Government Environmental Financial Assistance and Corporate Environmental Performance

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Abstract: We examine whether government financial assistance for environmentally friendly activities is associated with changes in recipient firms' future environmental performance. Our setting includes nearly $43 billion of green financial assistance in the form of loans and subsidies (cash grants and tax abatements/credits) from US federal and state governments to US publicly traded firms with a reporting requirement under the EPA's Toxic Release Inventory Program ("polluting firms"). Green assistance amounts in the form of subsidies (but not loans) are associated with an increase in future waste abatement activities for non-toxic chemicals and a smaller percentage of future waste released for both toxic and non-toxic chemicals. However, we also find that green subsidies (but not loans) are associated with *increases* in polluting firms' future toxic chemical waste intensity and pollution intensity (measures which account for facility production activity). These relations seem counter to government environmental policy goals. In contrast, when we consider environmental outcomes that are not measured at the chemical level, green assistance amounts in the form of loans (but not subsidies) are negatively associated with future EPA violations and both severe and far-reaching environmental risk incidents, as well as positively associated with future environmental innovation. These relations are consistent with green loans helping polluting firms improve their environmental performance. Overall, our results highlight that the effectiveness of environmental fiscal policies depend critically on both the form of assistance (loans versus subsidies) and the environmental performance metrics considered.

JEL classifications: M48, H23, Q52, Q55, Q58

Keywords: government environmental financial assistance; green loans; green subsidies; waste and pollution intensity; EPA violations; environmental risk incidents; green innovation

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1 Introduction

Governments intervene in the private sector for many reasons, including protecting national interests, promoting economic stability and growth, enhancing social welfare, and correcting perceived market failures. Governments can employ a range of policy instruments, such as government ownership/control of specific industries/firms, fiscal and monetary policies, tax laws, regulations, and financial assistance, to achieve these objectives. This paper examines governments' intervention in the private sector to address the market failure of environmental pollution by focusing on their financial assistance for environmentally-friendly activities ("green assistance") to EPA-regulated polluting firms.

The global threat of climate change has prompted governments to implement policies aimed at fostering sustainable industrial practices. During the past two decades, the United States (US) has administered ambitious green assistance programs to support corporations and organizations in their transition to environmentally sustainable business practices.[1] Green assistance provides financial support for environmentally beneficial activities and seeks to reward emission reductions and encourage green innovation, rather than penalize pollution (U.S. Environmental Protection Agency, 2024). Government-provided green assistance is administered through loans and subsidies (cash grants and tax abatements/credits) and aims to reduce recipients' costs related to investing in renewable energy, improving resource efficiency, supporting pollution control, and funding research and development (R&D) in advanced energy technologies. Green assistance awarded by US governments to US publicly traded firms are economically large - more than $42 billion during our 22-year sample to firms with an EPA Toxic Release Inventory reporting requirement - yet we know little about the extent to which green assistance achieves its intended goal of environmental performance improvements. Our study aims to shed light on this underexplored area.

Understanding the effectiveness of the allocation of public funds to influence private

[1] Our sample ends in 2021, which is one year prior to the Inflation Reduction Act of 2022's material expansion of US federal government green financial incentives (U.S. Congress, 2022) and four years prior to the One Big Beautiful Bill Act of 2025's material contraction of US federal government green financial assistance (U.S. Congress, 2025).

sector environmental performance is important to governmental policy makers, taxpayers, and corporate stakeholders. In the absence of evidence that quantifies whether and the extent to which green assistance is associated with improvements in environmental performance, such assistance risks being a poor use of taxpayer money subject to greenwashing criticisms from environmental watchdogs and skeptical corporate stakeholders. Given the importance of understanding this relation, it is natural to wonder why we lack large-sample evidence on the issue. While many studies comprehensively evaluate the environmental effectiveness of a single government program or focus on a single industry (Mian and Sufi, 2012; Fowlie et al., 2018), we do not know if these findings generalize to other green programs or industries. We are able to provide large-sample evidence on the relation between green assistance and corporate environmental performance by utilizing data in the Good Jobs First (GJF) Subsidy Tracker. To our knowledge, this is the most comprehensive publicly available compilation of green assistance data provided by US federal and state governments to corporations.

Our sample includes data on more than $42 billion of green assistance from 2000 through 2021 to 138 US publicly traded firms with an EPA Toxic Release Inventory (TRI) Program reporting requirement ("polluting firms"). US federal and state governments offer green assistance in the form of cash grants and tax abatements/credits, and the US federal government also offers green assistance in the form of non-forgivable loans. In the aggregate, green loans from the federal government are approximately $35 billion, while green cash grants (tax abatements/credits) from federal and state governments are approximately $7 billion ($1 billion). The federal government's 'Innovative Energy and Innovative Supply Chain' program and 'Advanced Technology Vehicles Manufacturing (ATVM)' program are the largest programs in terms of dollars awarded ($27.4 and $6.4 billion, respectively).

Our first set of analyses consider the relation between green assistance and firms' waste generation, mitigation, and pollution activities. The first step in environmental impact management is waste abatement at the source, which is often referred to as "source reduction." The greater the abatement activities, the lower the amount of waste generated through production activities. Once waste is generated, a firm has the following options for mitigating the environmental impact of the waste, listed in order of most to least preferred (Gallaher et al., 2008): recycle, recover, and treat. Waste that is not eliminated through one of these three actions is considered 'released' - the EPA's term for what is colloquially referred to as pollution. We obtain EPA data on abatement activities, waste generation, mitigation activities, and waste releases, with data measured at the firm-facility-chemical-year level. We are able to separately analyze toxic chemicals (e.g., arsenic and mercury compounds) and non-toxic chemicals (e.g., nitrate compounds and sodium salts). Our research design controls for relevant firm-year characteristics (including non-green government financial assistance in the forms of loans and subsidies) and employs an extensive set of fixed effects (firm-year, facility-chemical, chemical-year, firm-chemical, and industry-chemical-year). Identifying variation in these analyses comes from differences in green assistance across different firms within the same industry-chemical-year cell.

We find that green assistance amounts in the form of subsidies (but not loans) are associated with more abatement activities related to non-toxic chemicals through $t+3$. This finding is consistent with green subsidies helping to improve a firm's environmental footprint. However, we also find that green subsidies are associated with greater waste intensity (defined as chemical waste generated scaled by production activities involving this chemical) for toxic chemicals through $t+3$. As toxic chemicals are most concerning for human health and the environment, this positive relation seems counter to government environmental policy goals. We note that firms have many options for mitigating the negative environmental impacts of generated waste (e.g., through recycling, recovery, or treatment), so we next turn to analyses that consider these mitigation practices. We find no clear evidence of relations between green assistance (of either type) and the percentage of chemical waste that is recycled, recovered, or treated. Waste that is not mitigated through one of these practices is released into the environment as pollution.

We find that green assistance amounts in the form of subsidies are associated with a smaller percentage of toxic and non-toxic waste released through t+3. This finding is also consistent with green subsidies helping to improve a firm's environmental footprint. However, when we consider pollution intensity (defined as chemical waste released as pollution scaled by production activities involving this chemical), we find that green subsidies are associated with an *increase* in toxic chemicals pollution intensity through t+3. Similar to the waste intensity results previously discussed, this result also seems counter to government environmental policy goals. Rather, these results are consistent with an ineffective use of government resources.

We acknowledge that green assistance is generally not chemical-specific, so analyses that consider pollution activities at the facility-chemical-year unit of analyses are not the only way to consider green assistance effectiveness. Thus, we also conduct analyses that consider other aspects of corporate environmental performance. We consider environmental regulatory violations using EPA enforcement actions (the result of an EPA violation) at the facility-firm-year level. Using a research design that controls for relevant firm-year characteristics (including non-green assistance) and employs facility, firm, and industry-year fixed effects, we find that green assistance amounts in the form of loans (but not subsidies) are associated with a lower likelihood of an EPA violation. This relation indicates that loans help firms comply with environmental regulations and highlight the importance of considering assistance type. Consistent with better environmental compliance, we find that green assistance amounts in the form of loans (but not subsidies) are associated with a reduction in a firm's severe and far-reaching environmental risk incidents through t+3. These analyses are conducted at the firm-year level, control for relevant firm-year characteristics (including non-green assistance), and include firm and industry-year fixed effects.

Our final analyses consider green innovation as a measure of corporate environmental performance. The potential for knowledge spillover (i.e., positive externalities of green innovation) begin when green innovation is disclosed (Dyer et al., 2024; Kim and Valentine, 2021), so our first analysis considers green patent filings. We also consider forward-looking green patent citations to identify patents with the greatest positive externalities for innovation and patents' estimated economic value to identify patents with the greatest potential monetization opportunities (Kogan et al. (2017)). Analyses conducted at the firm-year level (with controls for relevant firm-year characteristics, firm fixed effects, and industry-year fixed effects) reveal that green assistance amounts - again in the form of loans but not subsidies - are associated with an increase in future green patent citations and estimated economic values through t+3. We do *not* observe these relations for *non*-green patent citations and economic values, indicating that green loans promote targeted environmental innovation rather than loan recipients' general innovation.

Our paper makes several contributions to the literatures on corporate financial assistance and corporate environmental performance. First, our study informs the discussion regarding the targeted allocation of public funds to correct a market failure related to private sector environmental externalities. Findings using our most granular unit of observation (at the firm-facility-chemical-year) and our most stringent set of fixed effects reveal that while green assistance in the form of subsidies are associated with more abatement of non-toxic chemicals and a smaller percentage of waste released for both toxic and non-toxic chemicals, we fail to find evidence that green financial assistance amounts (in the form of loans or subsidies) are associated with lower waste intensity or pollution intensity. Rather, we find that green subsidies are associated with greater waste intensity and pollution intensity for toxic chemicals. These relations call into question governments' decision to use taxpayer funds in this manner. In contrast, when we consider environmental outcomes that are not measured at the chemical level, we find that green assistance amounts in the form of loans (but not subsidies) are associated with improvements in firms' environmental performance. Specifically, analyses that focus on EPA environmental violations, environmental risk incidents that are severe and far-reaching, and green innovation as measured by future patent citations and economic values reveal that green loans (but not green subsidies) are associated with positive environmental outcomes for polluting firms. Our analyses provide insights useful for guiding future decisions in the realm of environmental and fiscal policy. These findings also have implications for how governments choose to structure the delivery method of green financial assistance programs.

Second, we add to the growing body of research on firms' environmental outcomes. Previous studies have examined EPA enforcement actions (Dasgupta et al., 2023; Foroughi et al., 2023), asset divestitures in response to environmental pressures (Duchin et al., 2025), and legal liabilities for environmental misconduct (Alberini and Austin, 2002; Stafford, 2002; Shapira and Zingales, 2017; Akey and Appel, 2021; Bellon, 2021). While these studies focus on the various government and regulatory "sticks" used to shape corporate environmental behavior, we focus on a government policy more akin to a "carrot." Along these lines, we contribute to the literature on industrial policy instruments. Studies on renewable energy incentives have highlighted the role of production tax credits (Bird et al., 2005), feed-in tariffs (Nicolini and Tavoni, 2017), and R&D funding (Peñasco et al., 2021). Examining government environmental financial assistance programs, which include loans, cash grants, and tax credits/abatements, allows us to study a broader policy tool of material economic magnitude (relative to studies that consider only a single industrial policy tool in isolation).

We note that government intervention of any type in the private sector is subject to political preferences. While governmental policies regarding the use of public funds to achieve private sector environmental outcomes change as a function of the political party in power, whether and the extent to which green financial assistance is related to corporate environmental outcomes is an important input to evidence-based environmental policy decision-making irrespective of political party preferences.[2]

[2]For example, the US federal government commitment to green financial assistance has experienced large swings in recent years, with the Inflation Reduction Act of 2022 greatly expanding and the One Big Beautiful Bill Act of 2025 rolling back and/or eliminating many federal government green financial assistance programs to corporations and individuals. Our analyses are unaffected by these two pieces of federal legislation because our sample ends in 2021.

