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Socially responsible investing and multinationals' environmental harm: Evidence from global remote sensing data

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SOCIALLY RESPONSIBLE INVESTING AND MULTINATIONALS' ENVIRONMENTAL HARM

EVIDENCE FROM GLOBAL REMOTE SENSING DATA*

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This paper examines how Socially Responsible Investment (SRI) capital affects the environmental footprint of multinational enterprises. We exploit the inverse relationship between local pollution and high-frequency-and-precision satellite-based measurements of vegetation health, captured through the normalized difference vegetation index (NDVI). Combining NDVI with SRI ownership data for 52,806 facilities belonging to 911 multinationals in 124 countries between 2006 and 2020 allows us to leverage both cross-sectional and within-facility variation in SRI exposure over time. We find that, on average, greater SRI ownership is associated with improved vegetation health in surrounding areas, consistent with reductions in firm-induced environmental damage. Using mergers as a plausibly exogenous source of variation in SRI ownership corroborates these findings. However, exploiting the global structure of multinational production networks, we find a striking asymmetry: improvements near facilities located in OECD countries coincide with deterioration near the same firms' facilities in non-OECD countries, consistent with pollution offshoring. Finally, we show that this asymmetry intensifies with more active investor oversight, suggesting that investor engagement alone is insufficient to mitigate environmental harm in the absence of strong domestic regulation or global coordinated monitoring.

JEL Classification: F23, G23, O33, Q56, Q58
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1. Introduction

Assets managed according to environmental, social, and governance (ESG) principles are large and expanding rapidly, with institutional investors widely viewed as key drivers of firms' environmental and social performance (Stroebel and Wurgler, 2021). These investors emphasize engagement rather than divestment as a means to address externalities such as climate risk (Krueger et al., 2020). Firms, in turn, frequently highlight in their sustainability disclosures environmental initiatives related to waste management, hazardous-waste reduction, recycling, on-site treatment, and water stewardship.[1] Yet rigorous evidence on whether this large-scale reallocation of ESG-aligned capital and investor pressure translate into real environmental improvements remains limited. Most measures of corporate environmental impact are self-reported, aggregated, and geographically incomplete, especially outside the richest economies. Furthermore, improvements in one jurisdiction may be offset elsewhere if firms reallocate activity in response to differences in regulation, bargaining power, or marginal abatement costs (Ben-David et al., 2021; Yang et al., 2022). These concerns are particularly salient for multinational enterprises (MNEs), which account for a substantial share of global pollution (Tanaka et al., 2022; Levinson, 2009; Noack et al., 2025).[2] Even if socially responsible investors matter, it remains unclear where firms adjust and whether these adjustments do improve their environmental footprint.

This paper provides new evidence on how SRI capital relates to multinational firms' environmental harm. We address longstanding challenges in both measuring pollution and capturing its displacement across borders by introducing a globally consistent, high-frequency, and spatially granular approach based on satellite data. Specifically, we exploit the well-established inverse relationship between environmental harm and the Normalized Difference Vegetation Index (NDVI), a satellite-derived measure of vegetation health.[3] While NDVI does not directly

[1] See e.g. Dow's 2023 Intersections Progress Report (https://corporate.dow.com/content/dam/corp/documents/about/066-00469-01-2023-progress-report.pdf), Lear's 2023 Sustainability Report (https://ir.lear.com/node/24541/pdf), Baxter's ESG disclosures (https://investor.baxter.com/investors/ESG--Corporate-Responsibility/), Newell Brands' 2024 Corporate Citizenship Report (https://www.newellbrands.com).

[2] The Environmental Protection Agency (EPA) estimates that the manufacturing sector, dominated by multinationals, produces about 60% of hazardous waste in the United States and is a major source of chemical discharges and air pollutants. Levinson (2009) further shows that U.S. manufacturing firms account for roughly 20% of global sulfur dioxide (SO_2), 15% of nitrogen oxides (NO_x), and 12% of carbon dioxide (CO_2).

[3] The NDVI is calculated from reflected red and near-infrared light. Higher NDVI values indicate

measure pollution *levels*, our approach relies on the premise that, holding other factors constant (e.g., vegetation type, weather fluctuations, climate trends, or industrial presence), increases in local environmental harm reduce the NDVI on average. A stable negative relationship between *changes* in environmentally harmful behavior and *changes* in the NDVI is sufficient for our purposes. We build on a growing body of evidence in environmental science documenting NDVI's sensitivity to pollutant exposure (e.g., Dean et al., 2024; Clevers et al., 2004; Zhang et al., 2022; Vashold et al., 2025), and we validate this relationship at scale in Section 3. using U.S.-wide panels that link facility-level toxic releases and chemical spills to local NDVI changes. The NDVI offers three key advantages to track environmental harm: it is (i) available worldwide, including regions lacking formal pollution monitoring; (ii) less susceptible to manipulation than disclosures; and (iii) fine-grained enough to detect local changes around individual facilities. To our knowledge, this is the first paper to employ satellite-based vegetation health data to systematically monitor firms' environmental footprint.

Our empirical analysis combines four main datasets to cover 13,651 grid cells in 124 countries containing over 52,000 production facilities owned by 911 parent companies. First, we obtain from Dun & Bradstreet Worldbase geolocated facility-level information for the universe of production facilities of publicly listed U.S. multinationals operating in polluting sectors.[4] We then match these facilities to parent-company institutional ownership from FactSet. We measure exposure to responsible investing by identifying institutional owners that are signatories of the Principles for Responsible Investment (PRI), the largest ESG initiative in the asset-management industry (Kim and Yoon, 2023; Gibson Brandon et al., 2022). Our main explanatory variable is the time-varying share of the parent's equity held by PRI signatories. Finally, we overlay the facility network with NDVI measured on a $0.1° \times 0.1°$ grid of cells (about 11×11 km at the equator), observed biweekly from 2006 to 2020.

Our empirical design exploits two dimensions of variation in exposure to SRI capital: time, and the relationship between each facility and its parent company. We relate NDVI around facility

denser, more photosynthetically active vegetation.

[4] Namely Agriculture, Forestry, and Fishing (SIC code 01-09), Mining (10-14), Construction (15-17), and Manufacturing (20-39). These sectors account for the majority of toxic pollutants released into land and water, and about 30% of total toxic air pollutants in the U.S.A. Source: U.S. Environmental Protection Agency (2024). *Inventory of U.S. Greenhouse Gas Emissions and Sinks*, and *Toxics Release Inventory (TRI) National Analysis*. Available at: https://www.epa.gov/ghgemissions/industry-sector-emissions and https://www.epa.gov/trinationalanalysis.

locations to the parent firm's quarterly exposure to ownership by PRI signatories, conditioning on high-dimensional fixed effects, weather, and built-environment controls. The fixed effects absorb, among others, time-invariant facility and firm characteristics, local seasonal patterns, and heterogeneous climate trends across agroclimatic zones. Identification comes from within-firm changes in socially responsible ownership over time, comparing how the NDVI evolves around the firms' facilities, conditional on controls and fixed effects. For intuition, consider two facilities in neighboring grid cells owned by different parent firms. We relate differences in socially responsible ownership across parents to differences in NDVI around these two facilities, over time.

A remaining concern is that inflows from socially responsible investors could coincide with broader changes in firm's economic or environmental attractiveness. We address this in three ways. First, we explicitly control for overall institutional ownership to separate the role of PRI signatories from that of institutional investors at large. Second, we control for time-varying local activity using night-time lights to separate environmental changes from production-driven shifts. Last but not least, we turn to a fundamentally different source of variation in SRI exposure: we leverage quasi-experimental variation from mergers in which a PRI signatory acquires a non-signatory asset manager, generating discrete exogenous increases in socially responsible ownership for the target's portfolio firms.

We first find that increases in socially responsible ownership improve local environmental conditions on average. These findings suggest that a one percentage point increase in responsible ownership is associated with a 63 tons reduction of toxic releases per facility. To put this estimate in perspective, 63 tons of releases is equivalent to the total pollution by five distinct facilities at the reporting threshold that triggers mandatory disclosure under the U.S. Environmental Protection Agency's Toxic Release Inventory program. These results are robust when we exploit two alternative sources of variation, namely facility-level specifications or quasi-experimental variation from mergers. Our results echo the view that ownership structure shapes firm behavior and suggest that socially responsible investors act as a form of governance pressure in environmental domains.

However, we also uncover evidence of pollution displacement from OECD to non-OECD countries. OECD economies are typically richer and exhibit greater investment in pollution monitoring and environmental oversight.[5] We find that vegetation health improvements are concentrated around facilities in OECD countries, whereas environmental degradation intensifies around facilities in non-OECD regions. Quantitatively, a one–percentage point increase in responsible ownership is associated with an average reduction of approximately 70 tons of emissions per OECD facility, but an increase of more than 200 tons per non-OECD facility. Because most facilities are located in OECD countries, the net global effect remains positive–roughly 90 tons per firm per year for the median multinational enterprise. This uneven distribution across countries highlights a tension between local improvements and global environmental justice. Put differently, using facility-level outcomes allows us to observe not only whether pollution reductions occur but also where harms are relocated–patterns that are invisible in firm-level ESG ratings or portfolio-level emissions footprints. Our results call for greater attention to cross-border enforcement.

The final part of the paper shows that investor stewardship matters. Using information extracted from mandatory self-reported fillings submitted by signatories to the PRI, we construct a novel measure of intensity of investors engagement that classifies signatories as Basic, Moderate, or Advanced.[6] We find that improvements are concentrated among firms owned by the most engaged institutions. However, displacement abroad is also strongest in these cases. The evidence is consistent with firms responding to investor pressure by improving outcomes in well-monitored regions while relocating harms elsewhere, underscoring the need for international monitoring.

This paper contributes to four strands of literature. First, we advance research on pollution displacement showing that firms may shift environmental externalities toward jurisdictions with weaker enforcement (Dai et al., 2021). This vibrant literature typically exploits differences in regulatory stringency to document the outsourcing of emissions across borders (Ben-David et al., 2021; Kundu and Ruenzi, 2024; Tanaka et al., 2022). Conceptually closer to our focus

[5] The Organisation for Economic Co-operation and Development (OECD) presents itself as "an international organisation that works to build better policies for better lives. [...] We work closely with policy makers, stakeholders and citizens to establish evidence-based international standards and to find solutions to social, economic and environmental challenges." Source: `https://www.oecd.org/en/about.html`, October 28, 2025.

[6] We use a large language model (LLM) to analyze unstructured PRI disclosure text and show that self-reported engagement labels correspond to substantively different stewardship practices. Advanced signatories often mention leadership roles and collaborative engagements, Moderates emphasize collaboration without leadership, and Basics provide brief, heterogeneous responses.

on the role of investors, ongoing work by Berg et al. (2023) demonstrates that investor pressure can induce geographically targeted divestment from polluting assets. We build on and extend this literature by introducing a novel global measure of environmental impact based on satellite-derived vegetation health, allowing us to map where sustainability-oriented investors reduce—or relocate—pollution. We find that improvements are concentrated around facilities in OECD countries, while degradation intensifies in non-OECD regions, particularly where ownership stems from highly engaged investors. Even committed stewardship appears insufficient to eliminate displacement in the absence of globally coordinated monitoring.

Second, we contribute to the growing empirical literature examining how socially responsible institutional investors affect firms' environmental outcomes. Building on seminal work showing that ownership structure shapes firm behavior (Shleifer and Vishny, 1986, 1997), recent evidence suggests that SRI ownership can reduce firms' environmental footprints when measured through firm-level GHG or CO_2 emissions (Azar et al., 2021; Kahn et al., 2023) or composite ESG scores (Dyck et al., 2019), although Heath et al. (2023) find no significant changes in observable firm actions. The work of Naaraayanan et al. (2021) zooms in on a panel of U.S. facilities and documents that an increase in investor activism reduces firms' toxic releases. We extend this literature along several dimensions. Exploiting a facility-level analysis in a global panel, we show that changes in responsible ownership translate, on average, into measurable improvements in local environmental conditions, both in fixed-effects regressions and in a quasi-experimental setting. Furthermore, consistent with recent theory (Heinkel et al., 2001; Berk and van Binsbergen, 2021; Broccardo et al., 2022; De Angelis et al., 2023; Oehmke and Opp, 2024), we document that the direction and magnitude of these effects depend systematically on the regulatory context and the intensity of investor stewardship.

Third, we contribute to recent research on institutional stewardship (Ceccarelli et al., 2024; Dimson et al., 2025; Gibson Brandon et al., 2022; Kim and Yoon, 2022; Lowry et al., 2025). We use PRI disclosures to construct a novel text-based measure that distinguishes passive signatories from active stewards. Not every signatory is equally committed: only 13% classify themselves as Advanced and 21% as Moderate. These differences in self-reported engagement are reflected in the impact investors have on portfolio firms, consistent with evidence in Gibson Brandon et al. (2022) that PRI signatory status is a noisy proxy for responsible ownership and that stewardship intensity varies widely across institutions. However, we also show that even strong institutional engagement does not fully prevent the displacement of environmental harm. This pattern of results suggests that engagement alone is insufficient if country- or customer-level monitoring quality is weak: the real effects of responsible investment are conditional on credible oversight.

