighboring facilities are under EPA scrutiny. At the same time, it is unlikely that EPA pressure in neighboring facilities results in more clean patent filings by the focal firm through channels other than firms' regulatory risk. We estimate the following model to capture firms' private incentives to provide environmental disclosure in response to expected EPA pressure:

$$CleanPat_{i,f,t} = \beta_0 + \beta_1 \left(Treat \times \sum_{\substack{\tau=-5 \\ \tau\neq-1}}^{5} \right)_{f,t+\tau} + \beta_2' X_{i,f,t}' + \lambda_f + \lambda_{ind,t} + \epsilon_{i,f,t} \qquad (3)$$

[9] In communication EPA with assessors, we confirm that the EPA values and encourages emission abatement innovation and that it can be a factor in whether and in which form a settlement is provided.

We report results for these DID estimations in Figure 1. A facility is designated as *Treated* if at least two facilities, owned by different parent firms, within a 25-mile radius are subject to formal actions by the EPA.[10] *Post* is an indicator variable equal to one for the year of, or any of five years subsequent to, the treatment and zero otherwise. We exclude facilities that were subject to formal EPA actions from $t-5$ to $t-1$ from our sample to ensure our results are not driven by focal facilities' enforcement status. The DID regression leverages a panel data structure with a Two-Way Fixed Effect (TWFE) approach, in alignment with the framework posited by Bertrand, Duflo, and Mullainathan (2004). It is noteworthy that our estimations are only very marginally affected by the concern highlighted by Baker, Larcker, and Wang (2022), wherein the bias engendered in their discussion is primarily due to many early-treated observations serving as controls for later-treated ones. This concern is unlikely to apply in our setting; a majority of observations that are untreated serve as controls, given the infrequent occurrence of formal EPA enforcement actions.

In column (1), we evaluate the underlying assumption of our DID estimation that EPA enforcement actions in nearby facilities are positively related to EPA enforcement actions in the focal facility.[11] We find that facilities are more likely to be subjected to EPA enforcement actions if nearby facilities received EPA actions in the five years prior. It is important to note that we include industry-by-year fixed effects in this estimation, as EPA enforcement actions may vary across industries over time. In addition, we control for the facility's total emissions, as more polluting facilities are more likely to be subject to EPA enforcement actions regardless of the EPA inspection schedule. Our results confirm the findings of Dasgupta, Huynh, and Xia (2023) by showing that spillovers in EPA scrutiny exist between geographically close facilities, increasing confidence in our approach that uses nearby EPA

[10]We require at least two nearby facilities to be subject to EPA enforcement actions to ensure the variation in local EPA scrutiny is not random. Nevertheless, our results also hold when only one facility is subject to EPA enforcement actions, although the effects are economically weaker. Our results are also robust to variation in the geographical distance between facilities, ranging from 20 to 50 miles (results available on request).

[11]The number of observations in column (1) is lower than in column (2) due to the Poisson estimation setting, which excludes facilities without EPA enforcement actions.

enforcement actions as a positive shock to regulatory pressure in the focal facility.

We then investigate whether such nearby enforcement actions incentivize firms to disclose their clean capabilities by filing more clean patents. We find in column (2) that firms file, on average, 12.86% (=($e^{0.121} - 1$) $\times$ 100%) more clean patents in the five years following EPA enforcement actions in nearby plants, equivalent to 1.25 additional clean patents filed. To the extent that nearby EPA actions increase firms' anticipated environmental regulatory costs, these results are consistent with the use of clean patent filings as a signal to regulators.

In Figure 1, we investigate the timing of firms' clean disclosure by considering every individual pre- and post-treatment year (i.e., $t < -5$, $t - 4$, ..., $t + 4$, and $t > +5$). We find no increase in clean patent filings in the years prior to nearby EPA actions, whereas clean patent filings significantly increase in the one to four years following nearby EPA enforcement actions. Moreover, we find that the effect increases up to two years post-treatment, and diminishes after. Firms' private benefits of environmental disclosure therefore exceed their private costs when faced with an expected increase in regulatory pressure, reflected in more disclosure via clean patent filings.

3.2.2 Effectiveness of Signaling to Regulators

Given our results in Panel A that firms respond to anticipated regulatory pressure by filing more clean patents, a natural question is whether these filings effectively reduce the stringency of EPA enforcement actions. The most straightforward metric to measure stringency is monetary penalties. However, fines alone do not fully capture the cost to firms, as the median fine is only six thousand dollars. Other costs, such as production interruptions and compliance expenses, have much more significant consequences for firms and are not directly captured by monetary fines. Therefore, we focus on a key aspect of EPA enforcement: a facility's High Priority-Violator (HPV) status. HPV is designed to be a substantial burden to firms, deterring repeated violations (Blundell, Gowrisankaran, and Langer, 2020). HPV status signals serious noncompliance with environmental regulations, involving heightened scrutiny, potential operational disruptions, and additional compliance costs. The longer a facility remains under HPV status, the greater the resources it must allocate to address the violations.

In Panel B of Table 3, we present the results of estimations of the relation between HPV status and the clean patent disclosure of firms. In this analysis each observation represents an HPV event. In column (1), we regress HPV duration on the number of clean patents filed prior to receiving HPV status. In column (2), we use an indicator variable that equals one if the firm has filed at least one clean patent and zero otherwise. We find that the number of clean patents filed by a firm is negatively related to the duration of HPV status. Firms subject to HPV status with at least one clean patent experience a 33% reduction in HPV duration compared to those that did not file clean patents. Given that the mean HPV duration equals 600 days, this represents a 200-day reduction. This result supports the idea that the EPA responds positively to clean patent disclosure, viewing them as evidence of a firm's commitment to addressing pollution-related regulatory issues.

3.3 Credible Signaling to Investors

3.3.1 Market Value of Clean Patents following EPA Actions

The large direct and indirect costs of repeated environmental violations are also a significant concern for a firm's investors, who adjust portfolio choices in response to environmental risk exposure, thereby affecting the firm's returns and cost of capital (e.g., Starks, Venkat, and Zhu, 2017; Bolton and Kacperczyk, 2021; Cao et al., 2021; Ilhan et al., 2023; Hsu, Li, and Tsou, 2023). We therefore investigate the use of clean patent filings as a credible signaling mechanism to investors by considering whether clean patents are associated with higher market valuations when filed during EPA enforcement actions. We follow Kogan et al. (2017) and consider market reactions to patent grant announcements as our measure of clean patent value. If clean patents provide private benefits by serving as credible signals of firms' emission abatement capabilities, thereby reducing future environmental regulatory risk, they should be associated with higher market valuations.

In Panel A of Table 4, we compare the market value of clean (column 1) and non-clean (column 2) patents filed during EPA enforcement action periods. Consistent with clean patents serving as a credible signal of commitment to pollution abatement following a shock to environmental regulatory exposure, clean patents are associated with approximately 9.8% higher valuations if filed during periods of heightened EPA scrutiny relative to non-enforcement periods. In contrast, non-clean patents are not associated with higher market valuations during EPA enforcement actions, indicating that we are not just picking up a reversal of the firm's stock price following the EPA enforcement action.

3.3.2 Firm-Level Heterogeneity in Investor Signaling

We also exploit cross-sectional firm-level heterogeneity in the relative importance of using clean patent filings to signal clean capabilities to investors. We explore three proxies for the strength of firms' private signaling benefits: the firm's information environment, its ownership structure, and its CEO compensation structure.