2 Data Sources

2.1 Environmental Financial Assistance Data

We use the Subsidy Tracker dataset from Good Jobs First (GJF) to identify green financial assistance provided by U.S. federal and state governments. GJF is a non-profit and non-partisan national policy resource center that tracks and promotes corporate and government accountability in economic development. The Subsidy Tracker is the most comprehensive collection of loans and subsidies granted by U.S. federal, state, and local governments to organizations and corporations.[3] Subsidy information is collected from various sources, including government disclosures (such as usaspending.gov, the official open data source of US federal spending information), Freedom of Information Act (FOIA) requests, and media reports. Federal government data are generally collected from administrative sources, meaning the amounts reflect dollars disbursed by a federal government agency during a specific year. Much of the state government data are also collected from administrative records, suggesting these amounts are also dollars disbursed.

Data are organized at the award level, and the dataset offers detailed insights into each loan or subsidy, including the granting government and agency, program descriptions, recipient organization details, assistance type (e.g., cash grants, tax abatements/credits, or loans), assistance amounts, and the year of allocation.[4] This dataset is widely used in recent literature examining various outcomes related to U.S. government financial assistance (Jansa and Gray, 2017; Huang, 2022; Drake et al., 2022; Dong et al., 2023; Raghunandan, 2024; De Simone et al., 2025; Aobdia et al., 2024; Casi et al., 2025).

We identify green financial assistance by manually filtering the dataset to include only assistance to US publicly traded firms related to government support for practices that benefit the environment. We match award recipients to Compustat following Casi

[3] Additional information can be found at `https://goodjobsfirst.org/about/`. While Subsidy Tracker provides some information on local government subsidies, GJF acknowledges that its data from this level of government is incomplete, so we exclude the single green assistance program granted by a local government in the sample (the Columbus, Ohio Region Green Fund) from our analyses.

[4] Some awards have missing information for some variables, and the data do not include loan details (e.g., interest rate, loan duration, etc.). See https://subsidytracker.goodjobsfirst.org/pages/data-sources for additional information.

et al. (2025) (a process detailed later in the manuscript) and focus our analyses on "polluting firms" (i.e., firms with an EPA TRI reporting requirement due to their polluting activities). In the aggregate, eleven state governments (Alaska, Florida, Kentucky, Massachusetts, Michigan, Missouri, New York, North Carolina, Ohio, Oregon, and Washington) and the US federal government provide \$42,544 million in green financial assistance to 138 polluting firms (445 firm-years) during our 22-year sample period (2000 through 2021).[5]

Figure 1 presents green assistance descriptive information. Panel A presents dollar amounts by type (cash grants, tax abatements/credits, or loans) and granting government (federal or state). In terms of economic magnitude, loans from the federal government comprise the largest group (\$34,819 million), followed by cash grants from the federal government (\$6,803 million), tax abatements/credits from state governments (\$520 million) and the federal government (\$401 million), and cash grants from state governments (\$1 million). Panel B shows how these amounts, by government and type, vary by year. Green assistance is provided in each year of our 22-year sample, with the largest amounts in 2009, 2014, and 2011, respectively. Variation in green assistance amounts over time illustrates the need for time-related fixed effects in our regression analyses.

Appendix A displays the names of the 32 green assistance programs in our sample, organized into five subsections by assistance type and awarding government and listed in alphabetical order within each subsection. The largest of the programs dollars-wise is the Innovative Energy and Innovative Supply Chain Program (more than \$27 billion; untabulated) - a program administered by the US Department of Energy (DOE) to help finance projects using new or significantly improved high-impact clean energy technologies (Innovative Energy) or advanced technologies in clean energy manufacturing or product supply chains (Innovative Supply Chain). The second largest program, which is also administered by the DOE, is the Advanced Technology Vehicles Manufacturing (ATVM) Program (more than \$6 billion; untabulated) - a program that supports the production of eligible advanced technology vehicles and components, including categories such as

[5] The aggregate amount is 88% of all green assistance dollars in the GJF Subsidy Tracker dataset.

medium- and heavy-duty vehicles, trains, maritime vessels, aircraft, and hyperloop technology. This appendix also shows that some cash grants (e.g., Section 1603 payments that reimburse a portion of the installation costs of various types of energy property including solar, wind, geothermal, biomass, fuel cells, hydropower, combined heat and power, landfill gas, municipal solid waste, and microturbines) are awarded in lieu of tax credits. Cash grants in lieu of tax credits, combined with tax credit/abatement amounts aggregating to only 2% of total green financial assistance, leads us to combine cash grants and tax abatements/credits in our regression analyses.

Table 1 displays descriptive information for green assistance by SIC1 industry, with firms in the transportation, communications, electric, and gas industry (SIC1 = 4) receiving the largest aggregate dollar amounts ($26,400 million) and firms in the manufacturing industry (SIC1 = 3) receiving the second largest aggregate dollar amounts ($14,411 million). This distribution aligns with expectations, as these industries have substantial environmental footprints. These two industries comprise 96% of green assistance highlights the need for industry fixed effects in our regression analyses.

2.2 Waste and Pollution Data

Our sample focuses on polluting firms with an EPA TRI reporting requirement, which allows us to obtain facility-chemical emissions data. TRI reporting is mandatory for U.S. establishments with at least 10 employees operating within specific industries and releasing specific chemicals above a specified threshold.[6] The TRI data provides detailed information on each facility that meets the reporting requirements, including address, NAICS information, and the number of pounds of each chemical released at a facility each year. Data are provided at the firm-facility-chemical-year level, which allows us to separately consider toxic and non-toxic chemicals using toxicity information provided by the EPA's Integrated Risk Information System (IRIS). We use Chemical Abstract Services (CAS) numbers to match chemicals between the IRIS and TRI databases. Toxic

[6] https://www.epa.gov/toxics-release-inventory-tri-program/basics-tri-reporting

chemicals are defined by the EPA as those that can cause one or more of the following: (i) cancer or other chronic human health effects, (ii) significant adverse acute human health effects, and (iii) significant adverse environmental effects. As of 2020, more than 600 individual chemicals and chemical categories were classified as toxic. Examples of toxic (non-toxic) chemicals include arsenic and mercury compounds (nitrate compounds and sodium salts).[7] We use a string-matching algorithm to link TRI establishments operated by US publicly traded parent firms to Compustat. We use these data to assess a firm-year-facility-chemical's waste intensity and pollution intensity following Duchin et al. (2025).

The 2005 EPA Pollution Abatement Costs and Expenditures (PACE) survey and EPA guidelines outline best practices in pollution prevention practices (commonly referred to as abatement) so waste is not generated, and waste management process for waste that is generated. The EPA encourages facilities to first prioritize reducing or eliminating the use of TRI-listed chemicals through preventive abatement activities, as abatement is considered the most effective for environmental protection. Three types of post-production waste management practices address waste after it has been generated. Recycling, or the act of reusing waste in new production, is the preferred management method, followed by energy recovery (often through combustion), and then treatment processes (such as incineration and oxidation, which neutralize hazardous chemicals). If waste cannot be recycled, recovered, or treated, the waste is released into the environment as a last resort (Li et al., 2021).

2.3 Environmental Protection Agency (EPA) Violations Data

Data on US EPA investigations and enforcement actions come from the agency's comprehensive Enforcement and Compliance History Online (ECHO) database, which provides information on federal administrative and judicial cases related to various en-

[7] The EPA notes that the TRI list of reportable toxic chemicals can vary from year to year due to EPA-initiated review and through the chemical petitions process. See https://www.epa.gov/toxics-release-inventory-tri-program/tri-listed-chemicals

vironmental statutes (e.g., the Clean Air Act and the Toxic Substances Control Act).[8] ECHO provides details about enforcement actions for investigations initiated by the EPA as well as state and local government environmental agencies. We compile all EPA enforcement cases that reached a conclusion (i.e., a settlement) between 2000 and 2021. For each enforcement case, we gather information on the case-specific identifier, dates of initiation and conclusion, and the plants implicated in the case. We match these enforcement cases with TRI plants using the EPA-provided TRI linking table.

2.4 Environmental Risk Incidents Data

We use data from RepRisk to examine a firm's environmental risk incidents. RepRisk harnesses the power of AI and machine learning, coupled with human intelligence, to screen more than 150,000 public sources of information on a daily basis to collect, screen, and categorize "business conduct and ESG risks that could have adverse impacts on financial performance, people, or the planet."[9] RepRisk is frequently used in accounting, finance, and economics research to measure public disclosure of a firm's environmental incidents with the potential for a negative impact on firm reputation (Duchin et al., 2025; Gantchev et al., 2019; Derrien et al., 2022; Akey et al., 2023).

2.5 Environmental Innovation Data

Data on green innovation comes from patent data compiled by Kogan et al. (2017). This dataset links details extracted from US Patent and Trademark Office (PTO) documents (e.g., assignees, citations, application dates, and issuance dates) to publicly traded firms. We measure green innovation by examining information about a firm's green patent activity (Bratten et al., 2025; Mbanyele et al., 2022; Cohen et al., 2020; Haščič and Mig-

[8] Environmental statutes covered by the ECHO database include the Clean Air Act (CAA), Clean Water Act (CWA), Resource Conservation and Recovery Act (RCRA), Emergency Planning and Community Right-to-Know Act (EPCRA) Section 313, Toxic Substances Control Act (TSCA), Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA), Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA or Superfund), Safe Drinking Water Act (SDWA), and Marine Protection, Research, and Sanctuaries Act (MPRSA).

[9] https://www.reprisk.com/research-insights/resources/methodology

otto, 2015). The European Patent Office, World Intellectual Property Organization, and the Organisation for Economic Cooperation and Development have each developed their own classifications for what constitutes a green patent, based on either International Patent Classification (IPC) or Cooperative Patent Classification (CPC) codes. We use the database created by Favot et al. (2023), which systematically organize the IPC and CPC green codes in the same manner as each of these three organizations, to identify green patents.

3 Sample Selection, Variables of Interest, and Descriptive Statistics

We begin our sample selection with the GJF Subsidy Tracker dataset. The sample begins in 2000 following Aobdia et al. (2024) and ends in 2021 due to some analyses requiring forward-looking information through 2024. The GJF dataset is first linked to Compustat by parent firm name using a fuzzy matching algorithm with extensive manual checks. We then follow the data cleaning steps discussed in Casi et al. (2025) Section 3 to ensure the validity of each parent-subsidiary-year in the Subsidy Tracker. These steps are necessary because within the Subsidy Tracker dataset each parent-subsidiary relation is based on the latest available year in which a researcher obtains the dataset - in our case, 2024. As subsidiaries owned by a parent in 2024 may not be owned by this same parent in years prior to 2024, failing to validate each parent-subsidiary-year link could induce measurement error and incorrect inferences.[10]

These cleaning steps include validating each parent-subsidiary-year link in the Subsidy Tracker dataset using the WRDS Company Subsidiary dataset. A GJF-provided parent-subsidiary-year link is considered valid if the WRDS Company Subsidiary dataset indicates the parent owns the subsidiary in that year. Once a parent-subsidiary is validated, we assume the parent owns the subsidiary in all subsequent years unless the SDC

[10] Casi et al. (2025) illustrate this issue with the following example: "[T]he Subsidy Tracker lists Whole Foods as a subsidiary of the parent firm Amazon as early as 2002 (the first year Whole Foods appears in the dataset), even though Whole Foods did not become an Amazon subsidiary until 2017. A researcher using the GJF-provided information without considering the validity of each parent-subsidiary-link will erroneously attribute subsidies awarded to Whole Foods from 2002 through 2016 to Amazon" (p.16)

Platinum dataset indicates another firm acquired the subsidiary in a future year. We attempt to rematch subsidiaries for which we break an invalid parent-subsidiary-year link to another parent firm in a different year using the WRDS Company Subsidiary dataset.