Last but not least, this paper contributes to the growing literature that leverages satellite data to comprehensively and consistently track economic activity at the global level (Donaldson and Storeygard, 2016). Such approaches are particularly valuable when ground data are scarce or when actors have misaligned incentives to conceal or distort information. For example, recent research uses nighttime light emissions to show that autocratic regimes are more likely to inflate GDP growth figures than liberal political systems (Martinez, 2022). Exploiting satellite-based daily air quality data, Zou (2021) finds that U.S. firms strategically reduce polluting production on the specific days when intermittent ground-based monitoring stations are active–particularly when their cities approach noncompliance with the Clean Air Act. Here, we show that vegetation indices such as NDVI provide a scalable tool to monitor firms' multispectral pollution footprints.[7] Although NDVI is widely used to assess ecosystem health (Alix-Garcia et al., 2015; Asher and Novosad, 2020; Girard et al., 2025), it remains underutilized as a tool to monitor environmental harm. We document a robust negative association between the NDVI and facility-level toxic releases in the United States and leverage this relationship globally where pollution data are sparse, unreliable, or subject to manipulation (Donaldson and Storeygard, 2016; Zou, 2021).[8] Because the NDVI is independent of firm disclosures, it complements standard pollution measures. By capturing the consequences of multispectral pollution, our approach also connects to work on biodiversity loss and preservation (Giglio et al., 2023; Garel et al., 2024), and to emerging disclosure frameworks such as the European Sustainability Reporting Standards (ESRS), the International Sustainability Standards Board (ISSB), and the Global Reporting Initiative (GRI), that extend beyond carbon to air, water, and ecosystems.

[7]While carbon dioxide (CO_2) is central to climate policy, it reflects only one dimension of environmental impact. A multispectral approach is important knowing that firms may substitute across pollutants in response to incentives (Gibson, 2019; Tanaka et al., 2022; Bartram et al., 2022).

[8]Taking the example of widely scrutinized CO_2 emissions: existing panel data are often self-reported and global estimates rely on reallocation. Satellite products such as Copernicus or NASA's OCO-2 and OCO-3 are promising but to date still have coarse resolution or incomplete coverage.

2. Data and Identification Strategy

We assemble a panel of cells that combines establishments' locations and ownership with satellite-based vegetation health at biweekly (16-day) frequency from 2006 to 2020. Our baseline unit is a global grid of cells of $0.1° \times 0.1°$ (approximately 11×11 km at the equator) that host at least one facility. This resolution provides fine spatial detail, as most cells contain a single establishment, while remaining computationally tractable.[9] The key variables for our final analysis are, at the cell-date level, the presence of U.S.-owned facilities, quarterly institutional ownership of the parent company, and the biweekly NDVI measure.

2.1 Data sources

U.S. public multinationals' facilities. We obtain the global network of establishments for publicly listed U.S. multinationals from Dun & Bradstreet (D&B) WorldBase. Crucially for our research question, while Orbis focuses on legal entities and ownership links (primarily subsidiaries), D&B provides globally consistent coverage of *production* facilities. The extract is a cross-sectional snapshot (2023 vintage). Our analysis therefore relies on the persistence of multinational production networks, which adjust slowly given sunk entry/exit costs (Dixit, 1989). The main implication is measurement error in the timing of openings and closures, adding noise to estimated effects.[10]

We restrict attention to SIC codes 01–39, which are major contributors to pollution and where investor pressure is most likely to affect environmental outcomes (Hartzmark and Shue, 2022). These SIC codes correspond to Agriculture, Forestry and Fishing (01-09), Mining (10-14), Construction (15-17), and Manufacturing (20-39). According to the U.S. Environmental Protection

[9]As a robustness check, we replicate key results on alternative cell sizes and in a facility-level panel. Appendix Table B-1 presents descriptive statistics by cell size.

[10]To gauge the stability of facility networks, we use the U.S. EPA Toxic Release Inventory (TRI), which lists facilities annually when they exceed reporting thresholds. For TRI parents with an identifier (`parentcodbnum`) observed in both 2006 and 2020, we compute, for each parent, the Jaccard similarity between the sets of reporting facilities in 2006 and 2020. The mean similarity is 0.76 (median = 1.00), indicating substantial persistence: most facilities operating in 2020 were already present in 2006. As TRI entries/exits can reflect threshold crossings as well as true openings/closures, three-quarters stability over 14 years underscores strong hysteresis in production networks. A remaining concern is that firms may restructure networks in response to responsible ownership (e.g., outsourcing more polluting activities to suppliers not covered by our facility data). If pervasive, such shifts could bias effects. We revisit this question in Section 4.; the pattern we document, with reductions in OECD facilities coupled with increases at non-OECD facilities, is consistent with intra-network reallocation rather than wholesale divestment or network restructuring (Duchin et al., 2024).

Agency (2024), these sectors account for the majority of toxic pollutants released into land and water, and about 30% of total toxic air pollutants.[11]

Crucially for the purpose of this study, the D&B data allows us to precisely locate all establishments and therefore match them to satellite measurements of vegetation health. We geolocate establishments using latitude/longitude provided by D&B for U.S. sites and ArcGIS World Geocoding for non-U.S. addresses. The raw D&B file includes 57,961 establishments in 124 countries, mapped to 985 parent companies. Panel (a) of Figure 1 plots facility locations.

Institutional ownership. Quarterly institutional ownership at the parent-company level comes from FactSet Ownership (Ferreira and Matos, 2008). Our measure of socially responsible investing is the proportion of a company's shares held by signatories of the Principles for Responsible Investment (PRI). The PRI is the largest global ESG initiative in asset management (Kim and Yoon, 2023), encompassing more than 5,000 signatories and roughly $121 trillion in assets under management as of September 2022, including investment managers (76%), asset owners (14%), and service providers (10%). Europe accounts for more than half of participants, North America is the second largest region. We collect signatory names and joining dates from PRI and hand-match them to FactSet institutions.

We refer to the resulting institutional ownership share as either RI or PRI ownership in the text; denoted in tables *PRI IO*. PRI signatories commit to six principles emphasizing integration of ESG in investment, active ownership, transparency, ESG principles promotion, collaboration, and annual reporting; see UN PRI Association (2024).[12] Noncompliance can result in delisting.

In the final part of the paper, we exploit the fact that between 2014 and 2020 signatories were required to report their level of engagement as part of their mandatory disclosure, classifying their involvement with PRI as Basic, Moderate, or Advanced. In particular, this information

[11] See : *Inventory of U.S. Greenhouse Gas Emissions and Sinks* and *Toxics Release Inventory (TRI) National Analysis*: `https://www.epa.gov/ghgemissions/industry-sector-emissions` and `https://www.epa.gov/trinationalanalysis`.

[12] "Principle 1: We will incorporate ESG issues into investment analysis and decision-making processes. Principle 2: We will be active owners and incorporate ESG issues into our ownership policies and practices. Principle 3: We will seek appropriate disclosure on ESG issues by the entities in which we invest. Principle 4: We will promote acceptance and implementation of the Principles within the investment industry. Principle 5: We will work together to enhance our effectiveness in implementing the Principles. Principle 6: We will each report on our activities and progress towards implementing the Principles." UN PRI Association (2024)

is contained in module SG09 of the PRI Transparency Reports.[13] This intensity disclosure was discontinued after 2020. We use the available information to decompose the PRI IO variable into ownership shares held by basic, moderate, and advanced signatories, thereby moving beyond a binary signatory indicator and capturing heterogeneity in commitment levels.

[Figure 1 about here.]

Vegetation health. To assess whether responsible ownership affects firms' local environmental conditions, we track vegetation health around facilities using the Normalized Difference Vegetation Index (NDVI) (Didan, 2015; Alix-Garcia et al., 2015; Asher and Novosad, 2020). Figure 1 shows a snapshot of the 0.05° 16-day composites, which we area-average to our grid of $0.1° \times 0.1°$ cells.[14] The NDVI captures "greenness" from red and near-infrared reflectance of leafy vegetation and ranges from -1 to 1 (values < 0 typically water/snow; ≈ 0 bare ground/built-up; 0.1–0.5 sparse vegetation; $\geq$ 0.6 dense vegetation). The NDVI varies systematically across space and seasons; our empirical specifications absorb local idiosyncrasies and weather-driven variations, and control for economic activity. Section 3. documents NDVI's responsiveness to pollution.

Controls. We include three main sets of controls. (i) Weather: we capture weather-related variability in vegetation health through monthly temperature and precipitation from the Climatic Research Unit (CRU) at $0.5° \times 0.5°$ resolution (Harris et al., 2020), entering levels and squares to allow nonlinear responses (see Dell et al., 2014). (ii) Local economic activity: development and settlement patterns that may affect vegetation independently of firms' pollution. We consider night-time lights harmonized by Li et al. (2020) for the period 2006-2018, alongside population and building counts from the EU Global Human Settlement Layer (GHSL).[15] (iii) Ecological heterogeneity: we consider agroclimatic-zone-by-year fixed effects based on the World Bank's Köppen–Geiger classification to capture ecological boundaries and allow zone-specific annual

[13] We retrieved all the 2014-2020 Public Transparency Reports from https://www.unpri.org/signatories/reporting-and-assessment/public-signatory-reports in April 2025. The engagement-intensity question appears in different modules across years: OA10 in 2014–2015, SG08 in 2016, and SG09 from 2017 onward. We refer to it as SG09 for brevity. The link may no longer lead to the files as the PRI stopped publishing the reports on their website shortly after. As of September 2025, the PRI indicates that historical reports are available to academics upon submission of a research proposal. Figure G-7 in the Appendix provides an example of the section of interest.

[14] Data source: https://www.earthdata.nasa.gov/data/catalog/lpcloud-mod13c1-061/.

[15] GHSL: https://ghsl.jrc.ec.europa.eu/download.php. The GHSL is available every five years, we interpolate it to annual frequency.

responses.

2.2 Sample and summary statistics

We start from 57,961 facilities linked to 985 parents in D&B data. We drop 572 establishments with insufficient address information and match 911 parents to FactSet institutions by name, yielding 52,806 facilities, 4,353 of which are in non-OECD countries. Panel A of Table 1 summarizes the final sample. The average parent operates 58 facilities (median 18), and 493 parents have at least one facility in a non-OECD country. Most facilities are in North America (40,222), followed by Europe (7,020), Asia (3,934), Latin America (1,407) and Africa (223).

Our final panel comprises 13,651 grid cells that host these 52,806 facilities. A cell-date observation enters the panel if it contains at least one establishment whose parent has recorded quarterly institutional ownership. The distribution of facilities per cell is highly skewed: the median cell-date contains a single establishment, with a small mass of multi-facility cells (Panel B of Table 1). The mean number of facilities per cell is 3.74. We show in section 4. that our findings are robust to trimming cells with more than one facility.

To relate cell-level NDVI to socially responsible ownership over time, when a cell hosts multiple facilities, we compute cell-level socially responsible ownership (*PRI IO*) as the simple average across establishments in that cell-date. The mean of *PRI IO* is 9%. Although NDVI ranges in principle from -1 to 1, we do not observe polar regions: in our sample the cell-level mean NDVI spans from -0.18 to 0.95, with an overall mean of 0.50 and a standard deviation of 0.20.

[Table 1 about here.]

2.3 Identification strategy

Our baseline analysis examines how socially responsible ownership relates to firms' environmental harm, measured via NDVI, in a global panel. Before turning to these results, Section 3. validates that NDVI responds to local industrial pollution in a large-N U.S. setting. Both analysis share a common panel framework; here we present the specification for the main relation of interest, the relation between the NDVI and PRI ownership:

$$NDVI_{i,t,y} = \beta_1\,\text{PRI IO}_{i,q-1,y} + \beta_2\,\text{IO}_{i,q-1,y} + \theta'\text{Weather}_{i,m-1,y} + \kappa'\text{X}_{i,y-1} + \gamma_{m\times y} + \delta_{i\times m} + \alpha_{z\times y} + \varepsilon_{i,t,y}, \quad (1)$$

where i indexes cells, t denotes 16-day periods, m the calendar month, q the calendar quarter, y the year, and z the agroclimatic zone. The outcome $NDVI_{i,t,y}$ tells vegetation health in cell i at time t, y. The regressor of interest, PRI $\text{IO}_{i,q-1,y}$, is the previous-quarter share of parent equity held by PRI signatories for the facility present in cell i (considering the average share when multiple facilities are present). We lag ownership by one quarter to ensure that changes in vegetation reflect prior shifts in ownership composition; this timing also aligns with the short adjustment window documented in our spill event study (Appendix E). We include overall institutional ownership, $\text{IO}_{i,q-1,y}$, to separate responsible ownership from broader institutional presence.

The specification conditions on high-dimensional fixed effects and local controls. Cell×calendar-month fixed effects ($\delta_{i\times m}$) correspond to a cell fixed effect interacted with 12 different dummy each representing one calendar month. These Cell×calendar-month fixed effects absorb local seasonality and time-invariant cell characteristics, such as local rainfall patterns, land cover, or facility and firm-level idiosyncrasies,[16] ensuring that β_1 renders the effect of changes in ownership, not differences in the types of firms owned. Year×month fixed effects ($\gamma_{m\times y}$) capture global shocks specific to a given year and month-of-the-year. Agroclimatic-zone×year fixed effects ($\alpha_{z\times y}$) allow heterogeneous shocks or climate trends across ecological zones. Weather controls include lagged monthly temperature and precipitation (levels and squares), $\text{Weather}_{i,m-1}$. The vector $\text{X}_{i,y-1}$ comprises lagged proxies for local economic activity and settlement (night-time lights, building counts, population). Standard errors are clustered at the cell level; the Online Appendix reports robustness to alternative error structures.[17]

[16] For the majority of cells hosting only one facility, this specification is entirely similar to looking at within-facility, and thus within-firms, changes in responsible ownership over time. For the minority of cells hosting more than one facility, the cell-month fixed effects partials out the average idiosyncracies of that group of facilities. We confirm that we obtain similar results when focusing on the sample of cells with only one plant per cell, a sample in which the cell-level fixed effects entirely equate facility-level fixed effects (*de facto* absorbing the firm fixed effect).