The cost-benefit trade-off of clean disclosure strongly depends on the firm's information environment, which is a key determinant of a firm's voluntary disclosure decision (Stocken, 2013). In our context, we expect the private benefits of clean disclosure following regulatory pressure to be higher for firms operating in a weaker information environment. We proxy for a firm's information environment by considering the dispersion in the firm's analyst forecasts, following a large body of literature (e.g., Krishnaswami and Subramaniam, 1999). We obtain data on analyst forecasts from the IBES database and calculate analyst forecast dispersion as the standard deviation of analysts' one-year EPS forecasts for firms with analyst coverage. In column (1) of Panel B, we document a significant increase in clean patent filings following EPA enforcement actions, consistent with greater private benefits of signaling clean disclosure to investors for firms operating in weaker information environments.

Second, we investigate the firm's ownership structure in terms of institutional ownership holdings. We obtain data on total institutional ownership from FactSet Ownership, which limits the sample period to 1999-2020. If EPA enforcement actions push firms to disclose clean innovation to investors, these effects should be stronger for firms with a more sophisticated investor base, as such investors are more likely to internalize the costs from increased EPA pressure. In column (2), we consider the firm's total institutional ownership holdings and find that higher institutional ownership is positively related to clean patent filings following EPA pressure, indicating that the effect of regulatory pressure on clean disclosure is concentrated in firms with more institutional owners, who may be more responsive to the disclosure of the firm's emission-abatement capabilities.

Third, we consider CEO compensation structure. If the direct and indirect costs from increased EPA pressure negatively affect firms' valuations, CEOs whose compensation is tied more closely to the firm's stock price should have stronger incentives to signal emission-abatement investments to investors. In column (3), we measure the CEO's compensation stock price sensitivity by estimating the compensation delta and interact it with the EPA's enforcement actions. CEO compensation delta is measured as the dollar change in wealth associated with a 1% change in the firm's stock price (in $000s) for the sample period 1992 to 2020 (Core and Guay, 2002; Coles, Daniel, and Naveen, 2006). We find a positive relation between CEO compensation stock price sensitivity and clean patent filings following EPA enforcement actions, suggesting that environmental regulatory pressure increases the market value of clean technology disclosure.

Taken together, these results indicate that firms file more clean patents following EPA enforcement actions if their private signaling benefits from doing so are higher, and are therefore more likely to exceed the private costs.

3.3.3 Robustness Test: Alternative Forms of Clean Technology Disclosure

If firms are trying to credibly signal to stakeholders, stakeholders should be able to observe and condition on the existence of clean patents using information from the USPTO's central repository (Brown and Arshem, 1993). Therefore, firms should have incentives to disperse and highlight information about their clean patents more widely through other means. To understand whether the firm reinforces its credible disclosure by disseminating the information through other means, we consider the extent to which firms use terminology related to clean technology in their mandatory annual and quarterly reports (10-K and 10-Q filings). We search the 10-K/Q filings for the co-occurrence of terms related to "clean" (e.g., variations of clean, green, environmental, sustainable, pollution, waste, toxic, emission, contamination, eco-friendly, energy-efficient, recyclable, and biodegradable) and terms related to "technology" (e.g., variations of technology, innovation, patent, research, and solution) in the same sentence.

We investigate the timing of firms' disclosure of clean technologies in 10-K/Q filings over years t-2 to t+2 relative to the filing of the clean patent. Figure 2 presents the coefficients of the regression estimates from the specification outlined in Table B3. We find that firms are not more likely to refer to clean technology in the years leading up to the filing of a clean patent. They are almost 0.7 percentage points more likely (or 3.5% more likely compared to the unconditional mean probability) to refer to clean technology in the year of the patent filing, with this likelihood further increasing to more than 0.9 percentage points (or 4.5% compared to the unconditional mean probability) in subsequent years. These results provide further evidence that firms may gain private benefits from disseminating information regarding their environmental capabilities to shareholders and stakeholders, with clean patent filings serving as a key indicator of the signal's credibility and verifiability.

3.3.4 Robustness Test: Reductions in Investor Information Asymmetries

If firms are disclosing their clean technology as a signal to investors, and clean patent filings can effectively provide information regarding the firm's emission-abatement capabilities, we should observe a reduction in information asymmetry between the firm and its investors. We therefore investigate whether clean patent filings are associated with reduced information asymmetry measures. We use the Amuhid illiquidity ratio Amihud (2002) and relative bid-ask spread as proxies for asymmetric information in Table B4.

We carry out this analysis at the firm-year level, as stock information asymmetry occurs at the firm level. The timing of firms' clean patent filings is not concurrent with EPA enforcement actions, and it is not obvious, ex-ante, when changes in firms' information asymmetry measures should be observable following EPA pressure. We focus on the patent filing information, as this is our signal of interest, and firms refer to their clean patent filings in their annual reports. Consistent with our conjecture that firms' clean disclosure reduces information asymmetries, we find that clean patent filings are associated with decreases in the Amihud illiquidity ratio (column 1) and the relative bid-ask spread (column 2).

4 Social Benefits from Environmental Disclosure

4.1 Direct and Indirect Emission Reductions

In the previous sections, we have identified firms' private incentives to provide credible environmental disclosure in the form of signaling benefits when faced with increased regulatory pressure. A key characteristic of patents, however, is the provision of technological spillovers to other parties. Importantly, these externalities from clean patents may create positive social benefits, such as reductions in emissions beyond the boundaries of the disclosing firm. In the next section, we therefore investigate the social returns from firms' regulation-induced credible signaling via clean patent filings. Moreover, because patents also provide technology spillovers to product market rivals, who may use the disclosed information to imitate or invent around the granted patent, we then also aim to derive the trade-off between social benefits and private product market costs of clean technology disclosure.

Unlike other forms of disclosure, patents are intended to generate technology spillovers in exchange for a temporary monopoly on the technology. The externalities from clean patents may therefore result in significant positive social benefits by reducing environmental emissions beyond the filing firm. Investigating patent filings allows us to track technology spillovers via patent citations (Jaffe, Trajtenberg, and Henderson, 1993; Bloom, Schankerman, and Van Reenen, 2013).In Table 5, we examine whether a firm's acquired "clean" knowledge, proxied by the count of citations of clean patents in the focal firm's patents, is associated with lower emissions. We find that facilities owned by firms that acquired more clean knowledge have significantly lower emissions in the one to five years following the knowledge acquisition, with the effect increasing up until year three.

In Table B5 in the Internet Appendix, we also document direct social benefits in the filing firm by estimating the real environmental impact in terms of toxic emissions. Specifically, we investigate whether toxic emissions are different (lower) in facilities owned by firms that filed clean technology patent applications. We find that clean patent filings are negatively related to a facility's total emissions in the one- to four-year period following the filing, after which the effect becomes insignificant. These results not only confirm the private benefits of clean patent filings by providing credible signals of a firm's emission abatement, they also show evidence of a direct social impact in the filing firm as well as indirect social benefits beyond the boundaries of the filing firm.

In additional tests in Table B6, we also distinguish the effect of firms' acquired clean knowledge on emissions in terms of air pollution (Panel A), water pollution (Panel B), and landfill (Panel C). We find that facilities whose parent firms cite more clean patents in their filings have lower air pollution, but we find no reductions in water pollution or landfill. Overall, these results indicate that technology spillovers from patent filings are associated with reduced emissions beyond the boundaries of the disclosing firm, albeit primarily in terms of air pollution. This may suggest that technologies addressing water or landfill pollution are less transferable to other firms and may be more specific to the filing firm's operational processes. Moreover, we find in Table B7 that these results increase in magnitude when considering firms' acquired knowledge in the two years following EPA actions. This may suggest that firms technology spillovers lead to greater social benefits when firms face greater regulatory pressure.