Using the cleaned Compustat-Subsidy Tracker matched dataset, we manually filter the data to identify government financial assistance for practices that benefit the environment. This involves reviewing the descriptions of all programs (approximately 800) in the GJF dataset to identify environmental-related programs. While some programs have names that are clearly related to the environment (e.g., "Clean Coal Power Initiative" and "Section 1603 Program: Payments for Specified Energy Property in Lieu of Tax Credits"), other programs are determined to be related to the environment only after reviewing program descriptions (e.g., 'Section 1705 Loan Program' is described as "loan guarantees for projects focusing on renewable energy systems, electric power transmission systems, and leading-edge biofuels projects" (GJF).

We then match these data to the firms in the EPA TRI Program ("polluting firms"), which yields approximately 14,000 firm-year observations with a TRI reporting requirement. After requiring non-missing firm-year characteristics commonly used as controls in related research on publicly traded firms' environmental performance (cash holdings, leverage, R&D expenditures, return on assets, sales growth, and size) (e.g., Duchin et al. (2025); Dasgupta et al. (2023)), our final sample of TRI reporters includes 12,870 firm-years, of which 445 (3%) receive green financial assistance from a US government.

Our independent variable of interest, *Green Fin Assist*, is measured as the sum of all green assistance amounts awarded to firm j by an US federal or state government in year t as a percentage of firm j's assets at the end of year t. All variables are defined in Appendix B. We also decompose this variable based on green financial assistance *type*. The variable *Green Fin Assist - Loan* is defined analogously but only financial assistance in the form of loans is included in the numerator. Similarly, the variable *Green Fin Assist - subsidy* is defined using only financial assistance in the form of subsidies (i.e., cash grants and tax abatements/credits) in the numerator. In our sample, the *Green*

Fin Assist mean is 0.019 (Table 2 Panel B). The *Green Fin Assist - Loan* mean is 0.015 while the *Green Fin Assist - Subsidy* mean is 0.004 (also in Table 2 Panel B), indicating that loan dollar values are nearly four times greater than subsidy dollar values. These variables' values are multiplied by 100 for readability in this table, meaning that the average green assistance amount is less than one percent of a firm's total assets. The variable's value is zero at the 75th percentile, which reflects that 97% of TRI reporter firm-years are not awarded green assistance.

Our dependent variables of interest capture various aspects of a firm's future environmental performance. We first focus directly on chemicals-related pollution, including abatement procedures that reduce waste generation, waste generation intensity, the percentage of waste generated that is recycled, recovered, or treated (preferred activities) versus released as pollution, and pollution intensity. These activities can be measured at the firm-year-facility-chemical level. We also consider the presence of a future EPA environmental violation, which can be measured at the firm-year-facility level. We then turn to variables that reflect future media and news coverage of firms' environmental risk incidents and firms' future green innovation in the form of future green patent filings, citations, and economic values.

We begin with pollution-related variables. To assess plant engagement in pollution prevention, we count the total number of source reduction activities implemented at each plant for each chemical in a given year, based on data from the EPA's Pollution Prevention (P2) database. The indicator variable *Abatement - All* is set equal to one if firm j reports at least one abatement action at facility f for chemical c in year t, and zero otherwise. Facilities report these activities annually by selecting from 47 codes across 8 broad categories. For post-production waste management, we calculate the percentage of total waste reduced through recycling (*%Recycled - All*), energy recovery (*%Recovered - All*), and treatment (*%Treated - All*), as well as the percentage of waste released into the environment (*%Released - All*). For example, the variable *%Recycled - All* is measured as the total pounds of waste that firm j recycles onsite at facility f related to chemical

c in year t, divided by total waste generated onsite at facility f related to chemical c in year t.

We construct variables related to waste and pollution intensity following Duchin et al. (2025). The variable *Waste Intensity* is defined as a facility-chemical's total waste generated in year t divided by its production ratio in year t. The production ratio measures the annual change in the output (or process outcome) a chemical is involved in. For chemicals directly used in the production process, the ratio reflects the product output in year t relative to year t-1. For example, if Chemical A is used to produce Product Z, then the production ratio for Chemical A in year t is calculated as the number of Product Z produced in year t divided by the number of Product Z produced in year t-1. For chemicals used indirectly in the production process (e.g., machinery cleaning), the EPA requires facilities to report the ratio reflecting the annual change in this indirect activity. To illustrate, if Chemical B is used to clean the liners used to produce Product Z, then the production ratio for Chemical B in year t is calculated as the number of Product Z liners cleaned in year t divided by the number of Product Z liners cleaned in year t-1. When a chemical is used in more than one direct or indirect production process, facilities report a weighted average (Akey and Appel (2021)). Similarly, *Pollution Intensity* is measured as a facility-chemical's total emissions in year t divided by its production ratio in year t.[11]

Table 2 Panel A first presents descriptive statistics for the 344,593 facility-chemical-year observations in our sample. We find an average of 0.11 preventive abatement activities per chemical (*Abatement-All*), and the mean *Waste Intensity-All* value is 0.591. Once waste is generated, on average 5.3% is recycled (*%Recycled-All*) and 1.3% is recovered (*%Recovered-All*) through processes that turn waste into usable energy. Another 23.6%

[11] For observations with missing production ratios, we follow Duchin et al. (2025) and set the production ratio to one in the first year a chemical is reported, then multiply forward each year by the reported production ratio at the facility-chemical level. Ratios outside the range [0, 3] are excluded (as these are likely due to data errors), and missing observations are replaced with a value of one. Within our sample, on average each chemical within a facility generates approximately 153,000 pounds of total waste, of which 27,000 pounds (18%) is released into the environment as pollution. The average firm in our sample produces approximately 389 million pounds of waste a year, of which 70 million pounds (18%) is released as pollution (both untabulated).

of the waste is treated (*%Treated-All*) to reduce its hazardous nature. This means that more than two-thirds of waste generated is released into the environment as pollution (*%Released-All*). The mean *Pollution Intensity-All* value is 0.107. There are 101,130 facility-year observations in our sample, and the indicator *EPA Violations Presence* is set to one if a firm's facility receives an EPA enforcement action in year *t*, and zero otherwise. Table 2 Panel A shows that the *EPA Violations Presence* mean is 0.043, indicating that 4.3% of facilities are in violation of EPA regulations each year.

Table 2 Panel B presents descriptive statistics at the firm-year level. We measure a firm's environmental risk incidents in four ways. The binary variable *Envir Risk Indicator* is set equal to one if a firm has an environmental-related risk incident in year *t*. We create additional binary variables that incorporate RepRisk's classification related to incident severity (the "harshness of the risk incident or criticism"), incident novelty ("whether it is the first time a company/project is exposed to a specific [issue] in a certain location"), and the reach of the information source discussing the incident (the "influence based on readership/circulation as well as by its importance in a specific country"). Each incident receives a severity score of 1(low), 2 (medium), or 3 (high), a novelty score of 2 (for new issues) or 1 (for recurring issues), and a reach score of 1 (limited), 2 (medium), or 3 (high). The variables *Envir Risk - Severe*, *Envir Risk - Novelty*, and *Envir Risk - Reach* are each set equal to one if a firm has an environmental-related risk incident in year *t* with a severity score greater than 1, a novelty score of 2, and a reach score greater than 1, respectively.[12]

We require a firm to be in the RepRisk database at least once during our 22-year sample period (to ensure RepRisk covers the firm), yielding a sample of 9,465 firm-years. Table 2 Panel B shows that within this sample, *Envir Risk Indicator* has a mean of 0.377, indicating that annually slightly over one-third of firm-years has an environmental risk

[12]Severity is a function of three dimensions: the potential consequences of the risk incident (e.g., with respect to health and safety: no further consequences, injury, or death), the extent of the impact (e.g., one person, a group of people, a large number of people), and whether the risk incident was due to an accident, negligence, or intent. For article reach, limited reach sources include local media, smaller NGOs, local governmental bodies, and social media, while medium reach sources include most national and regional media, international NGOs, and non-local governmental bodies. High reach sources are global media outlets. For additional information, see https://www.reprisk.com/insights/resources/methodology.

incident covered by RepRisk. Although conceptually distinct, the three variables that capture aspects of the incident or article are empirically related, with pairwise correlations ranging from 0.72 to 0.90 (untabulated).

Finally, we measure green innovation using green patent data in three ways. First, we calculate a firm's number of green patent applications in year t (*Patents - Green*) following Bratten et al. (2025) and Lerner and Seru (2022). Second, we source the number of forward-looking citations for a firm's patents from Kogan et al. (2017) through 2022 (the most recent year for which data are available), and adjust values by the average forward-looking citations for all patents filed in the same year (*Patents Citations - Green*). We also consider the economic value of a patent based on the present value of its estimated monopoly rents (*Patents Value - Green*) developed in Kogan et al. (2017). We create analogous variables for non-green patents to use in falsification tests. Table 2 Panel B shows that for the 8,125 firm-years with usable patent data, 58% of firm-years have green patent filings. Patent quantity and patent citations are positively but moderately correlated (0.27; untabulated), while patent value is only weakly correlated with patent count (0.05) and patent citations (0.06). These positive but small correlations highlight that the patent variables capture related but distinct aspects of firms' green innovation activities.

4 Research Design and Regression Results

Our analyses consider the relation between green assistance awarded by a US government to US publicly traded polluting firms and these firms' future environmental performance. Outcomes of interest include pollution activities, environmental violations, environmental risk incidents, and green innovation. We examine these relations by estimating modified versions of the following equation:

$$Y_{j,t+n} = \alpha + \beta_1 Green\ Fin\ Assist_{j,t} + X_{j,t} + \lambda_j + \gamma_{i,t} + \epsilon_{j,t+n} \tag{1}$$

We estimate Equation (1) using OLS unless otherwise stated. The subscript j denotes a firm, i denotes an industry, and t denotes a year. The vector $X_{j,t}$ refers to firm-year controls following Duchin et al. (2025) and Dasgupta et al. (2023): $Cash_{j,t}$, $Leverage_{j,t}$, R&D expenditures ($R\&DExp_{j,t}$), an indicator for missing R&D values ($R\&DMissing_{j,t}$),[13] return on assets ($ROA_{j,t}$), $Sales_{j,t}$, $SalesGrowth_{j,t}$, and $Size_{j,t}$. Control variables that are continuous in nature are scaled by firm j's end of year total assets. We also control for *Non-Green Fin Assist*, defined analogous to *Green Fin Assist* but with non-green assistance amounts in the numerator. For brevity, *Non-Green Fin Assist* is the only tabulated control variable. Firm fixed effects (λ_j) control for time-invariant firm characteristics that could be related to a firm's proclivity to seek and receive green assistance and to improving its environmental performance (even in the absence of green assistance). Industry-year fixed effects ($\gamma_{i,t}$) control for time-series variation in macroeconomic trends within an industry that could influence governments' propensity and ability to provide green assistance (in general and within specific industries) as well as within-industry interest in seeking green assistance.[14] Equation (1) includes additional fixed effects (detailed later in the manuscript) when the unit of analysis is more granular than firm-year.

4.1 Outcomes of Interest: Waste and Pollution

We begin our empirical analyses by investigating the relation between green assistance and activities related to waste and pollution at the firm-facility-chemical-year unit of analysis. A firm interested in improving its environmental performance should seek to first reduce the amount of waste it generates (abatement). Then, conditional upon generating waste, the firm should seek to recycle, recover, or treat its waste (with this order reflecting the most to least environmentally-friendly processes). Waste that is not addressed through one of these three practices is released as pollution into the environment.