[17] We omit spatial HAC estimators (Conley, 1999; Hsiang et al., 2011) because they are computationally infeasible at our resolution. Appendix C also questions their relevance: repeated cross-sectional tests reject spatial autocorrelation for TRI in all dates but one and for PRI IO in a large share of dates. While NDVI exhibits spatial dependence, spatial HAC is unwarranted when only the outcome – rather than

Identification comes from within-cell changes in responsible ownership over time after conditioning on fixed effects and controls. A particularly important aspect is that, by holding constant all time-invariant firm characteristics, such as baseline environmental performance, sector, ownership history, or managerial preferences, we move beyond cross-sectional comparisons to focus on within-firm changes. Intuitively, we ask whether NDVI around facilities improves as responsible ownership rises, comparing cells that host facilities from different firms while holding fixed local seasonality, global month-year shocks, and zone-specific climate trends.

We later complement this design with two additional approaches. First, we estimate facility-level specifications with explicit firm fixed effects and time-varying firm controls.[18] Second, we exploit mergers in which PRI signatories acquire non-signatory asset managers, generating discrete increases in responsible ownership for portfolio firms.

3. NDVI Response to Pollution and Improvements

3.1 Case studies

The contribution of this paper hinges on the proposition that vegetation health, as measured by the NDVI, responds to changes in facilities' environmental harm. The sensitivity of NDVI to pollutants is well documented in environmental science (e.g., Amer et al., 2017; Clevers et al., 2004; Garty, 2001; Sridhar et al., 2007). NDVI can decline due to soil contamination (Dean et al., 2024); water pollution that alters nutrient uptake (Resende Vieira and Christofaro, 2024); and atmospheric pollutants that induce oxidative stress in plants (Lim et al., 2004).[19] The recent study of Li et al. (2023) also show symmetry: NDVI improves when pollution falls. Appendix A reviews this literature. While these studies provide valuable evidence in controlled settings, they typically cover limited geographies. We therefore provide below two large-N

both the outcome and the regressor – displays spatial correlation (Colella et al., 2019). As an additional check, we later vary errors clustering; results are unchanged.

[18]Our baseline results favor a cell-level panel because, given the skewness of facilities distribution, while a majority of cells host exactly one facility, the majority of facilities have close neighbors. In the later case, the environmental harm coming from one facility may affect the NDVI around all its closely neighboring facilities. On the other hand, a facility-level panel allows us to introduce explicitly both firm (parent-level) fixed effects and firm-level controls similar to those in Dyck et al. (2019), including size, leverage, profitability, and asset structure. The rest of the specification follows Equation 1.

[19]We should note that the relationship between NDVI and CO_2 is more ambiguous: some work finds adverse effects on vegetation health (Lim et al., 2004), while other evidence points the other way (Ainsworth and Long, 2005). Following the literature in using a "bundle" of toxic releases, we find that their relation to the NDVI is unaffected by by hyperlocal CO_2 emissions.

validations at a geographic scale relevant for our ultimate analysis.

3.2 NDVI reaction to U.S. firms' toxic releases (TRI)

In this section, we exploit U.S.-wide data to ask whether NDVI around facilities is negatively associated with facility-level toxic releases.

The EPA's Toxics Release Inventory (TRI) provides plant-level annual releases for more than 600 substances, distinguishing on-site and off-site releases and reporting precise facility coordinates. The TRI's nationwide coverage allows us to test the NDVI-pollution link across diverse agroclimatic zones. Two well-known challenges to using the TRI data are changes in the chemical list over time and reporting thresholds that introduce artificial entry/exit. We mitigate these by restricting to facilities that report consistently for at least nine consecutive years, reducing noise from threshold effects and arbitrary churn.[20] Furthermore, we focus on 2006-2020, which is our SRI sample period, and a period with a stable list of chemicals.

The resulting dataset covers 5,027 cells containing 7,696 reporting facilities in the U.S. 25% of the cell–year observation host two or more facilities reporting releases; for these, we aggregate plant-level releases to the cell–year by summation. We consider the measure of total releases across chemicals as provided by the EPA as a measure of industrial pollution (the most common approach in the literature, e.g. Andrikogiannopoulou et al., 2025; Currie et al., 2015; Gibson, 2019; Li et al., 2025; Naaraayanan et al., 2021; Xu and Kim, 2021). The large majority of reported releases take place on-site (mean 74%, median 100%, Appendix Table B-3).

We estimate the NDVI response to toxic releases using a modified version of Equation (1), introducing the regressor of interest total toxic releases, $\text{TotRelease}_{i,y}$, aggregated from plant-level TRI to the cell-year and assigned to all 16-day observations within year y. Accordingly, we omit the institutional ownership terms (PRI IO and IO). The fixed effects and local controls are unchanged:

$$NDVI_{i,t,y} = \beta\,\text{TotRelease}_{i,y} + \theta'\text{Weather}_{i,m-1,y} + \kappa'\text{X}_{i,y-1} + \gamma_{y\times m} + \delta_{i\times m} + \alpha_{z\times y} + \varepsilon_{i,t}.$$

[20] Facilities report only when chemical- and industry-specific thresholds are exceeded. Roughly 40% of the unrestricted sample meets the nine-year criterion. See https://www.epa.gov/toxics-release-inventory-tri-program/basics-tri-reporting.

This specification asks whether NDVI declines when total toxic releases rise in the same cell-year, relative to cells under the same seasonal and agroclimatic trends and global month–year shocks.

[Table 2 about here.]

Table 2 reports a precisely estimated negative association between total releases and NDVI in all specifications. Columns (1) and (2) compare annual and biweekly designs; we favor biweekly because cell×month fixed effects more flexibly absorb local seasonality. Column (3) tests symmetry by restricting to cells with monotonically declining releases ($\text{release}_y \leq \text{release}_{y-1}$), and finds similar magnitudes, suggesting that NDVI responses are symmetric to improvements and deteriorations. Column (4) restricts to single-facility cells and yields comparable effects. Finally, Column (5) allows zone-specific vegetation trends via agroclimatic-zone×year fixed effects, with stable estimates.

Columns (6)–(7) probe the importance of the intensity and proximity of the pollution. Using the EPA's Risk-Screening Environmental Indicators (RSEI),[21] Column (6) shows larger NDVI declines for releases with above-mean toxicity per unit mass. Column (7) splits releases into on-site and off-site: NDVI responds to on-site discharges, whereas off-site releases have no discernible effect–a placebo-style result consistent with local pollution exposure being the only one that affects vegetation health.[22]

We address several additional confounds in the Online Appendix D. We confirm results robustness to alternative grid definitions, ruling out spatial aggregation artifacts (Table D-5). Results are qualitatively unchanged when we lag emissions by 12 months; although some specifications lose precision, consistent with NDVI primarily capturing contemporaneous environmental harm (Table D-7) and in line with our toxic spill event study (next Section). We also find that the TRI-NDVI association is orthogonal to these facilities' CO_2 emissions (Appendix Table D-8).[23]

[21] The EPA's RSEI model adjusts reported releases by chemical toxicity, exposure pathways, and potential population exposure. We allow the relation between total releases and the NDVI to differ depending on the fact that cells' releases have an above-mean RSEI toxicity score (or a below-mean score). Coverage is limited (post-2013) and excludes some chemicals. We impute zeros for missing RSEI values to preserve comparability.

[22] Put differently, if NDVI reflects localized environmental harm from firms, it should respond to on-site releases occurring within the grid cell where vegetation is measured, but not to off-site releases that are transferred or managed elsewhere.

[23] Interestingly, the correlation between emissions and total releases is limited, at 0.006. When considering both variables together in the equation, we find a small positive association between the facilities'

Finally, Table D-6 demonstrates stability across alternative error structures. Taken together, these results confirm that NDVI reacts systematically to localized industrial pollution.

3.3 NDVI reaction to accidental toxic spills

As a complementary validation, we study vegetation responses to major toxic chemical spills in an event-study design using the U.S. Coast Guard's National Response Center data. These acute shocks allow us to trace short-run stress and recovery (see Appendix E for the full analysis). We document a sharp and statistically significant increase in the probability of observing abnormally low NDVI in the month of the incident (event time $t = 0$). The effect is spatially localized: the increase is largest in the immediate vicinity of the accident site and attenuates steadily with distance. Importantly, we also find a gradual recovery, with the probability of abnormal NDVI returning to its pre-incident baseline within roughly four months ($t \approx +4$).

Taken together, the tests in this and the previous subsections support the view that NDVI responds to industrial pollution. Two features are especially relevant for what follows. First, the response is symmetric: NDVI declines when pollution rises, and improves when pollution falls, including within a short time window after acute spill events. Second, the response is local: NDVI loads on on-site releases and is strongest in directly impacted cells, attenuating sharply with distance, with no discernible effect for off-site transfers.

4. The average effect of responsible ownership

4.1 Levels of PRI ownership

Table 3 reports the main estimates. Columns 1-5 use the full sample and show a consistent, positive, and precisely estimated association between lagged socially responsible (PRI) ownership and vegetation health (NDVI). Across specifications, the coefficient on lagged PRI ownership is stable in the range 0.004–0.005 and is significant at the 1% level. The relationship remains robust as we sequentially add controls for built environment, population, and night-time lights, and as we introduce increasingly demanding fixed effects (year×month and agroclimatic-zone×year). Despite the high correlation between total institutional ownership and PRI ownership in recent

emissions and the NDVI.

years, the effects are distinct: including or excluding total institutional ownership leaves the PRI coefficient essentially unchanged (Columns 1-2).

[Table 3 about here.]

To gauge economic significance, we benchmark the PRI-NDVI coefficient to the pollution-NDVI relationship in Table 2. There, a one–standard deviation increase in toxic releases (12.67 million pounds) is associated with a 0.005 decline in NDVI, implying that a 1.0 NDVI unit corresponds to roughly 2.534 billion pounds (1,267,000 tons) of toxic emissions. Applying this conversion, a 0.00005 NDVI increase from a 1 percentage point (pp) rise in PRI ownership translates into a reduction of about 63.35 tons of toxic releases. Such a reduction is equivalent to getting rid of the entire pollution of more than five facilities at the EPA's 25,000 lb reporting threshold[24]. These magnitudes indicate a substantive environmental effect of responsible ownership.

Columns 6–7 examine two potential concerns related to the study sample. First, facility clustering within cells could complicate identification if facilities owned by different parents face simultaneous ownership shocks. We confirm that restricting to single-facility cells (Column 6) yields indistinguishable coefficients. Second, global scope may matter if multinationals with non-OECD exposure adjust differently. Restricting to "global" firms (firms with at least one non-OECD facility; Column 7) again leaves the PRI coefficient essentially unchanged. International scope does not materially alter the relationship between responsible ownership and environmental conditions.

Another concern is that the positive effects of SRI may reflect a CO_2-fertilization mechanism: if SRI raised output, pollution, and emissions, higher local CO_2 could increase NDVI. The data do not support this view. First, in the U.S. validation, vegetation health responds to toxic releases independently of facilities' CO_2 emissions (Table D-8). Second, facility CO_2 and toxic releases are only weakly correlated when jointly observed (Pearson $r = 0.02$), making it unlikely they capture the same pollution variation. Third, our specifications control for local economic activity (night-time lights, population, built environment), and cell-specific ambient trends are absorbed by high-dimensional fixed effects. Overall, the NDVI improvements under greater SRI ownership are unlikely to be CO_2-driven greening and instead point to reductions in facilities' harmful releases.

[24]https://www.epa.gov/trinationalanalysis/tri-data-considerations

An alternative interpretation is "superficial greening", whereby firms plant vegetation to appear responsible without reducing pollution. While such landscaping may yield some benefits relative to bare surfaces, it is not the objective of responsible investing. Two considerations make it unlikely to drive our results. First, purely cosmetic actions are difficult to reconcile with the heterogeneity we document across contexts in Section 5.1. Second, to affect our estimates, greening would need to occur *within* the $0.1° \times 0.1°$ analysis cell (approximately 11×11 km) and at a scale large enough to substantially move cell-level NDVI: small ornamental plantings are too limited, whereas larger initiatives (e.g., sponsoring a city park) risk being outside the facility's cell. While some landscaping may occur, it seems unlikely to explain the global patterns we find.

Taken together, the evidence indicates that socially responsible ownership improves vegetation health. Additional sensitivity tests in the Online Appendix corroborate these findings. Perhaps most importantly, a facility-level specification with explicit firm fixed effects and time-varying firm controls delivers similar estimates (Table 6).[25] Results are also robust to alternative clustering choices to address spatial dependence (Table F-11). The robustness checks in Table F-12 further show that results hold when accounting for temporal dependence: adding NDVI lags, extending to twelve biweekly lags, and differencing at the quarterly frequency.[26] Finally, Appendix Table F-10 confirms the findings in a panel of either larger or smaller cells (from 0.5×0.5 degrees to 0.05×0.05 degrees).

4.2 M&A Shocks as Identification

[Table 4 about here.]