4.2 Optimal Level of Clean Disclosure

Although our results so far have identified the social benefits of environmental disclosure via clean patent filings in terms of technology spillovers beyond the boundaries of the firm, such spillovers might also lead to negative effects for the firm from a product rivalry point of view. Clean patents enable competitors to use the invention without restrictions, design around the disclosed patent, and reduce their environmental regulatory costs at the expense of the disclosing firm. We empirically derive the trade-off between proprietary disclosure costs and social returns of clean patents' technology spillovers, following the approach in Bloom, Schankerman, and Van Reenen (2013). We allocate clean patents into IPC3 technology classes, which provides the basis for calculating technological proximity. The measure of technological activity for each firm is represented by the vector $\mathbf{T}_i = (T_{i1}, T_{i2}, \ldots, T_{iY})$, where $T_{i\tau}$ denotes the share of patents of firm i in technology class τ. We estimate this vector for each firm using all clean patents filed during the full sample period following Bloom, Schankerman, and Van Reenen (2013).

The basic measure of clean technological closeness between firms i and j is calculated using the uncentered correlation formula, following Jaffe, Trajtenberg, and Henderson (1993):

$$\text{TECH}_{ij} = \frac{\mathbf{T}_i \mathbf{T}_j'}{(\mathbf{T}_i \mathbf{T}_i')^{1/2} (\mathbf{T}_j \mathbf{T}_j')^{1/2}} \tag{4}$$

This index, denoted as TECH_{ij}, ranges from 0 to 1, indicating the degree of overlap in technology and is symmetric, meaning $\text{TECH}_{ij} = \text{TECH}_{ji}$. The pool of technology spillover R&D for firm i in year t, SPILLTECH_{it}, is constructed as:

$$\text{SPILLTECH}^{S}_{it} = \sum_{j \neq i} \text{TECH}_{ij} G_{jt} \tag{5}$$

where G_{jt} represents the stock of clean patents filed by firm j up to and including year t.

Next, we define the spillover to rival firms, i.e., proprietary disclosure costs:

$$\text{SPILLTECH}^{C}_{it} = \sum_{\substack{j \neq i \\ i_{SIC4} = j_{SIC4}}} \text{TECH}_{ij} G_{jt} \tag{6}$$

We then estimate how a marginal increase in technology spillovers/proprietary costs to the wider economy and industry rivals from clean disclosure affects firms' valuation in terms of Tobin's Q. In Table 6, we find that the size of the clean technology spillover pool available to all firms in the economy is positively related to firms' Tobin's Q (column 1). The availability of clean technology spillovers to industry rivals is, however, also related to increases in Tobin's Q among these rivals, providing a measure of firms' private product market rivalry costs (column 2). Nevertheless, the social returns from disclosing clean technology are greater than the private costs (column 3), indicating that environmental disclosure via clean patent filings may generate significant social benefits beyond the boundaries of the firm, which significantly outweigh the private costs of disclosure. Overall, these results imply an under-disclosure of clean technology. Our results therefore highlight the need for a better understanding of firms' private incentives to disclose information about their clean capabilities and technologies, as such clean disclosure may lead to significantly higher social returns beyond the boundaries of the disclosing firms.

5 Conclusion

We study firms' private incentives to provide credible environmental disclosure as a signaling mechanism to key stakeholders. We investigate environment-related (clean) patent filings and the timing of these filings' public disclosure in a setting where we exploit facility-level variation in EPA enforcement actions as a shock to firms' environmental regulatory risk exposure. We then derive the social benefits from such regulation-induced signaling via clean patent filings.

We document a significant increase in clean patent filings when a facility is subject to EPA enforcement actions, and show that firms choose to publicly disclose their patent applications faster when subject to EPA enforcement actions. We exploit EPA enforcement actions in neighboring facilities to document firms' incentives to signal to the environmental regulator. Moreover, we document firms' incentives to signal to investors by showing that clean patents are associated with higher market values if filed during EPA actions, and that clean disclosure is more likely for firms with greater potential benefits from the provision of information about their environmental capabilities.

We find evidence of positive social benefits of clean patent filings' technology spillovers in terms of reduced toxic emissions beyond the boundaries of the filing firm. We also find that the social benefits of clean patents outweigh the private costs, implying an under-disclosure of clean technology.

Tables and Figures

Figure 1
DiD Coefficients for Clean Patent filing

This figure plots the coefficient estimates for the DID analysis for at least two nearby plants' EPA formal action as treatment for the focal firm facility. The analysis is at the facility-year level.

$$CleanPat_{i,f,t} = \beta_0 + \beta_1 \left(Treat \times \sum_{\substack{\tau=-5 \\ \tau \neq -1}}^{5} \right)_{f,t+\tau} + \beta_2' X_{i,f,t}' + \lambda_f + \lambda_{ind,t} + \epsilon_{i,f,t+1}$$

The dependent variable is the number of clean patents filed in year t. β_1 are the coefficients of the interaction terms of the treatment indicator $Treat$ and $t + \tau$ with τ ranging from $\tau < -5$ to $\tau \geq 5$ except $t - 1$. τ indicates the number of years from the treatment. X' is a vector of control variables, λ_f are facility fixed effects, and $\lambda_{ind,t}$ are facility industry by year fixed effects. The sample period is 1987 to 2020.