[13] When XRD is missing in Compustat, we set $R\&DMissing$ equal to one and $R\&DExp$ equal to zero. When XRD is not missing, we set $R\&DMissing$ equal to zero and $R\&DExp$ equal to XRD.

[14] We define industries using NAICS codes because this is the industry classification that determines whether a firm is a TRI reporter (i.e., whether a firm is included in our sample). We use three-digit NAICS codes (NAICS3) following Duchin et al. (2025).

Pollution releases serve as the most direct measure of a firm's environmental impact. Green assistance that enhances a firm's environmental sustainability should manifest in at least one of the following ways: greater abatement activities; less waste generated per unit of production; a greater percentage of waste generated being recycled, recovered, or treated; and less pollution per unit of production.

We analyze the amount and intensity of emissions on a chemical-by-chemical basis for each facility rather than aggregating chemicals within a facility, as different chemicals produce different environmental externalities. This unit of analysis allows us to include firm-year, facility-chemical, chemical-year, firm-chemical, and industry-chemical-year fixed effects (a very stringent set of fixed effects). We are, however, able to separate chemicals into toxic and non-toxic subgroups.[15]

For analyses conducted at the firm-facility-year-chemical unit of analysis, the identifying variation for the *Green Fin Assist* coefficient comes from differences in green financial assistance across different firms within the same industry-chemical-year cell. For example, assume two firms in the aerospace manufacturing industry both handle chemical X in 2018. Firm A receives green assistance in the form of a loan in 2018, while Firm B does not. The regression compares chemical handling changes across Firm A's and Firm B's facility-chemical X observations in that narrow industry-chemical X-2018 cell, and sheds light on whether Firm A's facilities show relatively better next-period handling of chemical X when its firm-year assistance switches on, relative to Firm B's (net all fixed characteristics and common shocks).

Table 3 summarizes the results of estimating Equation (1) using the dependent variable *Abatement*, which captures the first step in environmental impact management. The greater a firm's abatement efforts, the less waste the firm generates. If green financial assistance helps firms improve or increase their abatement procedures, the green financial assistance coefficients should be positive and statistically significant. Panel A (B)

[15]Recent work recommends using a Poisson regression model when working with dependent variables constructed as the natural log of one plus the variable of interest when the variable of interest has many zero values Chen and Roth (2024). When we attempt to use a Poisson model to examine the relation between government financial assistance and both waste and pollution intensity, the model is over-specified (due to the extensive sets of fixed effects) and does not converge.

measures *Abatement* in year t+1 (years t+1 through t+3). While Panel A shows mostly negative relations between green financial assistance and abatement activities in year t+1, we are cautious about interpreting marginally significant coefficients as strong evidence. In Panel B, only one coefficient of interest exhibits a greater than marginal statistical significance. Column 6 shows that the relation between green financial assistance in the form of subsidies is associated with an increase in abatement of non-toxic chemicals. While toxic chemicals are most concerning for human health, we view this finding as consistent with green assistance in the form of subsidies offering some positive benefits through the reduction of non-toxic waste generation.

Table 4 presents the relations between green financial assistance and *Waste Intensity*. Recall that this dependent variable captures the pounds of chemical waste generated at a specific facility-year as a function of the firm's facility-year production activities that involve this chemical. Panel A fails to reveal a robust relation between firms' total green assistance amounts in year t and waste intensity in year t+1 (columns 1 through 3). The relation is marginally negative in column 3 but insignificant in columns 1 and 2. When we consider green assistance type (loans versus subsidies), we find that green loans are negatively associated with waste intensity (column 4). However, there is no relation between green loans and waste intensity when the regression is estimated separately for toxic and non-toxic chemicals (columns 5 and 6). Interestingly, we find a *positive* relation between future waste intensity and green subsidies for both toxic and non-toxic chemicals (columns 5 and 6). These findings suggest that as subsidies increase, waste intensity increases - a result that is inconsistent with subsidies improving polluting firms' environmental performance.

Table 4 Panel B extends the waste intensity measurement period through t+3, and shows that future waste intensity is unassociated with total green assistance (columns 1 through 3) or loans (columns 4 through 6). However, the positive relation between future waste intensity and green subsidies for toxic chemicals persists when considering this longer window. This relation seems counter to government environmental policy goals.

We note that given the many options available for mitigating the negative environmental impacts of waste before the waste is released as pollution (e.g., recycling, recovering, and treatment), these findings do not necessarily shed light on green assistance effectiveness with respect to environmental impact. Thus, we next turn to analyses that consider what polluting firms do with the waste they generate as a function of green financial assistance.

Table 5 presents the relations between green financial assistance and dependent variables that capture the percentage of a firm's generated waste that is recycled, recovered, treated, or released as pollution. If green financial assistance helps firms improve their environmental performance, we should find positive coefficients on our variables of interest when *%Recycled-All*, *%Recovered-All*, or *%Treated-All* (or their sub-components related to toxic versus non-toxic chemicals) are the dependent variables. These analyses are presented in Panels A through F, and include 36 regression results related to nine dependent variable specifications (the three dependent variables and each variable's two sub-components), three independent variable specifications (total, loan, and subsidy assistance), and two time periods (t+1 and t+1 through t+3). We find one column of results with a positive and statistically significant coefficient of interest, four columns with *negative* and statistically significant coefficients of interest, and 31 columns with statistically insignificant coefficients of interest. Collectively, we view these findings as failing to provide evidence that green financial assistance helps firms improve their environmentally-friendly practices related to waste recycling, recovery, or treatment.

If green financial assistance helps firms improve their environmental performance related to waste released as pollution, we should find negative coefficients on our variables of interest when *%Released-All* (or its sub-components) are the dependent variables. Panel D presents results that are broadly consistent with green financial assistance in the form of subsidies reducing the percentage of toxic and non-toxic chemical waste released as pollution. This is an encouraging finding for green subsidy effectiveness. Our next set of analyses builds upon this finding by explicitly incorporating the extent of a facility's production activities.

Table 6 Panel A reveals a negative relation between firms' green assistance amounts and future pollution intensity in $t+1$ (column 1), with the relation driven by pollution intensity related to non-toxic chemicals (column 3). These findings indicate that following green assistance, firms invest in more environmentally friendly production processes that reduce pollution intensity for less severe chemicals, but do not curtail the pollution intensity of chemicals that pose the greatest risks to human health and the environment. However, we find that when green assistance is split into loans and subsidies in columns 4 though 6, there is no relation between pollution intensity and either type of assistance. In Panel B, we extend the time period for measuring pollution intensity through $t+3$. While we continue to find no relation between green loans and future pollution intensity, this panel reveals a *positive* relation between green subsidies and toxic chemical pollution intensity. This, again, seems counter to public policy goals and we are currently investigating what might be driving this positive relation.

In sum, the results related to pollution activities in Tables 3 through 6 reveal that assistance amounts in the form of subsidies (i.e., cash grants and tax credits) but not loans are associated with more waste abatement activities for non-toxic chemicals and a smaller percentage of waste released for both toxic and non-toxic chemicals. However, neither type of green assistance is consistently associated with reductions in polluting firms' future waste intensity or pollution intensity. We acknowledge that green assistance is generally not chemical-specific, so analyses that consider waste and pollution intensity at the firm-facility-chemical-year unit of analyses are not the only way to consider green subsidy effectiveness. We next turn to other ways to measure environmental performance.

4.2 Outcome of Interest: EPA Violations

Firms that engage in excessive polluting activities may be identified by the EPA for breaching environmental regulations. To assess whether green assistance helps firms improve their environmental regulatory compliance, we estimate Equation (1) using the indicator *EPA Violations Presence* as the dependent variable. As this analysis is at the firm-facility-year unit of analysis, we also include facility fixed effects. We consider violations in both t+1 and t+1 through t+3.

Table 7 shows that total green assistance is marginally associated with a reduction in an EPA violation in t+1 and years t+1 through t+3. When we consider green assistance type, we find that the negative relation is statistically stronger when loans are separated from subsidies and is found only for loans (column 4). These findings indicate that loans help firms comply with environmental regulations, and highlight the importance of assistance type when assessing the relation between green government assistance and environmental performance outcomes.

4.3 Outcome of Interest: Environmental Risk Incidents

Reputational risk can arise from various environmental risk events (e.g., pollution incidents, regulatory violations, community opposition, etc.), which can adversely affect a firm's public image and stakeholders' trust. To assess whether green assistance helps firms reduce their environmental risk incidents, we estimate Equation (1) using four binary variables that capture different aspects of environmental risk: *Envir Risk Indicator*, *Envir Risk - Severity*, *Envir Risk - Novelty*, and *Envir Risk - Reach*. As RepRisk collects incident data at the firm-event date level, we aggregate incidents within a firm's fiscal year to conduct these analyses at the firm-year unit of analysis.

In Table 8, Panels A through D show that total green assistance amounts are associated with a reduction in the presence, severity, novelty, and reach of a firm's environmental risk incidents in year t+1 (Column 1). All four panels also show that this negative relation is due to green assistance in the form of loans (column 2). Interestingly, we find that green assistance in the form of subsidies is associated with an *increase* in the presence of an environmental risk incident in t+1 (Panel A Column 2), although when we consider the different attributes of these environmental incidents we find no relation with the severity or novelty of the incident and only a marginal relation with incident reach (Panels B, C, and D, respectively).

When we extend the future time period from t+1 through t+3, the negative relation between green loans and both environmental risk incidents that are severe and that have a greater reach persists (Panels B and D, column 4). The positive relation between the presence of an environmental risk incident and green subsidies also persists (Panel A column 4), although considering the three incident attributes in Panels B through D fails to yield a statistically significant relation. Collectively, these results provide mixed evidence - while green *loans* are associated with a decrease in severe environmental risk incidents and incidents covered in articles with greater readership reach, green *subsidies* are positively associated with the presence of an environmental risk incident. The findings in Table 8 again highlight the importance of assistance type when assessing the relation between green government assistance and environmental performance outcomes.

4.4 Outcome of Interest: Environmental Innovation

Developing new technologies, products, and procedures that promote environmental sustainability often leads to firms filing patent applications. If green financial assistance spurs green patentable technological advances, we should observe a positive relation between green assistance and future green patent filings, green patent future citations, and green patent estimated economic values (*Patents - Green*, *Patents Citations - Green*, and *Patents Value - Green*, respectively). We estimate Equation (1) using these three dependent variables using a Poisson regression model (the model recommended by Chen and Roth (2024) when a dependent variable is defined as the natural log of one plus Y when Y has many zero values). Analyses are conducted at the firm-year unit of analysis, and we measure our dependent variables in years t+1 through t+3. We also create analogous measures for non-green patents to use in falsification tests (i.e., to ensure that any relations we find are specific to *green* innovation, rather than innovation in general).

Table 9 Panel A fails to show any statistically significant relations between future green patent filings and green financial assistance amounts. However, Panel B shows that total green financial assistance is associated with forward green patent citation counts (column 2) and that this relation is driven by green financial assistance in the form of loans (column 5). Panel C shows that total green financial assistance is positively associated with future patent economic values (column 1), and that this relation is confined to green patent values (column 2). This positive relation is due to green financial assistance in the form of loans (columns 4 and 5). Collectively, these findings are consistent with green assistance in the form of loans promoting economically valuable environmental innovation that other research references and builds upon.

We fail to find a significant relation between green assistance and future non-green patent citations or future non-green patent values (Panels B and C, columns 3 and 6). These falsification tests, combined with the green patent citation and economic value results, are consistent with firms targeting their green assistance specifically to green innovation rather than innovation in general. We also note that non-green financial assistance is not positively associated with future patent citations (either green or non-green) in any of the three panels, which helps assuage the potential concern that firms awarded government financial assistance are more innovative. Interestingly, Panel C column 5 shows a *negative* relation between green assistance subsidies and green patent economic values. While this relation is isolated to a single column, it again highlights the importance of bifurcating green financial assistance into loans and subsidies.