Finally, we exploit mergers in the asset-management industry to isolate plausibly exogenous variation in responsible ownership. This identification follows recent practice that uses M&A

[25]Implementing this design requires two modifications to model (1). First, we maintain the panel at the facility level rather than collapsing to the cell level. The key explanatory variable becomes the lagged PRI ownership of the facility's parent, while NDVI remains measured at the cell level. If multiple facilities of the same parent are located in the same cell, we retain a single parent–cell observation. Second, to still absorb location-specific seasonality and also include parent fixed effects, we residualize NDVI with respect to cell-month fixed effects and use the residuals as the dependent variable. Firm-level controls follow Dyck et al. (2019) and include log total assets, leverage, profitability, tangibility, and Tobin's Q.

[26]Dynamic OLS with lagged NDVI is valid in this long-T panel, since Nickell bias is negligible and GMM estimators such as Arellano–Bond are not well suited here: they assume short T, rely on moment conditions that in our data are rejected (AR(2) and Hansen tests), and in large T panels risk instrument proliferation that undermines identification.

events as plausibly exogenous ownership shocks, e.g., Evans et al. (2025) and Evans et al. (2020). Specifically, we study deals in which a PRI signatory acquires a non-signatory asset manager. Such transactions generate abrupt increases in ownership by an environmentally committed investor across the target's portfolio companies. Because the change in ownership is triggered by a corporate control event in asset management–rather than by firm-specific portfolio rebalancing–it is plausibly orthogonal to the investee firms' underlying environmental trajectories. This setting mitigates concerns that PRI investors may disproportionately select firms already improving their environmental performance.

Treated parents are those held by the target in the quarter preceding the announcement and that appear in our MNE sample. Treatment intensity is measured by the target's pre-announcement equity share in the parent (*PreDealShare*). We begin with all SDC Platinum M&A deals between 2008 and 2020 (516,170), restrict to acquire-target pairs linked to Compustat using Ewens et al. (2024) (5,572), and then to deals between asset managers (662). We hand-match acquirers to PRI signatories and retain deals where the acquirer joined PRI before the announcement, yielding 20. Among these, three have targets that match to FactSet and are themselves non-signatories.[27] Despite the small number of events, coverage is broad: pre-announcement, the three targets hold equity in 76, 271, and 434 multinationals (8,781; 28,589; and 40,880 facilities, respectively). A cell is treated if it contains at least one facility of a multinational held by the target in the pre-announcement quarter. For each merger, we draw an equal number of untreated cells at random to form a control group and construct a stacked event-time panel spanning ten quarters before and after each announcement.

Table 4 reports stacked difference-in-differences estimates. In the first part of the table, we interact post-event year indicators with the treated-cell dummy to recover average treatment effects on NDVI. In even-numbered columns, we replace the binary treatment with *PreDealShare* (set to zero for controls), scaling effects by pre-merger exposure. We find no systematic change in the year after the announcement, but a clear positive effect emerging in year +2, which amplifies when accounting for local economic controls (Columns 1 to 2). Treated cells exhibit an NDVI increase of up to 0.004 units both for the general sample and the sample of global firms (Columns 2 and 3). The *PreDealShare* specifications in the second half of the table show the

[27] Namely, GE Asset Management Inc acquired by State Street Corp; E*TRADE Financial Corp acquired by Morgan Stanley; Eaton Vance Corp acquired by Morgan Stanley.

same pattern: year +1 effects are positive but imprecise, while by year +2 the NDVI increase is economically large and precisely estimated (roughly 0.16 per unit of pre-merger equity share, Column 5). Taken together, the results are consistent with mergers inducing genuine changes in local environmental conditions through shifts in institutional ownership, rather than reflecting coincident trends or reverse causality.

In sum, in this section, we reach similar conclusions when employing two complementary identification strategies to evaluate the real effects of SRI. The first strategy, based on variation in PRI ownership levels, allows us to exploit the full MNE sample. However, while the inclusion of high-dimensional fixed effects arguably absorbs a large share of potential confounders and mitigates concerns related to selection, we acknowledge that this approach offers less stringent causal identification than the merger design. The second strategy, based on mergers in which a PRI signatory acquires a non-signatory asset manager, provides a cleaner source of exogenous variation in responsible ownership. Its main limitation lies in the small number of events, which is limitating to fully explore key mechanisms that are of interest in the next section. Keeping these constraints in mind, the consistency of results across both strategies with fundamentally different sources of identifying variation strongly reinforces our interpretation that responsible ownership has real, causal effects on local environmental quality. Building up on this insight, we now turn to examining where and when these effects unfold.

5. Where and How Does Socially Responsible Investing Work?

5.1 Geographic Asymmetries in Sustainable Investment Impact

[Table 5 about here.]

In this section, we examine whether the effect of socially responsible ownership on vegetation health varies with facility location. Specifically, we explore how socially responsible investing impact differs between OECD and non-OECD countries.[28] The typical OECD country is

[28]We fix OECD membership as of 2006, the start of our sample. That list includes: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States, Czech Republic, New Zealand, Republic of Korea.

richer and exhibits greater interest and investment in pollution monitoring and environmental oversight.

Multinationals could respond to responsible ownership in two opposite ways. On the one hand, stricter regulation and monitoring in OECD economies may induce firms to clean up where scrutiny is greatest, potentially displacing the environmental harms to weaker-enforcement jurisdictions (a logic of pollution export documented, e.g. by Tanaka et al., 2022, for battery recycling). On the other hand, if baseline pollution is higher in non-OECD regions, the scope for improvement might be larger there, yielding bigger gains outside the OECD.

To distinguish these channels, in Table 5, we interact PRI ownership with an indicator for non-OECD location. As in the baseline, socially responsible ownership is positively and significantly associated with NDVI. The coefficient on lagged PRI ownership ranges from 0.005 to 0.006 *per unit of ownership*, i.e., 0.00005–0.00006 per 1 pp. Using the calibration from Table 2 (1 NDVI unit $\approx$ 1,267,000 tons of toxic releases), a 1 pp increase in PRI ownership in OECD countries implies a reduction of roughly 63–76 tons of toxic releases. This reduction is equivalent to the combined releases of approximately 5–6 facilities operating just above the EPA's annual activity threshold for TRI reporting.

By contrast, the interaction of responsible ownership with the non-OECD indicator is negative. The implied effect in non-OECD countries is -0.00009 to -0.00023 NDVI per 1 percentage point increase in socially responsible investing, corresponding to an increase of approximately 114–291 tons of toxic releases when using the calibration from Table 2. This magnitude is equivalent to the annual releases of roughly 9–23 facilities operating at the EPA's TRI activity threshold. Back-of-the-envelope aggregation suggests that for the average firm (about 58 facilities, including 6 outside the OECD) and the median firm (about 18 facilities, typically 1–2 outside the OECD), the net effect of a 1 pp ownership increase remains positive overall, with a total reduction on the order of 90–290 tons per year. The geographical distribution of these gains is, however, highly uneven.

As a robustness check, we replace the OECD split with a continuous measure of institutional quality using the World Bank's Regulatory Quality Index from the Worldwide Governance Indicators (WGI).[29] This index captures perceptions of the government's ability to formulate

[29] Worldwide Governance Indicators, 2024 Update, World Bank (www.govindicators.org), accessed

and implement sound policies and regulations that support private sector development. We match country-year index scores to facilities and estimate heterogeneous effects across quintiles of regulatory quality. Appendix Table F-13 shows that PRI ownership is positively associated with NDVI only in the upper two quintiles of regulatory quality; in contrast, the interaction is negative and statistically significant in the lowest quintile. These results hold in the full sample, in the single-facility cell subsample, and among multinationals with at least one non-OECD facility. Furthermore, in Table 6, we confirm that the results hold when introducing parent-company fixed effects and time-varying firm-level controls in a facility-level panel.

These heterogeneous effects align with the classic view that ownership influences corporate behavior within the constraints imposed by legal and institutional environments (Shleifer and Vishny, 1997; La Porta et al., 1998). In jurisdictions with weaker regulatory enforcement and investor protection, socially responsible investors appear less able to constrain pollution, resulting in displacement toward non-OECD regions where governance pressures are less binding.

[Table 6 about here.]

Overall, these findings highlight the importance of the institutional and regulatory contexts for the effectiveness of sustainable finance. PRI signatories appear able to improve environmental performance where monitoring and enforcement are strong, but their influence weakens in low-governance environments, where risks of pollution displacement persist. These results point to a need for cross-border accountability mechanisms to ensure that ESG-driven improvements are not geographically uneven or regressive in their environmental consequences.

5.2 Engagement Intensity and the Power of Stewardship

[Table 7 about here.]

A common concern with using PRI signatory status as a proxy for responsible ownership is that it may be a weak signal of actual stewardship, given monitoring frictions and potential for greenwashing (Gibson Brandon et al., 2022; Kim and Yoon, 2022). We therefore test whether the PRI–NDVI relationship varies with the *intensity* of investors' self-reported engagement.

We exploit PRI transparency documentation to construct a novel, simple, and replicable mea-

on October 2, 2025.

sure of investors' engagement. PRI Transparency Reports include a standardized module (SG09) in which signatories classify their engagement intensity as *Basic*, *Moderate*, or *Advanced*. Reports are available annually from 2014 through 2020, providing a consistent scale over that period.[30] Panel A of Table 7 shows that 60% of signatories report *Basic* engagement, 23% report *Moderate*, and 16% report *Advanced*. Panel B documents high persistence: the probability of remaining in the same category year-over-year is 89% for Basic, 79% for Moderate, and 91% for Advanced; among Moderates, upgrades to Advanced (13%) outnumber downgrades to Basic (8%).

[Table 8 about here.]

Because these labels are self-reported, we also analyze the optional open-ended justification text that signatories use to provide more information on their selection. Appendix Figure G-8 summarizes reported themes by engagement level and Appendix G describes the methodology to extract and classify themes. *Advanced* signatories are far more likely to reference collaborative stewardship—and especially leadership roles—than others (about 80% mention leadership), consistent with agenda-setting and coalition-building. *Moderate* signatories emphasize collaboration but less frequently cite leadership. *Basic* signatories provide shorter, more heterogeneous responses; they rarely mention leadership and are roughly thirteen times more likely than *Advanced* signatories to simply note signatory status. Overall, stronger self-reported engagement is characterized by participation and leadership in collaborative initiatives, consistent with the "Leader" concept in Ceccarelli et al. (2024), who show that only a small subset of institutions drives improvements in firms' ESG scores.

For each parent-quarter, we construct three ownership shares–*Basic PRI IO*, *Moderate PRI IO*, and *Advanced PRI IO*–by summing equity held by signatories in each tier. For years prior to 2014, we backfill engagement levels to 2006 or to the year in which the institution first became a PRI signatory, whichever occurs later, leveraging the high persistence documented in Panel B.

Table 8 presents the results. Column (1) reproduces the baseline PRI effect on the subsample with engagement information; a 1 pp increase in overall PRI ownership is associated with an

[30] After 2020, PRI revised its questionnaire and removed the SG09 engagement-intensity question; earlier reports were publicly accessible via the UN PRI Reporting and Assessment portal.

NDVI increase of about 0.00004–0.00005, consistent with Table 3 results. Columns (2)–(4) replace overall PRI ownership with the three tier-specific shares. All three tiers load positively, with a clear gradient in magnitude: effects rise from *Basic* to *Moderate*/*Advanced*. In Column (5), we include the three shares jointly. The *Moderate* and *Advanced* coefficients remain positive and statistically significant, whereas the *Basic* coefficient is small and not significant. Thus, the PRI-NDVI relationship is not uniform across signatories: measurable environmental gains are concentrated among institutions that undertake at least structured, moderate-level stewardship, with little evidence that minimal "box-ticking" engagement translates into on-the-ground improvements. These results are consistent with a mechanism in which active stewardship drives real environmental changes at the facility level, consistent with stewardship-oriented investors fostering green capital expenditures by firms (Wiedemann, 2025).

5.3 Engagement does not prevent the displacement of environmental harm

[Figure 2 about here.]

Combining the approaches from the previous sections, Figure 2 plots coefficients from regressions of cell-level NDVI on lagged PRI ownership interacted with investor engagement intensity (Basic/Moderate/Advanced) and an indicator for facilities located outside the OECD. The figure reveals sharp asymmetries. Within the OECD, higher PRI ownership is associated with improvements in vegetation health, with effects that strengthen with engagement intensity. Outside the OECD, PRI ownership is consistently associated with lower NDVI–even for highly engaged investors. This set of results extends the heterogeneity in Table 5: engagement intensity alone does not deliver improvements when country-level enforcement is weak.

This pattern aligns with theories in which investor pressure is effective only under credible enforcement and strong monitoring. In the presence of regulatory arbitrage and strategic compliance, we would expect displacement to weaker jurisdictions when oversight is unreliable (Baron, 2001); and shareholder monitoring frameworks stress credible oversight as a precondition for real effects (Admati and Pfleiderer, 2009; Edmans, 2009). Consistent with these predictions, PRI ownership –especially by more engaged investors– coincides with better environmental outcomes where governance is strong, but with declines in vegetation health outside the OECD, suggestive of significant displacement. To our knowledge, this is the first evidence that the real effects of ESG engagement systematically diverge with countries' institutional quality, improving under strong governance and reversing under limited enforcement.

6. Conclusion

This paper studies the real environmental consequences of sustainable investing by asking whether–and where–socially responsible institutional ownership translates into measurable improvements in local ecological conditions around industrial facilities worldwide.