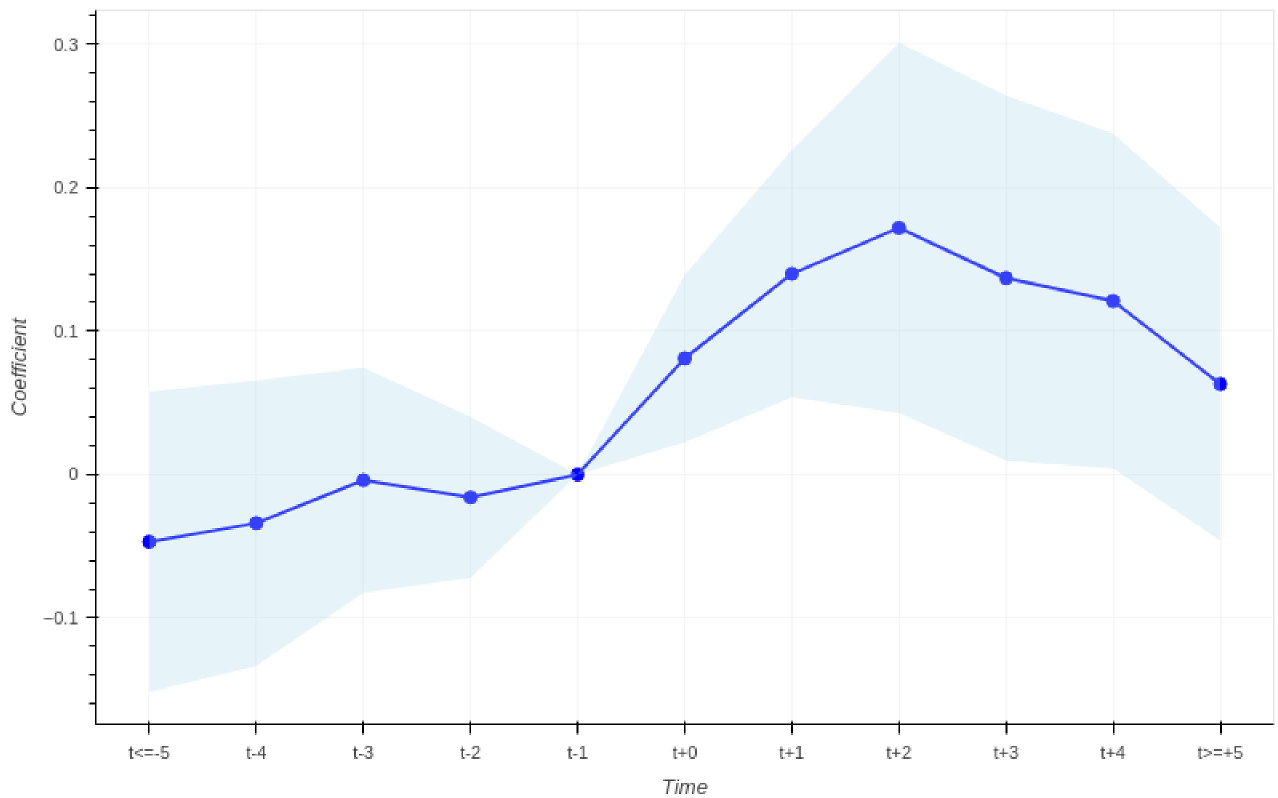

Figure 2
Time-series of Coefficient Estimates for Relation between 10-K/Q Reporting and Clean Patents

This figure presents the coefficients for clean patent filings in a regression analysis of firm disclosures related to clean technology in their 10-K/Q filings for results presented in Table B3. The analysis is conducted at the firm level.

$$10K/Q_{i,t+\tau} = \beta_0 + \beta_1 \text{Clean Pat}_{i,t} + \beta_2 \text{Controls}_{i,t} + \lambda_i + \delta_t + \epsilon_{i,t}$$

We search for the co-occurrence of clean terms and technology terms within the same sentence in the 10-K/Q text. Clean terms include clean, green, environmental, sustainable, pollution, waste, toxic, emission, contamination, eco-friendly, energy-efficient, recyclable, and biodegradable. Technology terms include technology, technologies, innovation, patent, research, and solution, adjusted for their variations. The dependent variable is a binary indicator representing whether the firm mentions co-occurrences of clean and technology terms, scaled by 100 for interpretability. We report β_1 for $\tau = -2, -1, 0, 1, 2$ in the figure. The key independent variable is the number of clean patents filed in year t. All regressions include firm fixed effects (λ_i) and year fixed effects (λ_t). The shaded area represents the 95% confidence intervals calculated using clustered standard errors at the firm level. The sample period is 1993 to 2020.

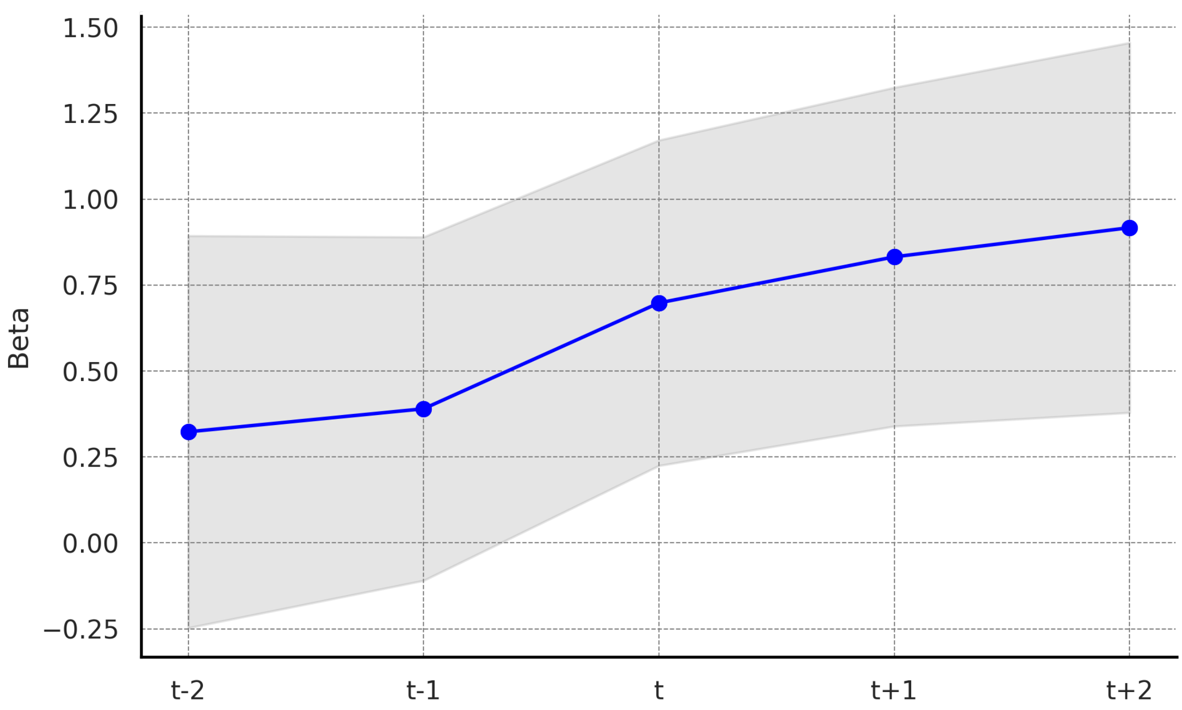

Table 1
Summary Statistics

The table presents the summary statistics for variables employed in our analysis. We report variables at the facility-year, firm-year, and patent level. For each dataset, we limit the sample to those used for estimation, including only firms with at least one clean patent disclosed and no missing control variables. Variables are defined in Appendix A2. Penalty is conditional on the facility receiving formal actions. The sample period spans from 1987 to 2020 for all variables, except for latency measures, which start post-AIPA in January 2001.

	N	Mean	Median	Std. Dev
Facility-Year				
Formal Actions	70,899	0.03	0.00	0.18
Penalty	2,251	183,898.19	6,400.00	1,124,308.43
Air	70,899	73,296.64	853.00	440,810.67
Water	70,899	21,867.00	0.00	890,846.12
Landfill	70,899	36,794.25	0.00	1,326,558.50
Firm-Year				
Clean Pat.	23,861	0.72	0.00	3.65
Non-Clean Pat	23,861	37.78	0.00	138.01
Ln(Sales)	23,791	7.17	7.21	1.90
Tobin's Q	23,790	1.65	1.39	0.85
R&D	23,819	0.02	0.01	0.03
Missing R&D	23,861	0.36	0.00	0.48
Cash	23,819	0.09	0.05	0.11
CAPX	23,636	0.05	0.04	0.04
PPE	23,786	0.32	0.28	0.19
Patent level				
Ln(Disclosure Latency)	23,410	5.95	6.30	0.64
Ln(Days to Mandatory Disclosure)	23,410	6.33	6.55	0.83
Percentage Latency	23,410	0.68	0.68	0.31
ln(ξ)	41,190	0.67	1.11	1.99
Disclosure Latency	23,410	461.97	547.00	272.62
Days to Mandatory Disclosure	23,410	759.50	700.00	542.55

Table 2
Regulatory Pressure and Clean Patent Filings

This table presents results on the relation between regulatory pressure and innovation output and disclosure timing. Panel A presents the results for clean patents and Panel B presents non-clean patents. Columns 1 and 2 are firm-year and facility-year Poisson regressions

$$Pat_{i,f,t} = \beta_0 + \beta_1 Formal\ Action_{f,t} + \beta_2' X_{i,f,t}' + \lambda_f + \lambda_{ind,t} + \epsilon_{i,f,t},$$

where $Pat_{i,f,t}$ is the number of clean/non-clean patent applications by firm i in year t. $Formal\ Action_{f,t}$, is the number of EPA formal actions recorded in the ECHO system, as described in Section 2.2. $\lambda_{ind,t}$ are industry fixed effects defined using the facility's NAICS 6-digit classification. In firm regressions (columns 3 and 4), total EPA formal actions for firm i are scaled by the number of operating facilities. T-statistics adjusted for clustered standard errors at firm level are reported in parentheses. ***, **, ** indicate significance at 1%, 5% and 10% level. The sample period is 1987 to 2020.