We conduct additional analyses to consider selection bias and reverse causality. The potential for selection bias arises because the same characteristics that motivate firms to apply for and receive government green financial assistance might also motivate firms to improve their environmental performance, even in the absence of receiving the financial assistance. Reverse causality could arise if firms improve their environmental performance prior to applying for (and receiving) green financial assistance, either to strengthen their assistance application or as part of their ongoing environmental or operational strategy. To examine this possibility, we investigate changes in recipient firms' environmental performance related to the dependent variables in Tables 3 through 9 during the three years prior to a firm's financial assistance award. These analyses fail to reveal statistically significant relations during this three-year pre-treatment period (untabulated), alleviating concern that assistance is awarded to firms already making incremental environmental progress. These findings suggest that observed improvements in environmental performance occur after assistance is awarded, rather than the observed environmental outcome changes being a continuation of pre-existing trends.

5 Conclusion

Environmental performance has become increasingly important for firms as they intensify efforts to adopt environmentally sustainable practices. Environmental stewardship has transformed into a point of pride for many firms and is often showcased as a competitive advantage (Khan, 2024). It is not clear as to whether government intervention in the private sector on this dimension contributes to improved environmental stewardship. We believe this gap in the literature has persisted due to a lack of large sample data on green financial assistance from governments to organizations. We overcome this limitation by harnessing information in the GJF Subsidy Tracker - the most comprehensive source of publicly available information on green financial assistance provided by US federal and state governments to US publicly traded firms.

Determining whether and the extent to which green financial assistance is associated with future improvements in environmental performance is a necessary step in evaluating the effectiveness of this particular government policy tool. A finding that green assistance is unassociated with improvements in awardee firms' future environmental performance calls into question the use of such large amounts of public funds for this purpose. In contrast, a finding that green assistance is associated with improvements in awardee firms' future environmental performance allows policy makers to compare the monetary cost of green assistance with the documented environmental improvements.

Using firm-facility-chemical-year data and a stringent set of fixed effects, we find that green assistance amounts in the form of subsidies are associated with more abatement of non-toxic chemicals and a smaller percentage of waste released for both toxic and non-toxic chemicals. However, we find that green financial assistance amounts in the form of subsidies are associated with *greater* toxic chemical waste intensity and pollution intensity. These positive relations call into question governments' decision to use taxpayer funds in this manner.

In contrast, when we consider environmental outcomes that are not measured at the chemical level, we find that green assistance amounts in the form of loans (but not subsidies) are associated with improvements in firms' environmental performance. Specifically, analyses that focus on EPA environmental violations, environmental risk incidents that are severe and far-reaching, and green innovation as measured by future patent citations and economic values reveal that green loans (but not green subsidies) are associated with positive environmental outcomes for polluting firms. These findings highlight the importance of assistance type in understanding green financial assistance effectiveness. These findings have implications for how governments choose to structure the delivery method of green financial assistance programs, and we hope that our findings provide insights useful for guiding future decisions in the realm of environmental and fiscal policy.

Our paper's next steps include considering additional types of pollution using data from the EPA's Greenhouse Gas Reporting Program (GHGRP) and investigating the channels through which financial assistance type could impact assistance effectiveness (e.g., differences in ex-ante application criteria and ex-post monitoring for green loans relative to green subsidies; differences in the susceptibility of assistance type to political capture; etc.). We also hope to strengthen identification by considering exogenous shocks to specific green assistance programs as well as the geographical distribution of firms' facilities with a focus on multi-state firms. For example, if a firm with operations in both states A and B receives green financial assistance in state A but not state B, then it is possible that environmental performance at facilities in state A improve while environmental performance at facilities in state B worsen. Our current pooled sample approach may be masking these across-state differences. We expect that investigating these dynamics will improve the ability of our paper to provide valuable insights into the broader implications of governments' green financial assistance programs for changes in firms' future environmental performance.

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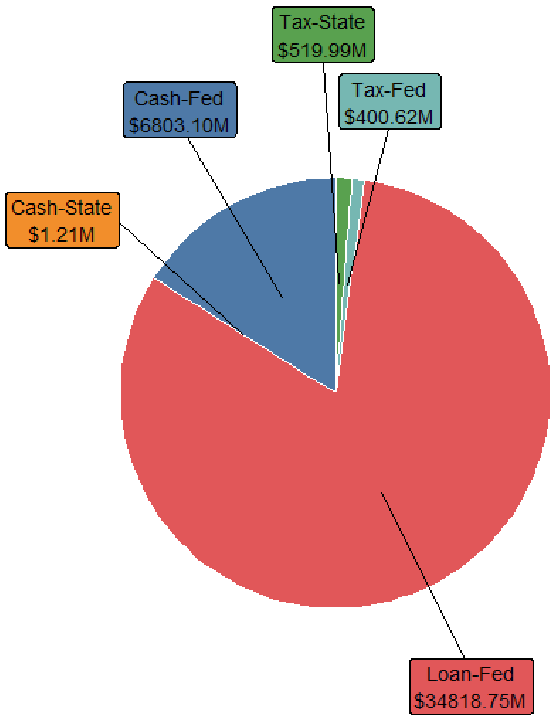
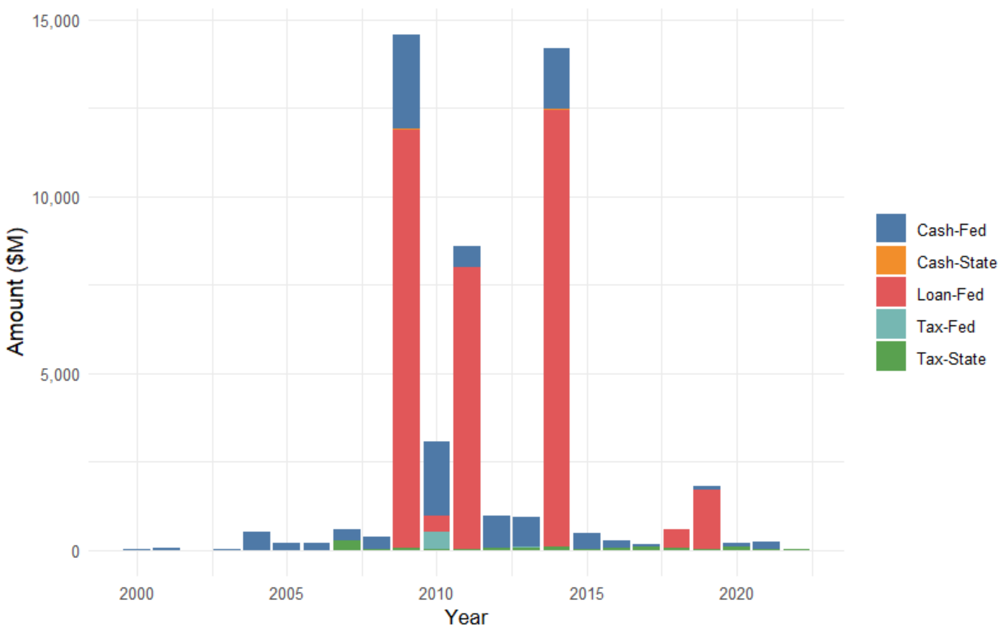
Figure 1: Green Financial Assistance Descriptive Statistics

Panel A: Total Green Financial Assistance (\$M), by Assistance Type and Awarding Government



Panel B: Annual Green Financial Assistance (\$M), by Assistance Type and Awarding Government



Notes: This figure provides descriptive statistics for green financial assistance awarded to polluting firms (U.S. publicly traded firms with a TRI reporting requirement) from 2000 through 2021. Financial assistance is categorized by type (loans (*Loans*), subsidies in the form of cash grants (*Cash*), and subsidies in the form of tax abatements/credits (*Tax*)) and the level of government awarding the financial assistance (federal (*Fed*) or state (*State*)). Panel A (B) presents total (annual) green financial assistance (\$M) by assistance type and awarding government.

Table 1: Green Financial Assistance by Industry

SIC1	Description	N Firms	Amount ($M)
1	Mining	8	345.217
2	Construction	37	1,203.185
3	Manufacturing	66	14,411.381
4	Transportation, Communications, Electric, Gas, and Sanitary Services	18	26,399.606
5	Wholesale Trade	5	2.514
9	Public Administration	4	181.770
	Total	138	42,543.673

Notes: This table presents industry frequencies (SIC1) for the firms that receive green financial assistance in our sample (U.S. publicly traded firms with an EPA TRI reporting requirement) from 2000 through 2021.

Table 2: Summary Statistics

Panel A: Descriptive Statistics (More Granular than Firm-Year)

	N	Mean	SD	P25	P50	P75
Facility-Chemical-Year Level Variables:						
Abatement - All	344,593	0.110	0.312	0	0	0
Abatement - Toxic	138,452	0.129	0.336	0	0	0
Abatement - Non-Toxic	206,141	0.096	0.295	0	0	0
Waste Intensity - All	344,593	0.591	2.668	0	0.003	0.103
Waste Intensity - Toxic	138,452	0.845	3.239	0.001	0.020	0.191
Waste Intensity - Non-Toxic	206,141	0.420	2.187	0	0	0.054
%Recycled - All	244,850	0.053	0.204	0	0	0
%Recycled - Toxic	105,348	0.058	0.203	0	0	0
%Recycled - Non-Toxic	139,502	0.049	0.205	0	0	0
%Recovered - All	244,850	0.013	0.090	0	0	0
%Recovered - Toxic	105,348	0.023	0.117	0	0	0
%Recovered - Non-Toxic	139,502	0.006	0.063	0	0	0
%Treated - All	244,850	0.236	0.379	0	0	0.488
%Treated - Toxic	105,348	0.342	0.404	0	0.039	0.795
%Treated - Non-Toxic	139,502	0.156	0.337	0	0	0
%Released - All	242,690	0.673	0.427	0.143	1	1
%Released - Toxic	104,282	0.542	0.433	0.059	0.575	1
%Released - Non-Toxic	138,408	0.772	0.394	0.667	1	1
Pollution Intensity - All	344,593	0.107	0.450	0	0.001	0.019
Pollution Intensity - Toxic	138,452	0.114	0.472	0	0.003	0.030
Pollution Intensity - Non-Toxic	206,141	0.102	0.434	0	0	0.009
Facility-Year Level Variables:						
EPA Violations Presence	101,130	0.043	0.203	0	0	0

Panel B: Descriptive Statistics (Firm-Year)

	N	Mean	SD	P25	P50	P75
Firm-Year Level Variables of Interest:						
Green Fin Assist	12,870	0.019	1.131	0	0	0
Green Fin Assist - Loan	12,870	0.015	1.122	0	0	0
Green Fin Assist - Subsidy	12,870	0.004	0.077	0	0	0
Envir Risk Indicator	9,465	0.377	0.485	0	0	1
Envir Risk - Severe	9,465	0.152	0.359	0	0	0
Envir Risk - Novelty	9,465	0.357	0.479	0	0	1
Envir Risk - Reach	9,465	0.157	0.363	0	0	0
Patents - All	8,125	190.019	668.829	1	9	73
Patents - Green	4,749	23.815	100.349	0	1	9
Patents - Non-Green	8,051	177.718	618.988	1	8	68.500
Patent Citations - All	7,763	360.636	3,689.541	0	5.672	75.563
Patent Citations - Green	4,235	2.029	9.276	0	0.425	1.796
Patent Citations - Non-Green	7,699	362.518	3,702.195	0	5.637	75.771
Patent Value - All	8,125	35.279	82.640	0.239	10.605	30.838
Patent Value - Green	4,749	25.373	59.682	0	6.008	25.717
Patent Value - Non-Green	7,699	21.395	68.739	0	3.537	15.739
Firm-Year Level Control Variables:						
Cash	12,870	0.102	0.113	0.023	0.064	0.141
Leverage	12,870	0.286	0.273	0.156	0.272	0.386
R&D Missing	12,870	0.363	0.481	0	0	1
R&D Exp	12,870	0.020	0.040	0	0.007	0.025
ROA	12,870	0.122	0.201	0.086	0.121	0.163
Sales	12,870	1.019	0.613	0.621	0.900	1.271
Sales Growth	12,870	0.089	0.342	-0.031	0.054	0.151
Size	12,870	7.516	2.146	6.248	7.617	9.024
Non-Green Fin Assist	12,870	0.052	1.216	0	0	0.001

Notes: This table presents descriptive statistics for the regression variables, organized by most to least granular in terms of unit of observation: facility-chemical-year and facility-year in Panel A, and firm-year in Panel B. In this table, dependent variables are measured over the period $t+1 \rightarrow t+3$. In Panel B, the four government green financial assistance variables (*Green Fin Assist*, *Green Fin Assist - Loan*, *Green Fin Assist - Subsidy*, and *Non-Green Fin Assist*), which are scaled by a firm's total assets, are multiplied by 100 for ease of readability. Variables are defined in Appendix B.