Leveraging high-frequency satellite data on vegetation health (NDVI), we provide a spatially and temporally detailed measure of environmental quality that is independent of firms' self-reports and available globally. We first validate the NDVI as an indicator of pollution-related environmental degradation. In U.S.-wide data, vegetation health declines when toxic releases rise and improves when releases fall, with stronger responses to more hazardous and on-site discharges and placebo-like nulls for off-site transfers. We also find that the NDVI exhibits short-run deterioration and recovery around accidental toxic spills.

Building on this foundation, we examine how social responsible ownership relates to changes in local environmental quality. Our results show a positive and statistically significant association: higher levels of sustainable institutional ownership are associated with improved vegetation health, suggesting that social responsible capital may help reduce environmental harm.

Our identification strategy supports a causal interpretation. Our main specification relies on high-dimensional fixed effects and rich local controls to isolate within-cell and within-firm variation over time. As a complementary approach, we exploit mergers in which a PRI signatory acquires a non-signatory asset manager, creating an exogenous shock to responsible ownership. Although such events are relatively rare, they lead to measurable increases in NDVI around treated facilities two years after the merger. The positive effects are stronger where pre-merger ownership stakes were larger.

However, these environmental gains are highly uneven. Geographically, they are concentrated in OECD countries, while effects in non-OECD regions are negative, consistent with pollution displacement when enforcement is limited. We also find that investor stewardship matters. Building a novel measure of engagement based on PRI transparency reports, we find a clear gradient: improvements are concentrated among institutions reporting structured, moderate-to-advanced-level engagement. Yet this effect is again highly asymmetric across geographies. Outside the OECD, even high-intensity engagement does not prevent pollution displacement.

Two broader implications follow. First, the effectiveness of sustainable finance is jointly determined by investor stewardship and countries' institutions. Active ownership complements strong enforcement; without enforcement, pressure risks shifting part of the environmental harm rather than reducing it. Second, NDVI offers a scalable complement to traditional disclosures, enabling monitoring of localized environmental outcomes across borders.

Sustainable investing can deliver tangible environmental benefits, especially when paired with meaningful engagement from institutional investors. Ensuring that these gains are not offset by cross-border displacement would require harmonized, facility-level disclosure, stronger international enforcement, and accountability mechanisms that travel with global production networks. Aligning private stewardship with public oversight is essential for durable and equitable environmental progress.

References

Admati, Anat R, and Paul Pfleiderer, 2009, The "wall street walk" and shareholder activism: Exit as a form of voice, *Review of Financial Studies* 22, 2645–2685.

Ainsworth, Elizabeth A., and Stephen P. Long, 2005, What have we learned from 15 years of free-air co_2 enrichment (face)? a meta-analytic review of the responses of photosynthesis, canopy properties and plant production to rising co_2, *New Phytologist* 165, 351–371.

Alix-Garcia, Jennifer M, Katharine RE Sims, and Patricia Yañez-Pagans, 2015, Only one tree from each seed? environmental effectiveness and poverty alleviation in mexico's payments for ecosystem services program, *American Economic Journal: Economic Policy* 7, 1–40.

Amer, Mohamed M., Andrew Tyler, Tarek Fouda, Paul Hunter, Ashraf Elmetwalli, Chris Wilson, and Mario Vallejo-Marin, 2017, Spectral characteristics for estimation heavy metals accumulation in wheat plants and grain, *J. Product. & Dev.* 22, 409–428.

Andrikogiannopoulou, Angie, Alexia Ventouri, and Scott E Yonker, 2025, Not in my backyard: intrinsic motivation and corporate pollution abatement, *Review of Finance* 29, 1067–1104.

Asher, Sam, and Paul Novosad, 2020, Rural roads and local economic development, *American economic review* 110, 797–823.

Azar, José, Miguel Duro, Igor Kadach, and Gaizka Ormazabal, 2021, The big three and corporate carbon emissions around the world, *Journal of Financial Economics* 142, 674–696.

Baron, David P, 2001, Private politics, corporate social responsibility, and integrated strategy, *Journal of Economics & Management Strategy* 10, 7–45.

Bartram, Söhnke M., Kewei Hou, and Sehoon Kim, 2022, Real effects of climate policy: Financial constraints and spillovers, *Journal of Financial Economics* 143, 668–696.

Ben-David, Itzhak, Yeejin Jang, Stefanie Kleimeier, and Michael Viehs, 2021, Exporting pollution: where do multinational firms emit CO2?, *Economic Policy* 36, 377–437.

Berg, Tobias, Lin Ma, and Daniel Streitz, 2023, Out of sight, out of mind: Divestments and the global reallocation of pollutive assets, Technical Report 436, SAFE Working Paper Series.

Berk, Jonathan B., and Jules H. van Binsbergen, 2021, The Impact of Impact Investing, *Stanford University Graduate School of Business Research Paper, Law & Economics Center at George Mason University Scalia Law School Research Paper Series No. 22-008* .

Broccardo, Eleonora, Oliver Hart, and Luigi Zingales, 2022, Exit versus voice, *Journal of Political Economy* 130, 3101–3145.

Ceccarelli, Marco, Simon Glossner, Mikael Homanen, and Daniel Schmidt, 2024, Which institutional investors drive corporate sustainability?, Working paper, SSRN.

Clevers, J. G. P. W., L. Kooistra, and E. A. L. Salas, 2004, Study of heavy metal contamination in river floodplains using the red-edge position in spectroscopic data, *Int. J. Remote Sensing* 25, 1–13.

Colella, Fabrizio, Rafael Lalive, Seyhun Orcan Sakalli, and Mathias Thoenig, 2019, Inference with arbitrary clustering .

Conley, Timothy G., 1999, Gmm estimation with cross sectional dependence, *Journal of Econometrics* 92, 1–45.

Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker, 2015, Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings, *American Economic Review* 105, 678–709.

Dai, Rui, Rui Duan, Hao Liang, and Lilian Ng, 2021, Outsourcing climate change, *European Corporate Governance Institute – Finance Working Paper No. 723/202* .

De Angelis, Tiziano, Peter Tankov, and Olivier David Zerbib, 2023, Climate impact investing, *Management Science* 69, 7669–7692.

Dean, John R., Shara Ahmed, William Cheung, Ibrahim Salaudeen, Matthew Reynolds, Samantha L. Bowerbank, Catherine E. Nicholson, and Justin J. Perry, 2024, Use of remote sensing to assess vegetative stress as a proxy for soil contamination, *Environ. Sci.: Processes Impacts* 26, 161–176.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken, 2014, What do we learn from the weather? the new climate-economy literature, *Journal of Economic Literature* 52, 740–98.

Didan, K, 2015, Mod13c2 modis/terra vegetation indices monthly l3 global 0.05deg cmg v006 [data set], NASA EOSDIS Land Processes DAAC.

Dimson, Elroy, Oğuzhan Karakaş, and Xi Li, 2025, Coordinated engagements, Working paper.

Dixit, Avinash, 1989, Entry and exit decisions under uncertainty, *Journal of Political Economy* 97, 620–638.

Donaldson, Dave, and Adam Storeygard, 2016, The view from above: Applications of satellite data in economics, *Journal of Economic Perspectives* 30, 171–198.

Duchin, Ran, Pengjie Gao, and Huacheng Xu, 2024, Sustainability or greenwashing: Evidence from the asset market for industrial pollution, *Journal of Finance* 79, —.

Dyck, Alexander, Karl V Lins, Lukas Roth, and Hannes F Wagner, 2019, Do institutional investors drive corporate social responsibility? international evidence, *Journal of financial economics* 131, 693–714.

Edmans, Alex, 2009, Blockholder trading, market efficiency, and managerial myopia, *Journal of Finance* 64, 2481–2513.

Evans, Richard B., Melissa Porras Prado, A. Emanuele Rizzo, and Rafael Zambrana, 2025, Identity, diversity, and team performance: Evidence from u.s. mutual funds, *Management Science* 71, 3026–3051.

Evans, Richard Burtis, Melissa Porras Prado, and Rafael Zambrana, 2020, Competition and cooperation in mutual fund families, *Journal of Financial Economics* 136, 168–188.

Ewens, Michael, Ryan H. Peters, and Shan Wang, 2024, Measuring intangible capital with market prices, *Management Science* Mapping SDC to Compustat, 1996–2023 available at https://michaelewens.com/data-and-code/.

Ferreira, Miguel A, and Pedro Matos, 2008, The colors of investors' money: The role of institutional investors around the world, *Journal of financial economics* 88, 499–533.

Garel, Alexandre, Arthur Romec, Zacharias Sautner, and Alexander F. Wagner, 2024, Do investors care about biodiversity?, *Review of Finance* Forthcoming.

Garty, Jacob, 2001, Biomonitoring atmospheric heavy metals with lichens: Theory and application, *Critical Reviews in Plant Sciences* 20, 309–371.

Gibson, Matthew, 2019, Regulation-induced pollution substitution, *Review of Economics and Statistics* 101, 827–840.

Gibson Brandon, Rajna, Simon Glossner, Philipp Krueger, Pedro Matos, and Tom Steffen, 2022, Do responsible investors invest responsibly?, *Review of Finance* 26, 1389–1432.

Giglio, Stefano, Theresa Kuchler, Johannes Stroebel, and Xuran Zeng, 2023, Biodiversity risk, Available at NBER.

Girard, Victoire, Teresa Molina-Millán, and Guillaume Vic, 2025, Artisanal mining in africa. green for gold?, *The Economic Journal* ueaf058.

Harris, Ian, Timothy J Osborn, Phil Jones, and David Lister, 2020, Version 4 of the cru ts monthly high-resolution gridded multivariate climate dataset, *Scientific data* 7, 1–18.

Hartzmark, Samuel M., and Kelly Shue, 2022, Counterproductive sustainable investing: The impact elasticity of brown and green firms Available at SSRN: https://ssrn.com/abstract=4359282 or http://dx.doi.org/10.2139/ssrn.4359282.

Heath, Davidson, Daniele Macciocchi, Roni Michaely, and Matthew C. Ringgenberg, 2023, Does Socially Responsible Investing Change Firm Behavior?*, *Review of Finance* 27, 2057–2083.

Heinkel, Robert, Alan Kraus, and Josef Zechner, 2001, The effect of green investment on corporate behavior, *Journal of financial and quantitative analysis* 36, 431–449.

Hsiang, Solomon M., Kyle C. Meng, and Mark A. Cane, 2011, Civil conflicts are associated with the global climate, *Nature* 476, 438–441.

Kahn, Matthew E, John Matsusaka, and Chong Shu, 2023, Divestment and engagement: The effect of green investors on corporate carbon emissions, Working Paper 31791, National Bureau of Economic Research.

Kim, Soohun, and Aaron Yoon, 2023, Analyzing active fund managers' commitment to esg: Evidence from the united nations principles for responsible investment, *Management science* 69, 741–758.

Kim, Yongtae, and Ahreum Yoon, 2022, Analyzing active fund managers' commitment to esg: Evidence from the united nations principles for responsible investment, *Management Science* 68, 8139–8159.

Krueger, Philipp, Zacharias Sautner, and Laura T Starks, 2020, The importance of climate risks for institutional investors, *The Review of financial studies* 33, 1067–1111.

Kundu, Santanu, and Stefan Ruenzi, 2024, Exporting carbon emissions? evidence from space, Working paper, University of Mannheim.

La Porta, Rafael, Florencio Lopez-de Silanes, Andrei Shleifer, and Robert W. Vishny, 1998, Law and finance, *Journal of Political Economy* 106, 1113–1155.

Levinson, Arik, 2009, Technology, international trade, and pollution from us manufacturing, *The American Economic Review* 99, 2177–2192.

Li, C., Z. Deng, Z. Wang, et al., 2023, Responses to the COVID-19 pandemic have impeded progress towards the sustainable development goals, *Commun Earth Environ* 4, 252.

Li, Wei, Qiping Xu, and Qifei Zhu, 2025, Ceo hometown preference in corporate environmental policies, *Management Science* .

Li, Xuecao, Yuyu Zhou, Min Zhao, and Xia Zhao, 2020, A harmonized global nighttime light dataset 1992–2018, *Scientific Data* 7, 168.

Lim, Chul, Menas Kafatos, and Patrick Megonigal, 2004, Correlation between atmospheric co2 concentration and vegetation greenness in north america: Co2 fertilization effect, *Climate Research* 28, 11–22.

Lowry, Michelle, Pingle Wang, and Kelsey D Wei, 2025, Are all esg funds created equal? only some funds are committed, *The Review of Financial Studies* hhaf084.

Martinez, Luis R, 2022, How much should we trust the dictator's gdp growth estimates?, *Journal of Political Economy* 130, 2731–2769.

Naaraayanan, S Lakshmi, Kunal Sachdeva, and Varun Sharma, 2021, The real effects of environmental activist investing, *European Corporate Governance Institute – Finance Working Paper No. 743/2021* .

Noack, Frederik, Dominic Rohner, and Tommaso Sonno, 2025, The environmental impact of multinational firms .

Oehmke, Martin, and Marcus M. Opp, 2024, A theory of socially responsible investment, *Review of Economic Studies* Forthcoming.

Resende Vieira, Fabianna, and Cristiano Christofaro, 2024, Contributions of the vegetation index (ndvi) in water quality prediction models in a semi-arid tropical watershed, *Journal of Arid Environments* 220, 105122.