Columns 3 and 4 present analysis for the relation between patent disclosure (publication) times and EPA actions. The analysis is conducted at the patent level with panel regressions of the form:

$$\text{Disclosure Latency/\% Delay}_{p,i,t} = \beta_0 + \beta_1 \text{Formal Action}_{p,i,t} + \beta_2 X''_{p,i,t} + \lambda_i + \delta_t + \epsilon_{p,i,t},$$

where Disclosure Latency is the log number of days between the patent filing date and the earliest publication date, and *% Delay* is the percentage latency, defined as the fraction of disclosure latency days scaled by the latest possible disclosure days. After the AIPA, firms must publish their patents 18 months after the filing date, regardless of patent grant. Firms can chose to publish the patents at any time. *Formal Action* is an indicator variable equal to one if the patent filing occurs in the same year as a formal EPA action and zero otherwise. T-statistics adjusted for clustered standard errors at firm level are reported in parentheses. ***, **, ** indicate significance at 1%, 5% and 10% level. The sample period is 2001 to 2020, after the AIPA.

Panel A - Clean Patents

	Clean Pat.$_t$		Ln(Disclosure Latency)	% Delay
	(1)	(2)	(3)	(4)
Formal Actions	0.374***	0.052***	-0.033**	-0.115***
	(2.72)	(2.89)	(-2.56)	(-2.65)
Controls	✓	✓	✓	✓
Firm FE	✓		✓	✓
Year FE	✓		✓	✓
Facility FE		✓		
Industry × Year FE		✓		
Obs.	7,662	70,899	23,392	23,392
Adj. R^2			0.31	0.48

Panel B - Non-Clean Patents

	Non-Clean Pat.$_t$		Ln(Disclosure Latency)	% Delay
	(1)	(2)	(3)	(4)
Formal Actions	0.128	0.016	0.002	0.003
	(1.03)	(1.30)	(0.19)	(0.14)
Controls	✓	✓	✓	✓
Firm FE	✓		✓	✓
Year FE	✓		✓	✓
Facility FE		✓		
Industry × Year FE		✓		
Obs.	7,662	70,899	450,767	450,770
Adj. R^2			0.23	0.45

Table 3
Clean Disclosure, Regulation Pressure and HPV Resolution

Panel A presents Difference-in-Differences regression results for the relation between clean innovation output/disclosure timing and regulatory pressure. In Columns (1) and (2), the analysis is conducted at the facility-year level. We remove a facility if it has received an EPA formal action during $t-5$ to t.

$$Y_{i,f,t} = \beta_0 + \beta_1 \text{Treat}_{i,f,t} \times \text{Post}_{i,f,t} + \beta_2 \text{Controls}_{i,f,t} + \lambda_f + \lambda_{ind,t} + \epsilon_{i,f,t}.$$

Formal Action is an indicator variable equal to one if the facility receives a formal action from the EPA and zero otherwise. *Clean Pats.* is the number of clean patent applications by firm i in year t. Sample Period covers 1987 to 2020. Panel B presents the results of the relationship between clean patent disclosures and the time taken to resolve a facility's HPV status. The analysis is conducted at the individual HPV incident level indexed by z.

$$\ln(\text{HPV Duration}_{z,i,t}) = \beta_0 + \beta_1 \text{CP}_{i,t} + \text{Control}_{i,t} + \epsilon_{z,i,t}$$

The dependent variable is the log of the number of days from the start of HPV status until its resolution. The key independent variables are the number of clean patents filed (Clean Pat.) after first formal action until in HPV year t and an indicator variable denoting whether at least one clean patent was filed (I(Clean Pat.)). T-statistics, adjusted for clustered standard errors at the firm level, are reported in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively. All potentially unbounded variables are winsorized at the 1% level. The sample period spans from 1987 to 2020.

Panel A - DID analysis of Nearby EPA Actions

	Formal Actions (1)	Clean Pats. (2)
Treat × Post	0.401***	0.121***
	(4.37)	(3.06)
Controls	✓	✓
Facility FE	✓	✓
Industry × Year FE	✓	✓
Obs.	21,928	69,962

Panel B - Effect of Clean Patents on HPV Resolution

	HPV Duration (days, log) (1)	 (2)
Clean Pat.	-0.001***	
	(-4.91)	
I(Clean Pats.)		-0.336***
		(-4.89)
Year FE	✓	✓
Firm FE	✓	✓
Obs.	5,827	5,827
Adj. R^2	0.19	0.20

Table 4
Clean Patent Value, Firm-Level Heterogeneity, and Disclosure

Panel A presents the results of the clean and non-clean patent values filed in the year of EPA enforcement and otherwise. The analysis is at patent level.

$$\ln(\xi)_{p,i,t} = \beta_0 + \beta_1 \text{Formal Action}_{p,i,t} + \beta_2 \text{Controls}_{p,i,t} + \lambda_i + \delta_t + \epsilon_{p,i,t},$$

where $\ln(\xi)_{p,i,t}$ is the natural log of patent market value from Kogan et al. (2017). *Formal Action* is an indicator variable equal to one if the patent filing occurs in the same year as a formal EPA action and zero otherwise. T-statistics adjusted for clustered standard errors at firm level are reported in parentheses. ***, **, ** indicate significance at 1%, 5% and 10% level. The sample period is 1987 to 2020.
Panel B presents the heterogeneity in the effects of EPA enforcement on clean patent disclosure. The analysis is at the facility-year level.

$$CP_{i,t} = \beta_0 + \beta_1(\text{EPA}_{i,t} \times X_{i,t}) + \beta_2 \text{EPA}_{i,t} + \beta_3 X_{i,t} + \beta_4 \text{Controls}_{i,t} + \lambda_i + \delta_t + \epsilon_{i,t}$$

$X_{i,t}$ are the conditioning variables. Analyst forecast dispersion (Panel A) is the standard deviation of analyst forecasts for EPS at $t-1$, recorded in IBES. Institutional ownership (Panel B) is the percentage of institutional ownership from TR S34. Delta (Panel C) is the dollar change in CEO compensation per 1% change in stock price from Coles, Daniel, and Naveen (2006). T-statistics adjusted for clustered standard errors at firm level are reported in parentheses. ***, **, ** indicate significance at 1%, 5% and 10% level. The sample period is 1987 to 2020 for Panel A, 1999 to 2020 for Panel B, and 1992 to 2020 for Panel C.