Table 3: Regression Results: Waste Abatement

Panel A: Abatement at t+1

Dependent Variable:	$Abatement_{t+1}$					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	-0.338	-0.423*	-0.324			
	(0.218)	(0.241)	(0.218)			
Green Fin Assist - Loan				-0.487*	-0.429	-0.506*
				(0.277)	(0.322)	(0.283)
Green Fin Assist - Subsidy				1.52	0.502	1.94*
				(1.06)	(0.896)	(0.993)
Non-Green Fin Assist	-0.053	-0.130	-0.027	-0.031	-0.046	-0.027
	(0.048)	(0.100)	(0.022)	(0.038)	(0.077)	(0.027)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	344,593	138,452	206,141	185,687	79,422	106,265
Adjusted R^2	0.42428	0.42381	0.41797	0.42484	0.42877	0.41796

Panel B: Abatement at t+1 to t+3

Dependent Variable:	$Abatement_{t+1 \to t+3}$					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	-0.331	-0.431*	-0.313			
	(0.217)	(0.236)	(0.218)			
Green Fin Assist - Loan				-0.501*	-0.376	-0.530*
				(0.281)	(0.327)	(0.287)
Green Fin Assist - Subsidy				2.00*	0.843	2.47**
				(1.12)	(1.19)	(0.952)
Non-Green Fin Assist	-0.069	-0.144	-0.043	-0.045	-0.057	-0.043
	(0.051)	(0.091)	(0.028)	(0.041)	(0.075)	(0.033)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	344,593	138,452	206,141	185,687	79,422	106,265
Adjusted R^2	0.50736	0.51814	0.49275	0.51083	0.52579	0.49490

Notes: This table reports estimates of the relation between green financial assistance and waste abatement activities, using OLS and data at the facility-chemical-year unit of analysis. Chemicals are categorized into three groups: all chemicals (*All*), toxic chemicals (*Toxic*), and non-toxic chemicals (*Non-Toxic*). Variables are defined in Appendix B. Standard errors clustered at the facility-year level are reported in parentheses below each coefficient. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 4: Regression Results: Waste Intensity

Panel A: Waste Intensity at t+1

Dependent Variable:	*Ln(Waste Intensity$_{t+1}$)*					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	-0.019	0.561	-0.094*			
	(0.028)	(0.451)	(0.052)			
Green Fin Assist - Loan				-0.33***	-0.610	-0.127
				(0.039)	(0.591)	(0.402)
Green Fin Assist - Subsidy				5.04**	17.2***	0.464**
				(2.24)	(4.84)	(0.188)
Non-Green Fin Assist	0.365***	0.109	0.446***	0.366***	0.123	0.446***
	(0.108)	(0.188)	(0.101)	(0.120)	(0.198)	(0.100)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	344,593	138,452	206,141	344,593	138,452	206,141
Adjusted R^2	0.9319	0.9117	0.9320	0.93169	0.91024	0.93211

Panel B: Waste Intensity at t+1 to t+3

Dependent Variable:	*Ln(Waste Intensity$_{t+1\rightarrow t+3}$)*					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	0.114	0.414	0.086			
	(0.406)	(0.490)	(0.411)			
Green Fin Assist - Loan				-0.213	-0.835	0.047
				(0.250)	(0.648)	(0.308)
Green Fin Assist - Subsidy				5.52**	18.2***	0.745
				(2.24)	(3.30)	(2.03)
Non-Green Fin Assist	0.132	-0.105	0.209*	0.133	-0.090	0.209*
	(0.154)	(0.257)	(0.115)	(0.155)	(0.267)	(0.115)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	344,593	138,452	206,141	344,593	138,452	206,141
Adjusted R^2	0.94408	0.92771	0.94344	0.94408	0.92772	0.94343

Notes: This table reports estimates of the relation between green financial assistance and waste intensity, using OLS and data at the facility-chemical-year unit of analysis. Chemicals are categorized into three groups: all chemicals (*All*), toxic chemicals (*Toxic*), and non-toxic chemicals (*Non-Toxic*). Variables are defined in Appendix B. Standard errors clustered at the facility-year level are reported in parentheses below each coefficient. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 5: Regression Results: Waste Management Practices

Panel A: %Recycled at t+1

Dependent Variable:	$\%Recycled_{t+1}$					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	-0.003	0.039	-0.007**			
	(0.005)	(0.048)	(0.003)			
Green Fin Assist - Loan				0.011	0.108	-0.003
				(0.017)	(0.104)	(0.006)
Green Fin Assist - Subsidy				0.048	-0.068	0.096
				(0.097)	(0.195)	(0.080)
Non-Green Fin Assist	0.038	-0.003	0.056***	0.028*	0.025	0.028***
	(0.024)	(0.036)	(0.018)	(0.013)	(0.039)	(0.007)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	300,332	131,834	168,498	159,771	75,463	84,308
Adjusted R^2	0.74195	0.71524	0.76172	0.73421	0.71276	0.75144

Panel B: %Recycled at t+1 to t+3

Dependent Variable:	$\%Recycled_{t+1\rightarrow t+3}$					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	-0.0007	0.046	-0.006			
	(0.004)	(0.051)	(0.003)			
Green Fin Assist - Loan				0.009	0.110	-0.009
				(0.018)	(0.102)	(0.008)
Green Fin Assist - Subsidy				0.133	-0.015	0.198**
				(0.129)	(0.233)	(0.094)
Non-Green Fin Assist	0.032*	-0.012	0.049***	0.012	0.017	0.010
	(0.018)	(0.037)	(0.013)	(0.016)	(0.038)	(0.013)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	244,850	105,348	139,502	129,982	60,243	69,739
Adjusted R^2	0.77597	0.76505	0.78392	0.77849	0.76429	0.78986

Panel C: %Recovered at t+1

Dependent Variable:	$\%Recovered_{t+1}$					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	0.001	0.003	0.001			
	(0.003)	(0.010)	(0.003)			
Green Fin Assist - Loan				-0.019	-0.028	-0.014
				(0.016)	(0.031)	(0.013)
Green Fin Assist - Subsidy				0.315	0.436	0.275
				(0.268)	(0.457)	(0.214)
Non-Green Fin Assist	0.007	0.011	0.004	0.003	0.004	0.002
	(0.007)	(0.017)	(0.003)	(0.009)	(0.025)	(0.002)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	300,332	131,834	168,498	159,771	75,463	84,308
Adjusted R^2	0.71224	0.68542	0.76129	0.69247	0.68288	0.72326

Panel D: %Recovered at t+1 to t+3

Dependent Variable:	$\%Recovered_{t+1\rightarrow t+3}$					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	-0.0007	-0.011	0.001			
	(0.002)	(0.012)	(0.002)			
Green Fin Assist - Loan				-0.008	0.008	-0.016
				(0.011)	(0.022)	(0.016)
Green Fin Assist - Subsidy				0.118	-0.312	0.314
				(0.205)	(0.386)	(0.289)
Non-Green Fin Assist	0.004	0.006	0.003	-0.004	-0.017	0.001
	(0.006)	(0.018)	(0.002)	(0.009)	(0.027)	(0.002)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	244,850	105,348	139,502	129,982	60,243	69,739
Adjusted R^2	0.76554	0.73789	0.81459	0.74052	0.73052	0.77108

Panel E: %Treated at t+1

Dependent Variable:	$\%Treated_{t+1}$					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	-0.015	-0.083	-0.006			
	(0.017)	(0.088)	(0.008)			
Green Fin Assist - Loan				-0.028	-0.123	-0.005
				(0.031)	(0.153)	(0.014)
Green Fin Assist - Subsidy				0.260	0.967	-0.045
				(0.314)	(0.680)	(0.259)
Non-Green Fin Assist	-0.014	-0.010	-0.014	-0.021	-0.014	-0.022
	(0.012)	(0.022)	(0.011)	(0.018)	(0.030)	(0.017)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	300,332	131,834	168,498	159,771	75,463	84,308
Adjusted R^2	0.85535	0.80112	0.89710	0.85095	0.79939	0.90044

Panel F: %Treated at t+1 to t+3

Dependent Variable:	$\%Treated_{t+1\rightarrow t+3}$					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	-0.040***	-0.195***	-0.018*			
	(0.013)	(0.054)	(0.010)			
Green Fin Assist - Loan				-0.026	-0.126	-0.004
				(0.018)	(0.100)	(0.012)
Green Fin Assist - Subsidy				0.143	0.715	-0.128
				(0.211)	(0.538)	(0.286)
Non-Green Fin Assist	-0.014	-0.024	-0.008	-0.012	-0.003	-0.013
	(0.014)	(0.028)	(0.009)	(0.013)	(0.030)	(0.011)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	244,850	105,348	139,502	129,982	60,243	69,739
Adjusted R^2	0.88963	0.84377	0.92170	0.88889	0.84757	0.92520

Panel G: %Released at t+1

Dependent Variable:	$\%Released_{t+1}$					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	-0.024	-0.166***	-0.004			
	(0.014)	(0.043)	(0.012)			
Green Fin Assist - Loan				0.024	-0.034	0.012
				(0.038)	(0.113)	(0.009)
Green Fin Assist - Subsidy				-0.913*	-2.41**	-0.299*
				(0.516)	(1.03)	(0.170)
Non-Green Fin Assist	-0.042	0.002	-0.062**	-0.024	-0.026	-0.024
	(0.030)	(0.039)	(0.027)	(0.014)	(0.046)	(0.016)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	300,332	131,834	168,498	159,771	75,463	84,308
Adjusted R^2	0.84639	0.80411	0.86643	0.83485	0.79627	0.85936

Panel H: %Released at t+1 to t+3

Dependent Variable:	$\%Released_{t+1\rightarrow t+3}$					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	-0.005	-0.070**	0.002			
	(0.014)	(0.030)	(0.013)			
Green Fin Assist - Loan				0.025	-0.031	0.016
				(0.030)	(0.101)	(0.018)
Green Fin Assist - Subsidy				-0.910**	-2.09***	-0.390***
				(0.417)	(0.687)	(0.057)
Non-Green Fin Assist	-0.029	0.035	-0.055***	-0.008	-0.010	-0.009
	(0.028)	(0.041)	(0.018)	(0.014)	(0.039)	(0.009)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	242,690	104,282	138,408	128,752	59,630	69,122
Adjusted R^2	0.88012	0.84652	0.89160	0.87485	0.84334	0.89109