Shleifer, Andrei, and Robert W. Vishny, 1986, Large shareholders and corporate control, *Journal of Political Economy* 94, 461–488.

Shleifer, Andrei, and Robert W. Vishny, 1997, A survey of corporate governance, *The Journal of Finance* 52, 737–783.

Sridhar, M., F. Han, S. Diehl, D. Monts, and Y. Su, 2007, Effects of Zn and Cd accumulation on structural and physiological characteristics of barley plants, *Brazilian Journal of Plant Physiology* 19.

Stroebel, Johannes, and Jeffrey Wurgler, 2021, What do you think about climate finance?, *Journal of Financial Economics* 142, 487–498.

Tanaka, Shinsuke, Kensuke Teshima, and Eric Verhoogen, 2022, North-south displacement effects of environmental regulation: The case of battery recycling, *American Economic Review: Insights* 4, 271–88.

UN PRI Association, 2024, Principles for responsible investment, Accessed May 2025.

Vashold, Lukas, Gustav Pirich, Maximilian Heinze, and Nikolas Kuschnig, 2025, Downstream impacts of mines on agriculture in africa, *Journal of Development Economics* 103671.

Wiedemann, Moritz, 2025, Green stewards: Responsible institutional investors foster green capex, Working paper.

Xu, Qiping, and Taehyun Kim, 2021, Financial Constraints and Corporate Environmental Policies, *The Review of Financial Studies* 35, 576–635.

Yang, Shuwang, Chao Wang, Hao Zhang, Tingshuai Lu, and Yang Yi, 2022, Environmental regulation, firms' bargaining power, and firms' total factor productivity: evidence from china, *Environmental Science and Pollution Research* 29, 9341–9353.

Zhang, Yichi, Xiaohui Jiang, Yuxin Lei, and Siqi Gao, 2022, The contributions of natural and anthropogenic factors to ndvi variations on the loess plateau in china during 2000–2020, *Ecological Indicators* 143, 109342.

Zou, Eric Yongchen, 2021, Unwatched pollution: The effect of intermittent monitoring on air quality, *American Economic Review* 111, 2101–26.

Table 1: NDVI and the multinational facilities network – summary statistics. Descriptive statistics on international establishments of public U.S. multinationals from Dun & Bradstreet (D&B) WorldBase. Our sample consists of industrial multinationals with SIC codes 01 to 39, representing Agriculture, Forestry and Fishing (01–09), Mining (10–14), Construction (15–17), and Manufacturing (20–39). Establishments are mapped to 0.1° latitude–longitude grid cells, which serve as the unit of observation in the analysis. Variable definitions and data sources are provided in Appendix Table B-2.

	N	Mean	Std	Min	p10	p25	p50	p75	p90	Max
A. MNEs facilities network										
Nr Facilities	52,806									
(outside OECD)	4,353									
Nr Parents	911									
(with facilities outside OECD)	493									
Facilities per parent	911	57.96	115.22	1.00	3.00	6.00	18.00	58.00	140.00	982.00
B. Cell-level panel										
Nr Cells	13,651									
Nr DB Facilities in cell	4,756,407	3.74	8.86	1.00	1.00	1.00	1.00	3.00	8.00	485.00
Average NDVI	4,756,407	0.50	0.20	-0.18	0.23	0.38	0.52	0.66	0.75	0.95
Average SRI ownership	4,756,407	0.09	0.08	0.00	0.01	0.02	0.06	0.16	0.21	0.53
Average Institutional ownership	4,756,407	0.79	0.16	0.00	0.59	0.72	0.81	0.89	0.97	1.00

Table 2: NDVI reaction to toxic releases. Results from OLS estimations. The dependent variable is the Normalized Difference Vegetation Index (NDVI), the explanatory variables come from the Toxic Release Inventory (TRI) database. All specifications include weather controls (average temperature and its square, total precipitation and its square) and economic controls (night-time lights, buildings in the cell, and population). The unit of observation is a 0.1° × 0.1° cell. Appendix Table D-4 reports the full specification. Column (6) incorporates EPA's Risk-Screening Environmental Indicators (RSEI) model. This allows us to test whether vegetation responds more strongly to hazardous releases. Variable definitions and data sources are provided in Appendix Table B-2. * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cell level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. var.				—— NDVI ——			
Sample	— Full —		TRI down	One plant		— Full —	
Tot. releases	-0.005***	-0.001**	-0.006*	-0.002**	-0.003**		
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)		
Tot. releases X RSEI above mean toxicity						-0.004***	
						(0.001)	
Tot. releases X RSEI below mean toxicity						-0.002	
						(0.001)	
Tot. on-site releases							-0.003**
							(0.002)
Tot. off-site releases							0.001
							(0.001)
Cell FE	Yes	No	No	No	No	No	No
Cell X month FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No	No	No
Year X month FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year X agroclimatic FE	No	No	No	No	Yes	Yes	Yes
Frequency	Yearly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly
Observations	98029	2255922	1692631	1890168	2248494	2248494	2248494

Table 3: NDVI and PRI ownership. Results from OLS estimations of model (1). The unit of observation is a $0.1° \times 0.1°$ cell. The dependent variable is the Normalized Difference Vegetation Index (NDVI). The main explanatory variable is *PRI IO*, which measures socially responsible ownership of establishments in a cell in the previous quarter. Global firms are those with at least one facility outside the OECD. All columns include weather controls. Variable definitions and data sources are provided in Appendix Table B-2. * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cell level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable			NDVI				
Split:		Full sample				One plant	Global firm
IO	0.001	-0.000	0.000	-0.001	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
PRI IO		0.004***	0.004***	0.005***	0.004***	0.004**	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Builts			-0.006***	-0.002*	-0.001	0.000	-0.001
			(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Population			-0.006	-0.125***	-0.070**	-0.252***	-0.070**
			(0.013)	(0.039)	(0.034)	(0.053)	(0.034)
Lights				-0.725***	-0.450***	-0.450***	-0.457***
				(0.020)	(0.018)	(0.025)	(0.019)
Cell-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Agroclimat FE	No	No	No	No	Yes	Yes	Yes
Observations	4445313	4445313	4445313	3782638	3774182	1868951	3394504

Table 4: NDVI and mergers and acquisitions. Stacked difference-in-differences estimates around three mergers where a PRI signatory acquired a non-signatory asset manager. *Treated cells* contain at least one facility of a multinational held by the target in the pre-announcement quarter; control cells are randomly sampled in equal number. *PreDealShare* The event-time panel spans ten quarters before and after each announcement. The dependent variable is cell-level NDVI. All specifications include cell–month–cohort, event-time–cohort fixed effects, and weather controls. Variable definitions are in Appendix Table B-2. * significant at 10%; ** at 5%; *** at 1%. Standard errors clustered at the cell-cohort level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable			NDVI			
Sample:	— Full sample —		Global firm	— Full sample —		Global firm
year +1 × Treated=1	0.001*	0.000	0.000			
	(0.000)	(0.000)	(0.000)			
year +2 × Treated=1	0.005***	0.004***	0.004***			
	(0.001)	(0.001)	(0.001)			
year +1 × Portfolio Weight				0.000	0.000	0.000
				(0.002)	(0.002)	(0.002)
year +2 × Portfolio Weight				0.341***	0.277***	0.277***
				(0.079)	(0.067)	(0.067)
Population		-0.000**	-0.000**		-0.000**	-0.000**
		(0.000)	(0.000)		(0.000)	(0.000)
Builts		-0.000***	-0.000***		-0.000***	-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)
Lights		-0.001***	-0.001***		-0.001***	-0.001***
		(0.000)	(0.000)		(0.000)	(0.000)
CellMonth-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
ET-Cohort FE	No	No	Yes	No	No	Yes
Observations	2,302,040	2,302,040	2,302,040	2,302,040	2,302,040	2,302,040

Table 5: NDVI and PRI ownership – inside versus outside the OECD. Results from OLS estimations. The unit of observation is a 0.1° × 0.1° cell. The dependent variable is the Normalized Difference Vegetation Index (NDVI). The main explanatory variable is *PRI IO*, which measures average PRI ownership of establishments in a cell in the previous quarter. *Non-OECD* equals one for cells outside the OECD. All columns include weather controls. Variable definitions and data sources are provided in Appendix Table B-2. * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cell level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable			NDVI			
Split:	Full sample				One plant	Global firm
PRI IO	0.005***	0.005***	0.006***	0.005***	0.005***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
outsideOECD × PRI IO	-0.013***	-0.009***	-0.023***	-0.022***	-0.018***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
IO	0.000	0.000	-0.001	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Builts		-0.005***	-0.001	-0.001	0.001	-0.001
		(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Population		0.006	-0.076**	-0.038	-0.209***	-0.038
		(0.013)	(0.036)	(0.034)	(0.060)	(0.034)
Lights			-0.713***	-0.439***	-0.440***	-0.444***
			(0.020)	(0.018)	(0.025)	(0.019)
Cell-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Agroclimat FE	No	No	No	Yes	Yes	Yes
Observations	4445313	4445313	3782638	3774182	1868951	3394504

Table 6: NDVI and PRI ownership – plant-level analysis with parent fixed effects. Results from OLS estimations. The unit of observation is the facility. The dependent variable is the residualized Normalized Difference Vegetation Index (NDVI), obtained from a regression of NDVI on cell-month fixed effects, measured in the 0.1° × 0.1° cell containing the facility. The main explanatory variable is *PRI IO*, which represents the lagged PRI ownership of the facility's parent company. *Non-OECD* equals one for facilities outside the OECD. Out of a total number of 52,806 facilities, 4,353 are outside the OECD. All columns include weather controls. Variable definitions and data sources are provided in Appendix Table B-2. * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cell level and reported in parentheses.

	(1)	(2)	(3)	(4)
Dep. Variable	NDVI resid			
PRI IO	0.002***	0.003***	0.003***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
outsideOECD			0.005***	0.004***
			(0.001)	(0.001)
outsideOECD × PRI IO			-0.033***	-0.028***
			(0.003)	(0.003)
IO	-0.001**	-0.000	-0.001**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Log Assets	-0.000*	-0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Tangibility	-0.003***	-0.001*	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Leverage	-0.001	-0.000	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Profitability	0.001**	0.000	0.001**	0.000
	(0.001)	(0.000)	(0.001)	(0.000)
Tobin's Q	-0.000	-0.000**	-0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Year-month FE	Yes	Yes	Yes	Yes
Parent FE	Yes	Yes	Yes	Yes
Year-Agroclimat FE	No	Yes	No	Yes
Observations	10775576	10752842	10775576	10752842

Table 7: NDVI and signatories' self-reported involvement with PRI. Summary statistics of PRI signatories' reported level of involvement, as disclosed in module SG09 of the PRI's Public Transparency Reports (see Appendix Figure G-7 for an example of the form). Panel A presents the annual distribution of signatories across the three engagement categories (Basic, Moderate, and Advanced) over the 2014–2020 period. Panel B reports the row-normalized transition matrix of engagement roles, showing the year-over-year probabilities that a signatory remains in, or moves between, levels.

Panel A: Share of signatories by involvement level

Obs (signatory-year)	Basic (%)	Moderate (%)	Advanced (%)
6721	60.36	23.51	16.13

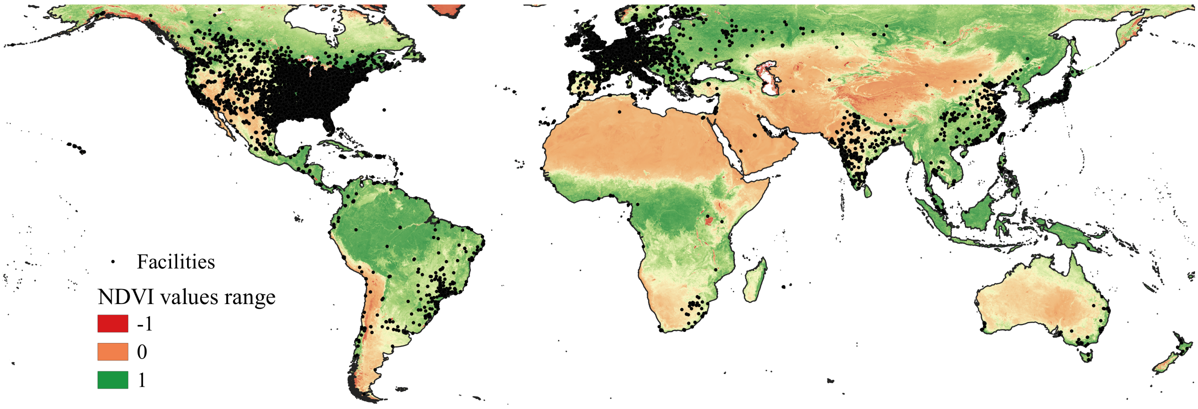
Panel B: Transition matrix

	Basic (t+1)	Moderate (t+1)	Advanced (t+1)
Basic (t)	0.89	0.09	0.02
Moderate (t)	0.08	0.79	0.13
Advanced (t)	0.02	0.07	0.91