Panel A - Patent values

	Clean Pat.	Non-Clean Pat.
	(1)	(2)
Formal Action	0.098**	0.052
	(2.45)	(1.05)
Controls	✓	✓
Year FE	✓	✓
Firm FE	✓	✓
Obs.	41,122	788,370
Adj. R^2	0.85	0.88

Panel B - Heterogeneous effects

	Clean Pat.$_t$		
	(1)	(2)	(3)
Analyst Forecast Dispersion	-0.015***		
	(-6.11)		
Analyst Forecast Dispersion × Formal Actions	0.002***		
	(2.66)		
Institutional Ownership		-0.674**	
		(-1.98)	
Institutional Ownership × Formal Actions		0.152***	
		(2.79)	
Ln(Delta)			-0.139***
			(-3.19)
Ln(Delta) × Formal Actions			0.065***
			(3.30)
Formal Actions	0.061***	0.074***	0.003
	(3.56)	(4.07)	(0.16)
Controls	✓	✓	✓
Facility FE	✓	✓	✓
Industry × Year FE	✓	✓	✓
Obs.	59,167	70,899	41,607

Table 5
Clean Patents, Toxic Emissions, and Knowledge Spillovers

This table presents regression results on the relation between pollution and technology spillovers from clean innovation. The analysis is at facility-year level.

$$\ln(\text{Emission})_{i,f,t+\tau} = \beta_0 + \beta_1 \text{Acquired Knowledge}_{i,t} + \beta_2 \text{Controls}_{i,f,t} + \lambda_f + \lambda_{ind,t} + \epsilon_{i,f,t+\tau}$$

Emission is facility's total onsite emissions (air, water and land) in years $t + \tau$ for $\tau = 1$ to $\tau = 5$. *Acquired Knowledge* is number of backward citations by the focal firm i's patents to clean patents. All regressions include the baseline controls in Table 2, which are suppressed for brevity. T-statistics adjusted for clustered standard errors at firm level are reported in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% level. Sample period covers 1987 to 2020.

	(t+1)	(t+2)	(t+3)	(t+4)	(t+5)
	(1)	(2)	(3)	(4)	(5)
Acquired Knowledge$_t$	-0.051**	-0.057***	-0.066***	-0.061**	-0.053**
	(-2.29)	(-2.69)	(-2.89)	(-2.47)	(-1.98)
Controls	✓	✓	✓	✓	✓
Facility FE	✓	✓	✓	✓	✓
Industry × Year FE	✓	✓	✓	✓	✓
Obs.	50,016	46,014	42,118	38,671	35,398
Adj. R^2	0.84	0.84	0.85	0.85	0.86

Table 6
Social Value and Private Costs from Technology Spillovers

This table presents the social value and private costs from clean patent disclosure. The analysis is conducted at the firm-year level.

$$\text{Tobin's Q}_{i,t+1} = \beta_0 + \beta_1 \text{Spilltech}^S_{i,t} + \beta_1 \text{Spilltech}^C_{i,t} + \beta_2 \text{Controls}_{i,t} + \lambda_i + \lambda_t + \epsilon_{i,t+1}$$

Spilltech is calculated following Bloom, Schankerman, and Van Reenen (2013). The measure of the social benefits of clean tech disclosure is $\text{SPILLTECH}^S_{it} = \sum_{j \neq i} \text{TECH}_{ij} G_{jt}$, where TECH_{ij} is Jaffe's measure of technology proximity and G_{jt} is the number of clean patent stocks filed by firm i. SPILLTECH^C_{it} is a measure of proprietary costs of clean tech disclosure, $\text{SPILLTECH}^C_{it} = \sum_{i_{SIC4}=j_{SIC4}}^{j \neq i} \text{TECH}_{ij} G_{jt}$. T-statistics adjusted for clustered standard errors at firm level are reported in parentheses. ***, **, ** indicate significance at 1%, 5% and 10% level. The sample period is 1987 to 2020 includes all CCM firms to evaluate the economic-wide spillover effects.

	Tobin's Q_{t+1}		
	(1)	(2)	(3)
Ln SPILLTECH^S (Clean)	0.274***		0.265***
	(3.99)		(3.75)
Ln SPILLTECH^C (Clean)		0.157**	0.014
		(2.43)	(0.22)
Controls	✓	✓	✓
Year FE	✓	✓	✓
Firm FE	✓	✓	✓
Obs.	157,610	157,610	157,610
Adj. R^2	0.94	0.94	0.94

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Appendix A. Additional Tables and Figures

Table A1
Most Cited Clean Patents

The table presents the most-cited clean patents. We present the patent number, the title, number of forward citations until 2020, and the patent grant date.

Pat. number	Title	Citations	Grant date
5080556	Thermal seal for a gas turbine spacer disc	946	19920114
6270916	Complete discharge device for lithium battery	486	20010807
5651821	Battery disposal and collection apparatus	483	19970729
6825620	Inductively coupled ballast circuit	386	20041130
6436299	Water treatment system with an inductively coupled ballast	379	20020820
5820646	Inline filter apparatus	379	19981013
4984594	Vacuum method for removing soil contamination utilizing surface electrical heating	363	19910115
6023554	Electrical heater	356	20000208
5318116	Vacuum method for removing soil contaminants utilizing thermal conduction heating	338	19940607
5190405	Vacuum method for removing soil contaminants utilizing thermal conduction heating	332	19930302

Table A2
Variable Definitions

Variable Name	Abbrev.	Description
Innovation Measures		
Clean Patent		Patent defined as abatement technologies using technology classifications [OECD Haščič and Migotto (2015)]
Non-Clean Patent		Patent not defined as abatement patent using technology classifications [OECD Haščič and Migotto (2015)]
Latest Disclosure		The number of days until the patent application must be published (for applications seeking foreign protection, the earlier of 18 months after filing abroad and the patent decision (grant or not) date, and for all others, the application decision date).
Actual Disclosure		The number of days until the USPTO publishes the patent filing, either at the request of the applicant or because the disclosure deadline passes, less 14 weeks for publication delays
Percentage Delay		The number of days until the disclosure of a patent filing, divided by the number of days until the latest possible disclosure
ξ		Market value of patent as in Kogan et al. (2017)
θ_{it}		Total market value of patents granted scaled by total assets
Forward Citations		Number of citations received by the patent as of 2022 [PatentsView]
Knowledge Spillover		Number of citations made to clean patents from any patents [PatentsView]
Renewal		Number of years the patent has been renewed (4, 8, 12, or 20) [USPTO]
Number of Assignments		Number of times the patent has been transferred to other parties [USPTO]
Chemical Release and EPA variables		
Air Pollution		Total Air Emissions (pounds) [TRI BASIC PLUS file]
Water Pollution		Total Surface Water Discharge (pounds) [TRI BASIC PLUS file]
Landfills		Total land release (pounds) [TRI BASIC PLUS file]
Total Emission		Total on-site Releases (pounds) [TRI BASIC PLUS file]
Formal Actions		Formal actions taken by the EPA or local government [EPA ECHO]
Penalties		Monetary Penalties levied by the EPA or local government [EPA ECHO]
HPV		High Priority Violator Status set by the EPA [EPA ECHO]
Firm growth		
Profits		Sales minus cost of goods sold [COMPUSTAT: SALE - COGS deflated by CPI]
Capital stock		[COMPUSTAT: PPEGT deflated by the NIPA price of equipment]
Employment		[COMPUSTAT: EMP]
Firm characteristics		
Total Assets		[COMPUSTAT: AT])
Sales		[COMPUSTAT: SALE])
Tobin's Q		Sum of total assets plus market value of equity minus book value of equity divided by total assets [COMPUSTAT (AT+CSHO× PRCC_F - CEQ) / AT)]
Sales Growth		Sales growth from last fiscal year end [COMPUSTAT ($SALE_t/SALE_{(t-1)}$ -1)]
Cash		[COMPUSTAT CHE/AT]
Capital Expenditure	CAPX	Capital expenditures divided by total assets [COMPUSTAT CAPX/AT]
Capital Intensity	PPE	Property, plant, and equipment scaled by asset [COMPUSTAT PPENT/AT]
R&D Expenses	R&D	R&D Research and development expenses divided by total assets [COMPUSTAT XRD/AT]
Missing R&D		If R&D Research and development expenses is missing
Analyst Forecast Dispersion		Standard Deviation of analysts' forecast of EPS within one year prior to actual results [IBES]
Institutional Ownership	IO	Total 13F institutional holdings [Refinitiv S34]
Local Institutional Ownership		13F institutional holdings near the TRI Facilities [Factset]
Compensation Delta		Dollar CEO compensation change per 1% change in stock price [Coles, Daniel, and Naveen (2006)]
Amihud Illiquidity		Yearly average of daily Amihud Illiquidity [CRSP $10^6\times\lvert ret\rvert/(vol\times prc)$] (logged)
Relative Spread		Yearly average of end-of-day bid-ask spread over the fiscal year [CRSP $100\times(ask-bid)/prc$] (logged)