Notes: This table reports estimates of the relation between green financial assistance and waste management practices related to the percentage of waste that is recycled (*%Recycled* in Panels A and B), recovered (*%Recovered* in Panels C and D), treated (*%Treated* in Panels E and F), and released (*%Released* in Panels G and H), using OLS and data at the facility-chemical-year unit of analysis. Chemicals are categorized into three groups: all chemicals (*All*), toxic chemicals (*Toxic*), and non-toxic chemicals (*Non-Toxic*). Variables are defined in Appendix B. Standard errors clustered at the facility-year level are reported in parentheses below each coefficient. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 6: Regression Results: Pollution Intensity

Panel A: Pollution Intensity at t+1

Dependent Variable:	*Ln(Pollution Intensity$_{t+1}$)*					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	-0.130**	0.036	-0.145**			
	(0.046)	(0.577)	(0.056)			
Green Fin Assist - Loan				-0.048	-0.116	0.012
				(0.039)	(0.559)	(0.144)
Green Fin Assist - Subsidy				-1.48	2.19	-2.79
				(2.14)	(6.02)	(1.79)
Non-Green Fin Assist	0.037	-0.060	0.074	0.037	-0.058	0.074
	(0.074)	(0.196)	(0.081)	(0.078)	(0.199)	(0.079)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	344,593	138,452	206,141	344,593	138,452	206,141
Adjusted R^2	0.9374	0.9142	0.9414	0.93740	0.91428	0.94141

Panel B: Pollution Intensity at t+1 to t+3

Dependent Variable:	*Ln(Pollution Intensity$_{t+1\rightarrow t+3}$)*					
Model:	*All*	*Toxic*	*Non-Toxic*	*All*	*Toxic*	*Non-Toxic*
Green Fin Assist	0.052	0.562	-0.014			
	(0.391)	(0.700)	(0.354)			
Green Fin Assist - Loan				0.018	-0.021	0.130
				(0.355)	(0.746)	(0.356)
Green Fin Assist - Subsidy				0.625	8.85**	-2.43
				(2.51)	(3.27)	(2.56)
Non-Green Fin Assist	-0.089	-0.156	-0.061	-0.088	-0.149	-0.061
	(0.073)	(0.198)	(0.061)	(0.074)	(0.201)	(0.061)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	344,593	138,452	206,141	344,593	138,452	206,141
Adjusted R^2	0.94902	0.93143	0.95113	0.94902	0.93143	0.95113

Notes: This table reports estimates of the relation between green financial assistance and pollution intensity, using OLS and data at the facility-chemical-year unit of analysis. Chemicals are categorized into three groups: all chemicals (*All*), toxic chemicals (*Toxic*), and non-toxic chemicals (*Non-Toxic*). Variables are defined in Appendix B. Standard errors clustered at the facility-year level are reported in parentheses below each coefficient. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 7: Regression Results: Environmental Violations

Dependent Variable:	*EPA Violations Presence*			
Model:	$t+1$		$t+1 \rightarrow t+3$	
Green Fin Assist	-0.096*		-0.162*	
	(0.055)		(0.084)	
Green Fin Assist - Loan		-0.094		-0.250**
		(0.058)		(0.114)
Green Fin Assist - Subsidy		-0.134		1.69
		(0.435)		(1.07)
Non-Green Fin Assist	0.032	0.032	0.027	0.027
	(0.025)	(0.025)	(0.039)	(0.039)
EPA Violation$_t$	-0.037***	-0.037***	-0.099***	-0.099***
	(0.008)	(0.008)	(0.012)	(0.012)
Firm-Year Controls	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	101,130	101,130	101,130	101,130
Adjusted R^2	0.02634	0.02634	0.18713	0.18713

Notes: This table reports the results from estimating the relation between green financial assistance and the presence of an EPA violation, using OLS and data at the facility-year unit of analysis. Variables are defined in Appendix B. Standard errors clustered at the firm level are reported in parentheses below each coefficient. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 8: Regression Results: Environmental Risk

Panel A: Environmental Risk Indicator

Dependent Variable:	*Envir Risk Indicator*			
Model:	$t+1$		$t+1 \rightarrow t+3$	
Green Fin Assist	-0.664***		0.003	
	(0.222)		(0.076)	
Green Fin Assist - Loan		-0.754***		-0.070
		(0.136)		(0.077)
Green Fin Assist - Subsidy		9.04**		7.89**
		(4.11)		(3.63)
Non-Green Fin Assist	0.150	0.138	0.219	0.210
	(0.387)	(0.388)	(0.293)	(0.294)
Firm-Year Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	9,465	9,465	9,465	9,465
Adjusted R^2	0.51897	0.51921	0.58905	0.58915

Panel B: Environmental Risk Severity

Dependent Variable:	*Envir Risk - Severe*			
Model:	$t+1$		$t+1 \rightarrow t+3$	
Green Fin Assist	-0.607***		-0.502***	
	(0.157)		(0.140)	
Green Fin Assist - Loan		-0.653***		-0.560***
		(0.107)		(0.086)
Green Fin Assist - Subsidy		4.33		5.84
		(4.97)		(5.78)
Non-Green Fin Assist	0.009	0.003	0.313	0.306
	(0.425)	(0.426)	(0.370)	(0.370)
Firm-Year Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	9,465	9,465	9,465	9,465
Adjusted R^2	0.51897	0.51921	0.58905	0.58915

Panel C: Environmental Risk Novelty

Dependent Variable:	*Envir Risk - Novelty*			
Model:	$t+1$		$t+1 \rightarrow t+3$	
Green Fin Assist	-0.825***		0.015	
	(0.071)		(0.080)	
Green Fin Assist - Loan		-0.892***		-0.039
		(0.095)		(0.110)
Green Fin Assist - Subsidy		6.47		5.83
		(5.88)		(3.69)
Non-Green Fin Assist	0.295	0.287	0.621	0.614
	(0.309)	(0.310)	(0.455)	(0.455)
Firm-Year Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	9,465	9,465	9,465	9,465
Adjusted R^2	0.41436	0.41447	0.51234	0.51236

Panel D: Environmental Risk Reach

Dependent Variable:	*Envir Risk - Reach*			
Model:	$t+1$		$t+1 \rightarrow t+3$	
Green Fin Assist	-0.654***		-0.610***	
	(0.222)		(0.162)	
Green Fin Assist - Loan		-0.740***		-0.668***
		(0.133)		(0.105)
Green Fin Assist - Subsidy		8.65*		5.72
		(5.00)		(5.55)
Non-Green Fin Assist	0.402	0.391	0.639*	0.631*
	(0.292)	(0.292)	(0.347)	(0.346)
Firm-Year Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	9,465	9,465	9,465	9,465
Adjusted R^2	0.47338	0.47367	0.55927	0.55939

Notes: This table reports the results from estimating the relation between green financial assistance and environmental risk incidents, using OLS and data at the firm-year unit of analysis. Panel A considers the presence of an environmental risk incident, while Panel B (C) [D] considers the presence of a risk incident classified as severe (novel) [with far reach]. Variables are defined in Appendix B. Standard errors clustered at the firm level are reported in parentheses below each coefficient. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 9: Regression Results: Green Innovation

Panel A: Patent Filings

Dependent Variable:	$Patents_{t+1\rightarrow t+3}$					
Model:	*All*	*Green*	*Non-Green*	*All*	*Green*	*Non-Green*
Green Fin Assist	0.914	0.147	0.655			
	(1.63)	(1.22)	(1.81)			
Green Fin Assist - Loan				0.782	0.057	0.516
				(1.67)	(1.21)	(1.90)
Green Fin Assist - Subsidy				16.0	9.11	14.8
				(9.98)	(9.03)	(10.2)
Non-Green Fin Assist	-0.172	0.263	-0.246	-0.176	0.240	-0.246
	(0.576)	(1.51)	(0.573)	(0.577)	(1.52)	(0.573)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,125	4,749	8,051	8,125	4,749	8,051
Pseudo R^2	0.94345	0.92315	0.94237	0.94347	0.92317	0.94238

Panel B: Patent Citations

Dependent Variable:	$Patent\ Citations_{t+1\rightarrow t+3}$					
Model:	*All*	*Green*	*Non-Green*	*All*	*Green*	*Non-Green*
Green Fin Assist	1.57	2.83***	1.54			
	(2.06)	(0.820)	(2.10)			
Green Fin Assist - Loan				1.45	2.78***	1.42
				(2.19)	(0.827)	(2.26)
Green Fin Assist - Subsidy				15.3	11.4	16.1
				(12.6)	(12.7)	(12.8)
Non-Green Fin Assist	0.168	-2.51*	0.164	0.164	-2.52*	0.160
	(0.758)	(1.41)	(0.757)	(0.759)	(1.41)	(0.758)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,763	4,235	7,699	7,763	4,235	7,699
Pseudo R^2	0.96316	0.62368	0.96327	0.96317	0.62370	0.96327

Panel C: Patent Economic Values

Dependent Variable:	*Patent Value*$_{t+1 \rightarrow t+3}$					
Model:	*All*	*Green*	*Non-Green*	*All*	*Green*	*Non-Green*
Green Fin Assist	1.93***	1.44***	1.54			
	(0.312)	(0.407)	(2.10)			
Green Fin Assist - Loan				1.96***	1.47***	1.42
				(0.312)	(0.409)	(2.26)
Green Fin Assist - Subsidy				-16.5	-13.7**	16.1
				(12.6)	(6.06)	(12.8)
Non-Green Fin Assist	0.648	0.451	0.164	0.657	0.469	0.160
	(0.717)	(1.46)	(0.757)	(0.714)	(1.45)	(0.758)
Firm-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,125	4,749	7,699	8,125	4,749	7,699
Pseudo R^2	0.85005	0.77034	0.96327	0.85011	0.77043	0.96327

Notes: This table reports the results from estimating the relation between green financial assistance and green innovation, using Poisson and data at the firm-year unit of analysis. Panel A focuses on patent filings, while Panel B (C) focuses on patent citations (economic values). Patents are categorized into three groups: all (*All*), green (*Green*), and non-green (*Non-Green*). Variables are defined in Appendix B. Standard errors clustered at the firm level are reported in parentheses below each coefficient. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Appendix A

Green Financial Assistance Program Information (by Assistance Type and Awarding Government)

[1] Loans from the US Federal Government ($34,819M)

Advanced Technology Vehicles Manufacturing (ATVM) Program

The program supports the production of eligible advanced technology vehicles and components, including categories such as medium- and heavy-duty vehicles, trains, maritime vessels, aircraft, and hyperloop technology.

Innovative Energy and Innovative Supply Chain

The program finances projects using new or significantly improved high-impact clean energy technologies (Innovative Energy) or advanced technologies in clean energy manufacturing or product supply chains (Innovative Supply Chain).

Section 1705 Loan Program

The program provides loan guarantees for projects focusing on renewable energy systems, electric power transmission systems, and leading-edge biofuels projects.

[2] Subsidies: Cash Grants from the US Federal Government ($6,803M)

Advanced Biofuel Production Payments

The program provides payments to eligible producers to support the increased production of advanced biofuels, which are derived from renewable biomass other than corn kernel starch.

Advanced Research Projects Agency - Energy (ARPA-E)

ARPA-E funds projects designed to revolutionize energy generation, storage, distribution, and usage. These projects are chosen for their potential to enhance energy security, reduce greenhouse gas emissions, and boost economic competitiveness.

Biomass Research and Development Initiative (BRDI)

The program funds projects that target three technical areas: feedstock development, biofuels and bio-based products development, and biofuels development analysis.

Clean Coal Power Initiative

The program aims to accelerate the commercial-scale development of advanced coal technologies incorporating carbon capture and storage.

Conservation Research and Development

The program focuses on technological advancements in energy efficiency across several areas: Building Technologies, Industrial Technologies, Vehicle Technologies, Solid State Lighting Technologies, and Advanced Manufacturing Technologies.

Electricity Delivery and Energy Reliability, Research, Development and Analysis

The program prioritizes the development of advanced grid technologies, integration of renewable energy, enhancement of energy storage, cybersecurity measures, and technical assistance for energy policies and infrastructure security.