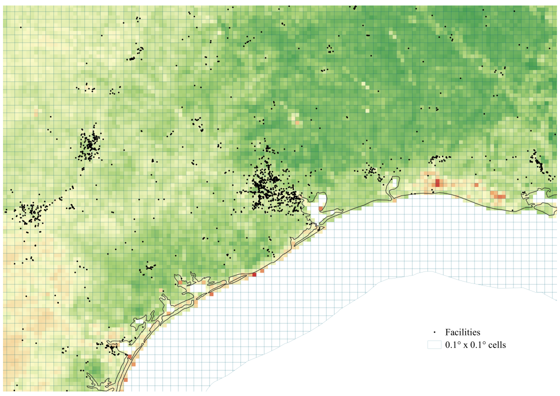
Table 8: NDVI and PRI ownership – by engagement intensity. Results from OLS estimations extending equation (1), disaggregating PRI ownership by engagement intensity. The unit of observation is a 0.1° × 0.1° cell. The dependent variable is the Normalized Difference Vegetation Index (NDVI), with ownership variables lagged by one quarter. All regressions include weather controls. Variable definitions and data sources are provided in Appendix Table B-2. * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cell level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Dep. Variable			NDVI		
PRI IO	0.004***				
	(0.001)				
Basic PRI IO		0.004*			0.003
		(0.002)			(0.002)
Moderate PRI IO			0.006**		0.006**
			(0.003)		(0.003)
Advanced PRI IO				0.006*	0.006*
				(0.003)	(0.003)
IO	-0.000	0.000	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Builts	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Population	-0.070**	-0.070**	-0.071**	-0.071**	-0.070**
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Lights	-0.450***	-0.451***	-0.450***	-0.450***	-0.450***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Cell-month FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
Year-Agroclimat FE	Yes	Yes	Yes	Yes	Yes
Observations	3774182	3774182	3774182	3774182	3774182

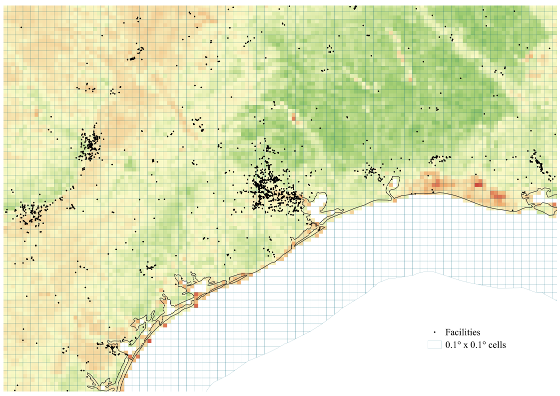
Figure 1: NDVI and production plants owned by U.S. multinationals. Panel (a) shows the international establishments of public U.S. multinationals in SIC codes 01-39, obtained from D&B WorldBase overlayed with the gradient of NDVI value in June 2006. Panel (b) zooms on the surrounding of Houston and adds the grid of cells of 0.1×0.1 degrees (our baseline level of analysis). Panel (c) repeats the image of Panel b for January 2006.



(a) The global network of U.S.-owned facilities and NDVI values in June

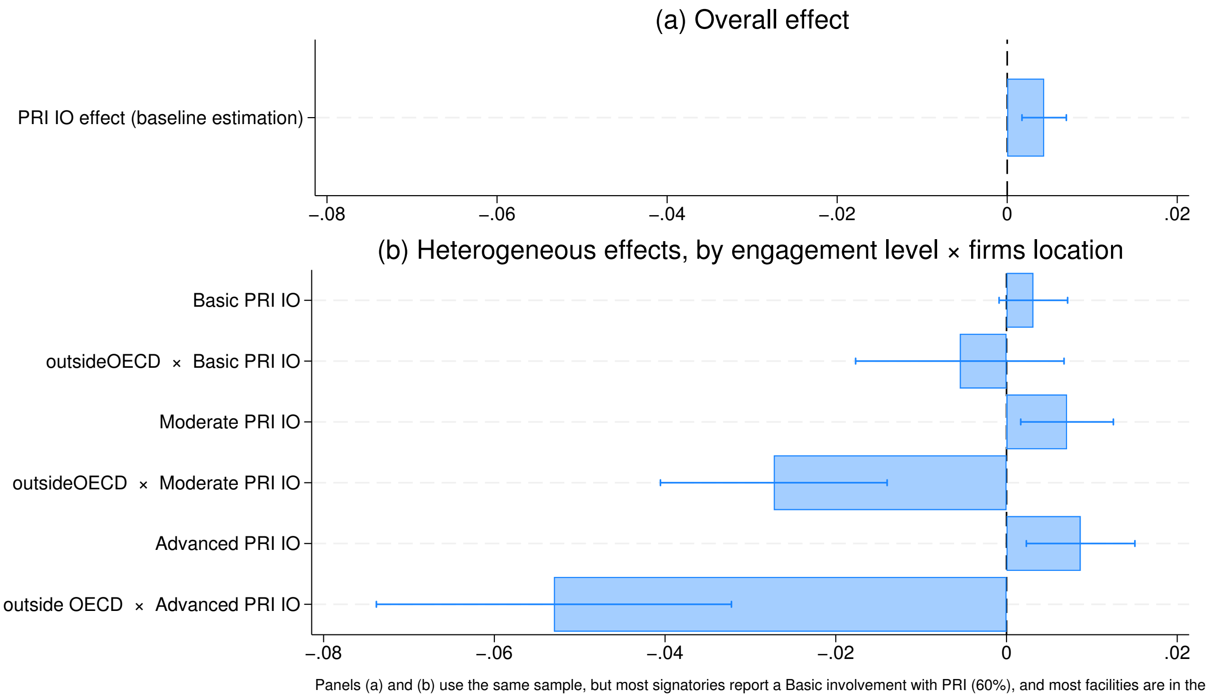


(b) Houston with 0.1°×0.1°cells in June



(c) Houston with 0.1°×0.1°cells in January

Figure 2: NDVI and PRI ownership – by engagement intensity and OECD location. The figure plots the coefficient estimates from a single regressions for the levels of Basic, Moderate, and Advanced PRI IO, as well as their interaction terms with *Outside OECD*. The average firm comprises about 58 facilities, including 6 outside the OECD. Controls include institutional ownership, weather controls (temperature, precipitation and their squares), economic controls (nighttime lights, buildings, population), and fixed effects by cell–month, year–month, and agroclimatic-zone–year. Error bars show the 95% confidence interval. Variable definitions and sources are provided in Appendix Table B-2.



Socially responsible investing and multinationals' environmental harm

Evidence from global remote sensing data

ONLINE APPENDIX

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November 3, 2025

This Internet Appendix reports supplemental material referenced in the main text and provides additional empirical validation and robustness exercises. It includes figures, extended methodological detail, and data source documentation.

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A NDVI: Literature Review, Relevance and Uses.

Spatio-temporal variation in vegetation quality and quantity can be caused by several factors, which are in turn captured by the NDVI. In particular, precipitation, vegetation type, soil type, temperature, and land use type are major driving forces that cause variations in the NDVI over time.

In this paper, we rely on the established reactivity of NDVI to pollution. NDVI appears to diminish with pollution through both air, soil, or water. Below, we describe a few examples of these relations as presented in the environmental science literature:

- *Atmospheric Pollutants:* Gas forms (oxidized and reduced forms of carbon and nitrogen) and particulate matter (PM) (PM10 and PM2.5 and toxic heavy metals) can harm vegetation either directly, through toxic effects, or indirectly, by altering soil pH and making toxic metal salts, such as aluminium, more soluble. PM can also have a detrimental mechanical effect by covering leaf surface and blocking stomata, which reduces light penetration and impairs process of photosynthesis, leading to a significant decline in rate of photosynthesis (Gheorghe and Ion, 2011; Rai, 2016). For instance, Moraes et al. (2003) find that PM emissions of an industrial complex had adverse impacts on surrounding vegetation. The forest species that were studied suffered visible injuries, reductions in net photosynthesis, growth parameters, adsorbate concentrations, and increased F, N, and S foliar concentrations. A similar study by Alfani et al. (2000) reports high levels of heavy metals and or elements in plant leaves close to major industrial plants.
- *Soil Pollution:* Soil pollution for example through heavy metals may affect plants through the soil or water, and phenomena such as soil salinity and soil erosion have a harmful impact on vegetation health. Salinity occurs when salt is present in places where it should not be, which can negatively impact quality of water and ability of plants to absorb water and nutrients. Salinity can be caused by human-induced factors such as contamination of soils with salt-rich waste waters and industrial by-products (Louwagie et al., 2011).
- *Water Pollution:* Land use and human activities such as industrial production can also alter quality of water, affecting uptake of nutrients by surrounding vegetation. Mining, for instance, generates discharge wastewater that negatively impacts quality of surface and groundwater, and may pose risks to drinking water supplies and losses of vegetation on land and in aquatic environments.[1] In oil and gas industry, process of extracting shale gas results in generation of significant quantities of wastewater through hydraulic fracturing. This wastewater can have high levels of dissolved solids, such as salts, along with naturally occurring radioactive materials and metals, as well as or chemicals utilized during drilling and well completion (Resende Vieira and Christofaro, 2024).

NDVI vs. pollutant-specific data Remote sensing measures that capture air quality and pollution have been widely used in environmental studies as well as in economics.[2] However, focusing on impact of industrial activities on air quality only is limiting given evidence of pollution substitution. Gibson (2019); Bi (2017) find that plants in U.S.

[1] A relationship studied from an economic perspective by Aragón and Rud (2016); Vashold et al. (2025).

[2] See Donaldson and Storeygard (2016) for a survey of literature.

increase their level of toxic water releases by 105% following introduction of Clean Air Act (CAA), which regulates air emissions in particular counties. Similarly, Greenstone (2003) reports that reduction in air pollution might be largely attributed to use of devices such as scrubbers and electrostatic precipitation. These devices effectively remove pollutants from air, but remaining residuals are discharged into water bodies, landfills, or injected into ground. Interestingly, the NDVI is also highly sensitive to residual atmospheric contamination (Xiao et al., 2003). For these reasons, we turn to the NDVI as an indicator of variations of local industrial pollution through both air, water, and ground pollution.

B Data and sample

Table B-1: Distances in Kilometers at the Equator for Different Degrees of Latitude. These calculations are based on a simplified approximation using the average Earth's circumference at the equator of approximately 40,075 kilometers (24,901 miles). The actual distances at specific latitudes may vary slightly from these estimates. To calculate the distance covered by degrees of latitude, we need to know the approximate circumference of the Earth at the given latitude.

Degrees of Latitude	Distance (in Kilometers)	Data
0.05	5.56	NDVI input data
0.10	16.67	Final dataset
0.5	55.56	CRU input data

Table B-2: Variable Construction and Data Sources

Variable	Definition/Measurement	Data Source/Notes
NDVI	Normalized Difference Vegetation Index, biweekly cell-level greenness measure. Ranges from -1 (no vegetation) to +1 (dense).	MODIS MOD13C1 v061, NASA LP DAAC
IO	Total institutional ownership.	FactSet
PRI IO	Institutional ownership by PRI signatories. Averaged across facilities in a grid cell.	FactSet Ownership + PRI Reports (2014–2020)
Basic PRI IO	Subset of PRI IO where signatories report "Basic" ESG engagement in module SG09.	PRI Reports
Moderate PRI IO	As above, for "Moderate" ESG engagement.	PRI Reports
Advanced PRI IO	As above, for "Advanced" ESG engagement.	PRI Reports
Outside OECD	Indicator equal to one for facilities outside OECD countries.	OECD country classification
Toxic Releases (Total)	Annual total chemical mass released (all TRI chemicals).	EPA TRI
RSEI Toxicity	Toxicity-weighted pollutant scores capturing health risks, used to classify TRI releases as above or below median toxicity.	EPA RSEI
On-site Releases	Subset of releases occurring on facility premises.	EPA TRI
Off-site Releases	Subset transferred off-site.	EPA TRI

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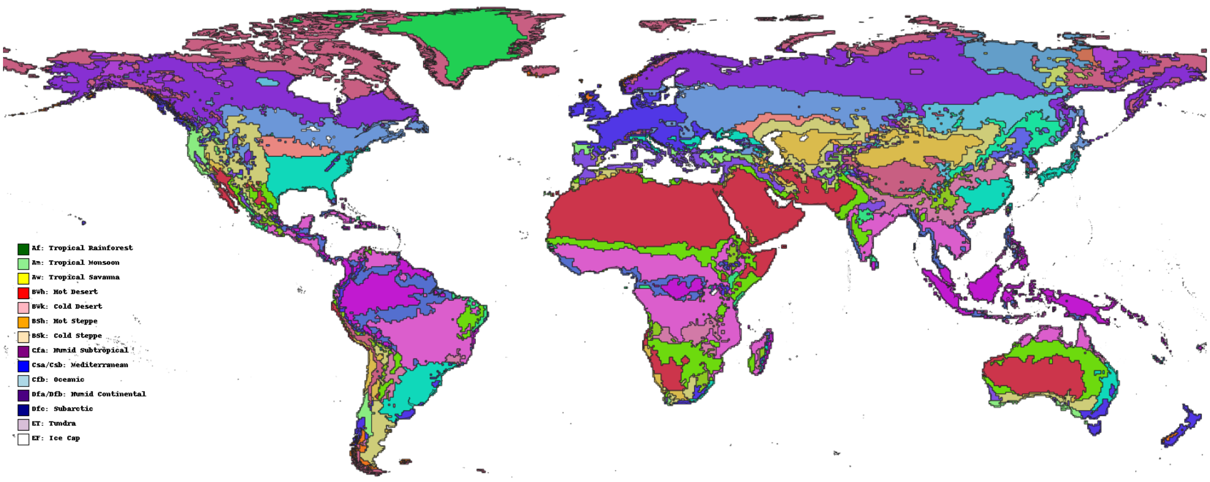
Variable	Construction / Definition	Data Source
CO_2 Emissions	Total CO_2 from stationary sources at the facility level. Used in robustness and GHG intensity analyses.	EPA FLIGHT (GHG Reporting Tool)
Rain	Monthly average precipitation for each grid cell of 0.5×0.5 degree.	CRU TS v4, Univ. of East Anglia
Temperature	Monthly average temperature for each grid cell of 0.5×0.5 degree.	CRU TS v4
Night-Time Lights	Calibrated light intensity averaged annually, proxy for economic activity.	DMSP/VIIRS, Harmonized via Li et al. (2020)
Built-up Area	Built environment surface from GHSL. Interpolated to annual frequency.	GHSL, European Commission
Population	Population count from GHSL, interpolated to annual.	GHSL
Facility Count	Number of firm-owned facilities in each grid cell. Used as a weight or control.	Dun & Bradstreet WorldBase
Firm-Level Controls	Time-varying characteristics of the parent firm: log total assets, leverage, profitability (ROA), tangibility, and Tobin's q, following Dyck et al. (2019).	Compustat
Portfolio Weight	Target asset manager's pre-announcement equity share in the parent firm. Set to zero for control cells. Used to scale treatment intensity in the stacked DiD specification.	FactSet Ownership + SDC Platinum M&A + PRI Reports
Regulatory Quality	Country-year score from the Worldwide Governance Indicators (WGI), capturing perceptions of the government's ability to formulate and implement sound policies and regulations that promote private sector development. Matched to facilities by host country and year.	World Bank WGI

Table B-3: NDVI and TRI sample-summary statistics. The table reports summary statistics for cells linked to a TRI facility between 2006 and 2020. Variables include the number of facilities per cell, yearly average NDVI, total toxic releases, and the fraction of onsite releases (undefined when total releases are zero). Variable definitions and sources are in Appendix Table B-2.