Appendix B. Online Appendix

Table B1
Summary Statistics for Clean Patenting Firms

The table presents the summary statistics for variables employed in our analysis . We report variables at firm-year. Variables are defined in Appendix A2. The sample period is 1987 to 2020.

	Enforced				— Non-Enforced					
	N	Mean	Med	SD	N	Mean	Med	SD	Diff.	t-stat
Firm-Year										
Ln(Sales)	5,109	8.66	8.69	1.60	3,093	7.52	7.55	1.71	1.14***	29.88
Tobin's Q	5,109	1.77	1.50	0.94	3,093	1.83	1.52	1.24	-0.06**	-2.21
R&D	5,109	0.02	0.02	0.03	3,095	0.04	0.03	0.05	-0.02***	-16.06
Missing R&D	5,109	0.18	0.00	0.38	3,102	0.14	0.00	0.35	0.03***	4.05
Cash	5,109	0.08	0.06	0.08	3,095	0.10	0.07	0.11	-0.02***	-9.22
CAPX	5,066	0.05	0.05	0.04	3,074	0.05	0.04	0.04	-0.00	-0.94
PPE	5,109	0.32	0.29	0.18	3,095	0.27	0.25	0.15	0.05***	13.36

Table B2
Disclosure Timing Robustness — Controlling for Tech Class

This table presents a regression analysis of the relation between patent disclosure (publication) times and EPA actions. The analysis is conducted at the patent level.

$$\text{Disclosure Latency}/\%\ \text{Delay}_{p,i,t} = \beta_0 + \beta_1 \text{Formal Action}_{p,i,t} + \beta_2 \text{Controls}_{p,i,t} + \lambda_i + \delta_{IPC\times t} + \epsilon_{p,i,t},$$

where *ln(Disclosure Latency)* is the log number of days between the patent filing date and the earliest publication date, and *% Delay* is the percentage delay, defined as the fraction of disclosure latency days scaled by the latest possible disclosure days. After the American Inventor Protection Act (AIPA), firms must publish their patents after 18 months of the filing date, regardless of patent grant. Firms can chose to publish the patents at any time. *Formal Action* is an indicator variable equal to one if the patent filing occurs in the same year as a formal EPA action and zero otherwise. T-statistics adjusted for clustered standard errors at firm level are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level. The sample period is 2001 to 2020, after the AIPA.

	Clean Pat.		Non-Clean Pat.	
	Ln(Disclosure Latency)	% Latency	Ln(Disclosure Latency)	% Latency
	(1)	(2)	(3)	(4)
Formal Action	-0.031**	-0.115***	0.006	0.002
	(-2.50)	(-2.72)	(0.49)	(0.09)
Ln(Sales)	0.014	0.041	0.039	0.038
	(0.18)	(0.31)	(0.72)	(0.69)
Tobin's Q	0.024	0.115	0.012	0.021
	(0.40)	(1.07)	(0.94)	(0.85)
Cash	-0.785	-1.144	0.368**	0.280
	(-1.02)	(-0.87)	(2.38)	(0.97)
CAPX	-1.985*	-3.348	0.395	-0.319
	(-1.79)	(-1.62)	(0.71)	(-0.39)
PPE	1.393***	1.985**	0.856***	1.093***
	(3.21)	(2.27)	(3.37)	(2.63)
R&D	-3.424**	-2.770	0.754	0.381
	(-2.25)	(-0.96)	(1.11)	(0.54)
Missing R&D	-0.006	-0.232	-0.116	-0.069
	(-0.03)	(-0.61)	(-0.86)	(-0.46)
HHI	0.452	0.768	0.125	0.128
	(1.03)	(0.89)	(0.76)	(0.80)
Ln(Days to Mandatory Disclosure)	0.405***	-0.672***	0.332***	-0.653***
	(8.57)	(-6.78)	(14.56)	(-13.08)
IPC3 × Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Obs.	23,392	23,392	450,767	450,770
Adj. R^2	0.32	0.49	0.25	0.46

Table B3
Disclosure through 10-K/Q

This table reports the results of regressing firm disclosure of clean technology in their 10-K/Q filings. The analysis is conducted at the firm level.

$$10K/Q_{i,t+\tau} = \beta_0 + \beta_1 \text{CP}_{i,t} + \beta_2 \text{Controls}_{i,t} + \lambda_i + \lambda_t + \epsilon_{i,t}$$

We search for the co-occurrence of clean terms and technology terms within the same sentence in the 10-K/Q text. Clean terms include clean, green, environmental, sustainable, pollution, waste, toxic, emission, contamination, eco-friendly, energy-efficient, recyclable, and biodegradable. Tech terms include technology, technologies, innovation, patent, research, and solution. All terms are adjusted for their variations. The dependent variable is an indicator variable if the firm mentions co-occurrences of clean and tech terms measured at different times, scaled by 100 for interpretability. We report β_1 for $\tau = -2, -1, 0, 1, 2$. The key independent variable of interest is the number of clean patents filed in year t. We report t-statistics adjusted for clustered standard errors at the firm level in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively. All potentially unbounded variables are winsorized at the 1% level. The sample period is from 1993 to 2020.

	I(Disclosure of Clean Tech in 10-K/Q)				
	t-2	t-1	t	t+1	t+2
	(1)	(2)	(3)	(4)	(5)
Clean Pat.	0.323	0.390	0.698***	0.832***	0.917***
	(1.11)	(1.53)	(2.89)	(3.31)	(3.34)
Controls	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Obs.	17,656	19,297	21,325	19,367	17,760
Adj. R^2	0.53	0.53	0.53	0.54	0.54

Table B4
Clean Patent Disclosure and Information Asymmetry

This table presents regression results for the relation between clean patent disclosure and information asymmetry measures. The analysis is conducted at the firm-year level. We require a stock has at least 100 trading days in a year. We estimate regressions of the form:

$$\text{Asymmetric Information}_{i,t} = \beta_0 + \beta_1 \text{Clean Pat}_{i,t} + \beta_2 \text{Controls}_{i,t} + \lambda_i + \lambda_t + \epsilon_{i,t}.$$

$Asym.\ Info.^{Illiquidity}$ is the Amihud illiquidity ratio, $Asym.\ Info.^{Rel.Spread}$ is the relative bid-ask spread. T-statistics adjusted for clustered standard errors at firm level are reported in parentheses. ***, **, ** indicate significance at 1%, 5% and 10% level. The sample period is 1987 to 2020.