Energy Efficiency and Renewable Energy Information Dissemination Outreach, Training and Technical Assistance

The program provides financial assistance for information dissemination, outreach, training, and technical analysis to promote energy efficiency in transportation, buildings, industry, and the Federal sector.

Energy Efficiency and Renewable Energy Technology Deployment, Demonstration and Commercialization

The program provides financial assistance for the deployment, demonstration, and commercialization of Energy Efficiency and Renewable Energy technologies. It includes Biomass, Building Technologies, Federal Energy Management, Geothermal, Hydrogen and Fuel Cells, Industrial Technologies, Solar, Vehicle Technologies, Weatherization, Intergovernmental, and Wind and Hydropower projects.

Fossil Energy Research and Development (FER&D)

The program advances technologies for the efficient, reliable, and environmentally responsible use of fossil fuels. It focuses on carbon capture and storage, enhancing power system efficiency, and sustainable use of domestic fossil fuels.

Industrial Carbon Capture and Storage (CCS) Application

The program demonstrates advanced CO2 capture from industrial sources for storage or beneficial use, and promotes innovative CO2 utilization technologies.

Inventions and Innovations (I&I) Program

The program offers up to $200,000 in financial assistance for early-stage development and technical validation of energy-saving inventions across industry, power, transportation, and buildings. It focuses on technologies showing substantial energy efficiency improvements and commercial promise.

Nuclear Energy Research, Development and Demonstration

The program promotes nuclear energy to meet national energy, environmental, and security needs through research, development, and demonstration at national labs, universities, and U.S. industry.

Power Plant Improvement Initiative

The program aims to enhance the reliability and efficiency of U.S. electrical power systems through advanced coal-based technologies. This initiative solicits applications for cost-shared projects that demonstrate significant advancements in power plant performance, including increased efficiency and reduced environmental impacts.

Renewable Energy Research and Development

The program aims to conduct balanced research and development across solar, biomass, hydrogen and fuel cells, wind, hydropower, and geothermal energy technologies. Grants competitively fund the development and transfer of these renewable energy technologies to the non-federal sector.

Section 1603 Program: Payments for Specified Energy Property in Lieu of Tax Credits

The program provides payments in lieu of investment tax credits to eligible applicants for specified energy property used in business operations or income generation. These payments reimburse a portion of the installation costs for various types of energy property, including solar, wind, geothermal, biomass, fuel cells, hydropower, combined heat and power, landfill gas, municipal solid waste, and microturbines.

[3] Subsidies: Tax Abatements/Credits from US State Governments ($520M)

Brownfield Redevelopment Tax Credit, NY, FL, MA, MI

The program offers incentives to businesses undertaking cleanup of contaminated properties, aiming to mitigate public health and environmental risks at abandoned or underused commercial and industrial sites.[16] Program coverage: 1996-2023.

Brownfield Tax Increment Financing (TIF), MI

The program involves using the increased property taxes from redeveloped, formerly blighted or contaminated properties to reimburse developers for costs incurred in addressing environmental issues during construction.[17] Program coverage: 2012-2023.

Business Energy Tax Credit (BETC), OR

The program offers tax credits up to 35% of eligible costs for investments in renewable energy facilities. Program coverage: 2007-2010, 2012-2014.

Charcoal Producers Tax Credit, MO

The program offers a credit equivalent to 50% of the cost of best available control technology equipment used in charcoal production. Program coverage: 2000-2012.

Energy Incentive Program, OR

The program is designed to promote energy efficiency, facilitate the adoption of renewable energy technologies, and advance sustainability goals at commercial buildings and industrial processes. Program coverage: 2013-2021.

Incentives for Energy Independence Act, KY

The program promotes renewable energy and alternative fuels that generate specified minimum electricity levels from solar, wind, biomass, landfill gas, hydropower, or similar sources, with a minimum $1 million capital investment requirement.[18] Program coverage: 2008-2019.

Oil and Gas Production Tax Credits, AK

The program includes adjustments to interest rates, tax credits for expenditures by oil and gas service companies, rates and credits for oil and gas production taxes, regulations on gas use within the state, installment payment schedules for oil and gas production taxes, and the establishment of funds and boards to oversee these initiatives.[19] Program coverage: 2008-2022.

Renewable Energy Cost Recovery Light/Power Business PUT credit, WA

The program allows light and power businesses to claim credits for incentive payments

[16] The Florida Brownfields Redevelopment Act (Florida Department of Environmental Protection), the Massachusetts Brownfields Tax Credit (Massachusetts Department of Revenue), the Missouri Brownfield Remediation Program (Missouri Department of Economic Development), and the New York Brownfield Redevelopment Credit (New York State Department of Taxation and Finance).

[17] Michigan Department of Environment, Great Lakes, and Energy (EGLE)

[18] Kentucky Cabinet for Economic Development

[19] Production Tax Documents (Alaska Department of Revenue).

and fees related to renewable energy systems, capped at 1.5% of taxable power sales or $250,000, whichever is greater.[20] Program coverage: 2008-2022.

Renewable Energy Sales and Use Tax Exemption, WA

The program subsidizes equipment used to generate electricity from sources like fuel cells, wind, solar, biomass, tidal, wave, and geothermal energy, as well as technology for energy recovery from exhaust.[21] Program coverage: 2013-2019.

Solar Energy Systems Manufacturers or Wholesalers, WA

The program imposes a 0.275% tax rate on manufacturers and wholesalers of solar energy systems and related components. The tax aims to boost local production and distribution of solar technologies.[22] Program coverage: 2016-2022.

Tax Credits for Investing in Renewable Energy Property, NC

The program allows businesses to claim a percentage of eligible costs incurred in installing and maintaining renewable energy systems (solar, wind, biomass, and other) as a credit against their state income taxes.[23] Program coverage: 2010-2022.

[4] Subsidies: Tax Credits/Abatements from the US Federal Government ($401M)

Qualifying Advanced Coal Project Credit (48A) Program

The program incentivizes investments in projects focused on advancing coal-based generation and gasification technologies. These initiatives aim to improve the efficiency and environmental impact of coal-based energy generation.

Qualifying Advanced Energy Project Credit (48C) Program

The program incentivizes projects that include upgrading or establishing facilities for renewable energy, energy-efficient technologies, electric vehicles, and reducing industrial greenhouse gas emissions (defined in 26 USC § 48C(c)(1)).

[5] Subsidies: Cash Grants from US State Governments ($1M)

Energy Efficiency Program, OH

The program helps businesses and manufacturers reduce energy use and improve energy efficiency, which results in lower energy costs. Program coverage: 2008-2013.

Notes: This appendix lists the 32 government environmental financial assistance programs in our sample by type and government (in alphabetical order within type and government). Information is from the GJF Subsidy Tracker.

[20] Revised Code of Washington Section 82.04.294 (Washington State Legislature)
[21] Tax Incentive Programs (Washington Department of Revenue).
[22] Revised Code of Washington Section 82.16.130 (Washington State Legislature)
[23] North Carolina Tax Credits for Renewable Energy Property.

Appendix B

Variable Definitions

Abatement	Indicator variable set equal to one if, for facility f and chemical c, firm j reports at least one abatement action in year t, and zero otherwise.
Cash	Firm j's cash and short-term investments (CHE_t) divided by total assets (AT_t).
Envir Risk Indicator	Indicator variable set equal to one if firm j has at least one environmental risk incident in year t, and zero otherwise.
Envir Risk - Novelty	Indicator variable set equal to one if any firm j environmental risk incident in year t is classified by RepRisk as relating to a new issue (as opposed to a re-occurring issue), and zero otherwise.
Envir Risk - Reach	Indicator variable set equal to one if the article reach of any firm j environmental risk incident in year t is classified by RepRisk as medium or higher (at least 2 on a scale of 1 to 3), and zero otherwise.
Envir Risk - Severe	Indicator variable set equal to one if the severity of the issue for any firm j environmental risk incident in year t is classified by RepRisk as medium or higher (at least 2 on a scale of 1 to 3), and zero otherwise.
EPA Violations Presence	Indicator variable set equal to one if facility f of firm j receives at least one EPA enforcement action in year t, and zero otherwise.
Green Fin Assist	Firm j's green financial assistance awarded by a US federal or state government in year t divided by total assets (AT_t).
Green Fin Assist - Loan	Firm j's green financial assistance in the form of loans awarded by a US federal government in year t divided by total assets (AT_t).
Green Fin Assist - Subsidy	Firm j's green financial assistance in the form of subsidies (cash grants or tax abatements/credits) awarded by a US federal or state government in year t divided by total assets (AT_t).
Leverage	Firm j's current liabilities (DLC_t) plus long-term debt (DLTT_t) divided by total assets (AT_t).
Non-Green Fin Assist	Firm j's non-green financial assistance awarded by a US federal or state government in year t divided by total assets (AT_t).
Patents	Natural logarithm of one plus the number of patents filed by firm j in year t. We create versions of this variable for all patents (*Patents - All*), green patents (*Patents - Green*), and non-green patents (*Patents - Non-Green*).

Patent Citations	Natural logarithm of one plus the number of forward-looking citations received by firm j's patents filed in year t, adjusted by the average forward-looking citations for all patents filed in year t. We create versions of this variable for all patents (*Patents Citations - All*), green patents (*Patents Citations - Green*), and non-green patents (*Patents Citations - Non-Green*).
Patent Value	Natural logarithm of the estimated economic value of firm j's patent in year t, calculated as the present value of its associated monopoly rents following Kogan et al. (2017). We create versions of this variable for all patents (*Patents Value - All*), green patents (*Patents Value - Green*), and non-green patents (*Patents Value - Non-Green*).
Pollution Intensity	Natural logarithm of one plus the total pounds of pollution released by firm j at facility f related to chemical c in year t, divided by firm j's production ratio at the facility-chemical level in year t. We create versions of this variable for all chemicals (*Pollution Intensity - All*), only toxic chemicals (*Pollution Intensity - Toxic*), and only non-toxic chemicals (*Pollution Intensity - Non-Toxic*).
R&D Missing	Indicator set equal to one if firm j's research and development expenditures value (XRD_t) is missing, and zero otherwise.
R&DExp	Firm j's research and development expenditures (XRD_t) divided by total assets (AT_t). When XRD is missing, we set this variable equal to zero.
%Released	For firm j's facility f and chemical c, the total pounds of waste released onsite in year t divided by total onsite waste generated in year t.
%Recovered	For firm j's facility f and chemical c, the total pounds of waste recovered onsite in year t divided by total onsite waste generated in year t.
%Recycled	For firm j's facility f and chemical c, the total pounds of waste recycled onsite in year t divided by total onsite waste generated in year t.
ROA	Firm j's operating income (OIBDP_t) divided by total assets (AT_t).
Sales	Firm j's sales (SALE_t) divided by total assets (AT_t).
Sales Growth	Firm j's sales in year t (SALE_t) less sales in year *t-1* (SALE_{t-1}), divided by sales in year *t-1* (SALE_{t-1}).
Size	Firm j's market value of equity at the end of year t, calculated as the natural logarithm of the product of stock price per share (PRCC_F_t) and common shares outstanding (CSHO_t).
%Treated	For firm j's facility f and chemical c, the total pounds of waste treated onsite in year t divided by total onsite waste generated in year t.

Waste Intensity	Natural logarithm of one plus the total pounds of waste generated by firm j at facility f related to chemical c in year t, divided by firm j's production ratio at the facility-chemical level in year t. We create versions of this variable for all chemicals (*Waste Intensity - All*), only toxic chemicals (*Waste Intensity - Toxic*), and only non-toxic chemicals (*Waste Intensity - Non-Toxic*).

Notes: This appendix provides variable definitions. Capitalized variable names in parentheses refer to Compustat variable names.