	Asym. Info.^{Illiquidity}	Asym. Info.^{Spread}
	(1)	(2)
Clean Pat.	-0.009**	-0.008**
	(-2.30)	(-2.32)
Ln(Sales)	-1.280***	-0.378***
	(-28.37)	(-13.17)
Tobin's Q	-0.563***	-0.195***
	(-21.24)	(-12.80)
Cash	-1.411***	-0.599***
	(-6.30)	(-3.92)
CAPX	-5.291***	-2.299***
	(-12.03)	(-9.15)
PPE	1.133***	0.657***
	(4.33)	(4.15)
R&D	2.752*	2.486***
	(1.89)	(3.26)
Missing R&D	0.155	0.031
	(1.44)	(0.47)
Firm FE	✓	✓
Year FE	✓	✓
Obs.	20,824	20,839
Adj. R^2	0.94	0.93

Table B5
Clean Patents and Toxic Emissions

This table presents regression results on the relation between pollution and clean innovation. The analysis is conducted at the facility-year level.

$$\ln(\text{Emission})_{i,f,t+\tau} = \beta_0 + \beta_1 \text{Clean Pat}_{i,f,t} + \beta_2 \text{Controls}_{i,t} + \lambda_f + \lambda_{ind,t} + \epsilon_{i,f,t+\tau},$$

Emission represents the pounds of air, water, and land pollutants emitted by facility f of firm i in year $t+\tau$ for $\tau = 1$ to $\tau = 5$. *Clean Pat* denotes the number of clean patents at time t. All regressions include the baseline controls from Table 2, which are omitted here for brevity. T-statistics, adjusted for clustered standard errors at the firm level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period spans from 1987 to 2020. We lose some observations compared to the baseline regressions because facilities may report no emissions or zero emissions.

	t+1	t+2	t+3	t+4	t+5
	(1)	(2)	(3)	(4)	(5)
Clean Pat_t	-0.117***	-0.106***	-0.114***	-0.094**	-0.074
	(-3.65)	(-3.41)	(-2.76)	(-2.06)	(-1.48)
Controls	✓	✓	✓	✓	✓
Facility FE	✓	✓	✓	✓	✓
Industry × Year FE	✓	✓	✓	✓	✓
Obs.	50,016	46,014	42,118	38,671	35,398
Adj. R^2	0.84	0.84	0.85	0.85	0.86

Table B6
Clean Patents, Toxic Emissions, and Acquired Knowledge

This table presents regression results on the relation between pollution and acquired knowledge from clean innovation. The analysis is at facility-year level.

$$\text{Emission}_{i,f,t+\tau} = \beta_0 + \beta_1\text{Acquired Knowledge}_{i,f,t} + \beta_2\text{Controls}_{i,f,t} + \lambda_f + \lambda_{ind,t} + \epsilon_{i,f,t+\tau}$$

Emission represents facility emissions to air, water, and land for years $t+\tau$ where $\tau = 1$ to $\tau = 5$. *Acquired Knowledge* is the number of backward citations made by the focal firm i's patents to clean patents. All regressions include the baseline controls from Table 2, which are not shown here for brevity. T-statistics, adjusted for clustered standard errors at the firm level, are reported in parentheses. ***, **, * indicate significance levels 1%, 5%, 10%. The sample period spans from 1987 to 2020.

	(t+1)	(t+2)	(t+3)	(t+4)	(t+5)

Panel A. Air Pollution

	(1)	(2)	(3)	(4)	(5)
Knowledge Spillover$_t$	-0.063***	-0.066***	-0.077***	-0.069***	-0.058**
	(-2.63)	(-3.02)	(-3.40)	(-2.92)	(-2.35)
Controls	✓	✓	✓	✓	✓
Facility FE	✓	✓	✓	✓	✓
Industry × Year FE	✓	✓	✓	✓	✓
Obs.	49,088	45,158	41,321	37,915	34,694
Adj. R^2	0.84	0.84	0.84	0.85	0.85

Panel B. Water Pollution

Knowledge Spillover$_t$	-0.052	-0.070*	-0.055	-0.082*	-0.062
	(-1.24)	(-1.82)	(-1.41)	(-1.88)	(-1.41)
Controls	✓	✓	✓	✓	✓
Facility FE	✓	✓	✓	✓	✓
Industry × Year FE	✓	✓	✓	✓	✓
Obs.	12,153	11,397	10,629	10,007	9,340
Adj. R^2	0.86	0.86	0.86	0.86	0.87

Panel C. Land Pollution

	(1)	(2)	(3)	(4)	(5)
Knowledge Spillover$_t$	0.091	0.149	0.143*	0.171	0.165
	(0.74)	(1.22)	(1.83)	(1.34)	(1.56)
Controls	✓	✓	✓	✓	✓
Facility FE	✓	✓	✓	✓	✓
Industry × Year FE	✓	✓	✓	✓	✓
Obs.	5,549	5,164	4,720	4,402	3,997
Adj. R^2	0.86	0.87	0.87	0.87	0.88

Table B7
Clean Patents, Toxic Emissions, and Acquired Knowledge-EPA

This table presents regression results on the relation between pollution and acquired knowledge from clean innovation. The analysis is at facility-year level.

$$\text{Emission}_{i,f,t+\tau} = \beta_0 + \beta_1 \text{Acquired Knowledge}_{i,f,t} + \beta_2 \text{Controls}_{i,f,t} + \lambda_f + \lambda_{ind,t} + \epsilon_{i,f,t+\tau}$$

Emission represents facility emissions to air, water, and land for years $t+\tau$ where $\tau = 1$ to $\tau = 5$. *Acquired Knowledge* is the number of backward citations made by the focal firm i's patents to clean patents, but only includes clean patents filed by the firm within 2 years following EPA actions. All regressions include the baseline controls from Table 2, which are not shown here for brevity. T-statistics, adjusted for clustered standard errors at the firm level, are reported in parentheses. ***, **, * indicate significance levels 1%, 5%, 10%. The sample period spans from 1987 to 2020.

	(t+1)	(t+2)	(t+3)	(t+4)	(t+5)

Panel A. Air Pollution

	(1)	(2)	(3)	(4)	(5)
Knowledge Spillover$_t$	-0.079***	-0.087***	-0.100***	-0.089***	-0.080***
	(-2.94)	(-3.29)	(-3.48)	(-3.25)	(-3.03)
Controls	✓	✓	✓	✓	✓
Facility FE	✓	✓	✓	✓	✓
Industry × Year FE	✓	✓	✓	✓	✓
Obs.	49,088	45,158	41,321	37,915	34,694
Adj. R^2	0.84	0.84	0.84	0.85	0.85

Panel B. Water Pollution

	(1)	(2)	(3)	(4)	(5)
Knowledge Spillover$_t$	-0.027	-0.040	-0.031	-0.055	-0.055
	(-0.56)	(-0.91)	(-0.65)	(-0.98)	(-1.18)
Controls	✓	✓	✓	✓	✓
Facility FE	✓	✓	✓	✓	✓
Industry × Year FE	✓	✓	✓	✓	✓
Obs.	12,153	11,397	10,629	10,007	9,340
Adj. R^2	0.86	0.86	0.86	0.86	0.87

Panel C. Land Pollution

	(1)	(2)	(3)	(4)	(5)
Knowledge Spillover$_t$	0.052	0.176	0.133*	0.214**	0.191*
	(0.40)	(1.37)	(1.65)	(2.55)	(1.94)
Controls	✓	✓	✓	✓	✓
Facility FE	✓	✓	✓	✓	✓
Industry × Year FE	✓	✓	✓	✓	✓
Obs.	5,549	5,164	4,720	4,402	3,997
Adj. R^2	0.86	0.87	0.87	0.87	0.88