	N	mean	std	min	p10	p25	p50	p75	p90	max
Nr Cells	5027									
Nr TRI Facilities per cell	67092	1.41	0.93	1.00	1.00	1.00	1.00	1.00	2.00	14.00
Average NDVI	67092	0.51	0.13	0.04	0.34	0.43	0.53	0.62	0.67	0.84
Total Release (1,000 pounds)	67092	587.83	12673.40	0.00	0.00	0.03	4.75	55.84	467.13	1124384.89
Onsite Release (%)	57685	0.74	0.39	0.00	0.01	0.48	1.00	1.00	1.00	1.00

Figure B-1: Agroclimatic zones. The map shows the Köppen–Geiger climate classification system, as published by the World Bank.



C Spatial Diagnostics for PRI Ownership and Toxic Releases

This section documents the limited spatial correlation in our key *regressors*–responsible ownership and toxic releases. Even though NDVI exhibits spatial dependence, when the regressor of interest is not spatially correlated, spatial HAC corrections are not required (Colella et al., 2019).[3]

We compute Moran's I for cell-level PRI ownership each date (quarter-year) and report the corresponding p-values in Figure C-2 (Moran, 1950; Kondo, 2021). Spatial autocorrelation is modest: across 59 quarter-year snapshots, Moran's I is significant at the 10% level in 38 dates, at the 5% level in 26 dates, and at the 1% level in only 4 dates. A clear temporal pattern emerges. Early in the sample (pre-2012Q3), PRI ownership is relatively rare and somewhat geographically clustered; later, as PRI becomes more prevalent across firms and locations, spatial dependence dissipates and p-values rise, indicating no detectable autocorrelation. Figure C-3 vs. Figure C-4 provide a visual overview of these patterns. Overall, spatial autocorrelation in PRI ownership declines precisely when the regressor becomes most important.

We repeat the exercise for annual toxic releases. Figure C-5 shows no evidence of spatial autocorrelation in any TRI year but one.

In the absence of spatial dependence in the regressors of interest, spatial HAC estimators are unwarranted (Colella et al., 2019). At our scale, these estimators were also computationally infeasible. For completeness, our sensitivity sections vary clustering schemes; results are unchanged.

[3] In the authors' words: "the presence of spatial correlation leads to an increase in the likelihood of making a Type 1 error if unaccounted for, only if both the outcome variable and the variable of interest exhibit spatial autocorrelation." (p.13)

Figure C-2: Spatial diagnostic for PRI ownership, 2006Q1-2020Q4. The figure shows p-values of the global Moran's I statistic for each quarter, based on Kondo (2021).

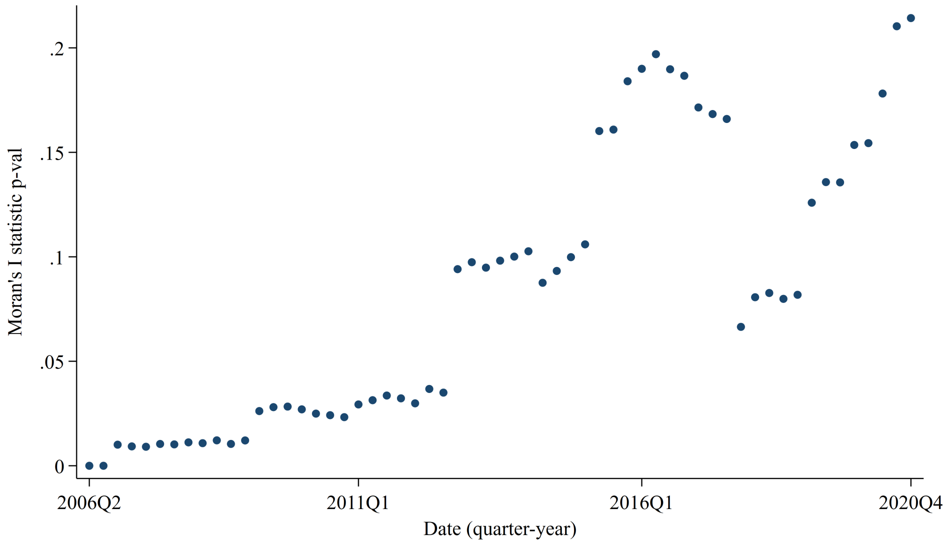


Figure C-3: PRI ownership in the cell and its neighbors, 2006Q4. The figure shows values of the PRI ownership variable in each cell and its neighboring cells in the fourth quarter of 2006, based on Kondo (2021).

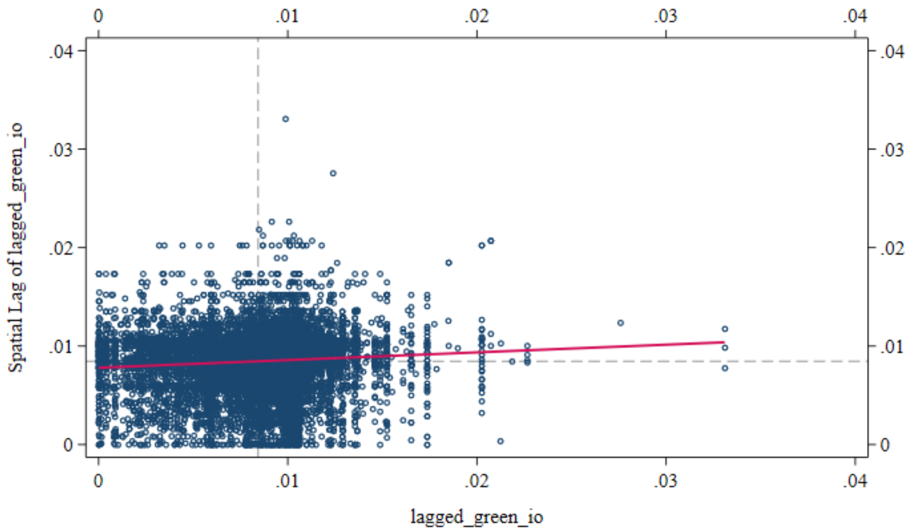


Figure C-4: PRI ownership in the cell and its neighbors, 2020Q4. The figure shows values of the PRI ownership variable in each cell and its neighboring cells in the fourth quarter of 2020, based on Kondo (2021).

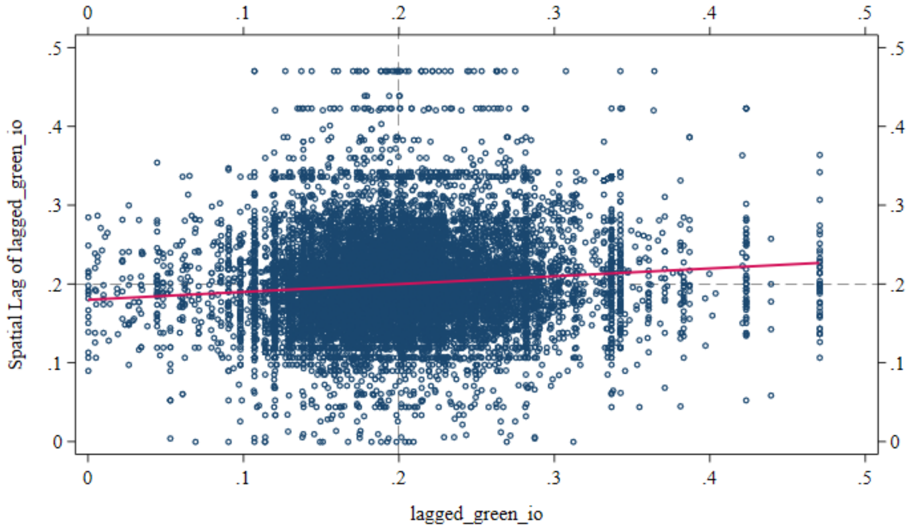
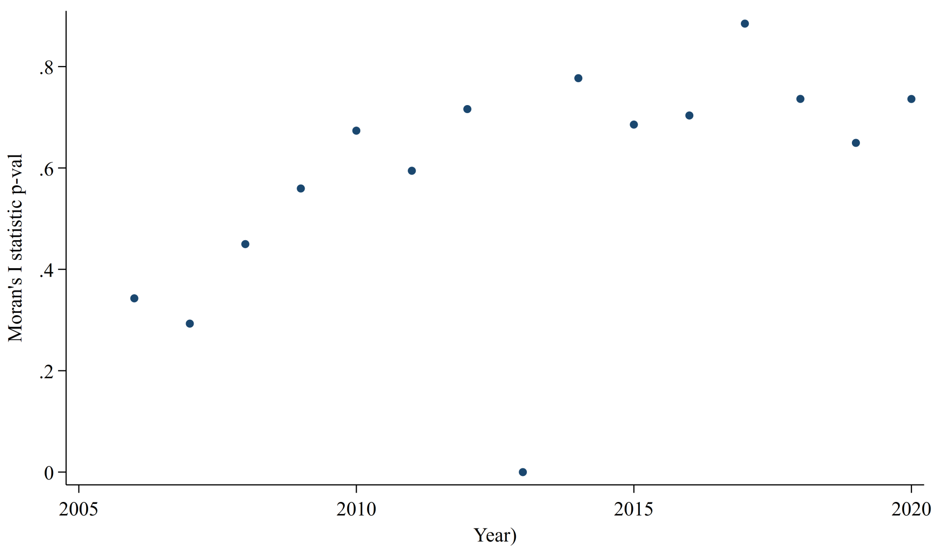


Figure C-5: Spatial diagnostic for TRI, 2006-2020. The figure shows p-values of the global Moran's I statistic for each year, based on Kondo (2021).



D NDVI-TRI Additional Results

In this Appendix section, we present several variations of the validation test of the TRI-NDVI relationship reported in Table 2. We show how different control variables enter the estimations and confirm that the estimated relationship remains robust regardless of the controls included. This includes the (controversial) case of vegetation health and CO_2 emissions. Finally, we examine how results vary with the size of spatial cells considered and with the timing of the treatment. These results are presented in Tables D-4 to D-8.

We show that the adverse effects of industrial pollution on vegetation are consistent across various sample specifications, do not dependent on spatial clustering of facilities, and react most to contemporaneous pollution than to past pollution. We repeat the battery of tests presented in Table 2 for the larger cells of 0.5×0.5 degrees, corresponding to the widely used PRIO-Grid cells. We also repeat that test for a smaller cell size of 0.05×0.05 degrees as the smaller the cell, the higher the likelihood that we observe only one plant in each cell. We present the results in Appendix Table D-5, both exercises confirm the findings from Table 2. In Table D-4 we show the full specification with the control variables. In Table D-6 we confirm result stability to alternative error structures. In Table D-7 we show results when considering toxic releases with a 12 months lag: results are qualitatively similar although they sometimes loose precision, in line with the fast degradation, and recovery of vegetation that we observe in case of toxic spill.

To address concerns that our estimates might be biased by unobserved factors correlated with both vegetation health and pollution, we further examine a key player: CO_2. A potential bias is a local "CO_2 fertilization" effect whereby higher CO_2 raises NDVI. The EPA's Facility Level Information on Greenhouse Gases Tool (FLIGHT) reports facility-level emissions from stationary industrial sources, set to zero when not collected. Table D-8 suggests a limited relationship between CO_2 emissions and the NDVI (Column 1). Crucially, our estimates of the NDVI-toxic-release link are unchanged with or without the CO_2 control, indicating that vegetation health responds to toxic releases over and above any CO_2 effect.

Table D-4: NDVI and toxic releases- controls. Results from OLS estimations with standardized variables. The dependent variable is NDVI, explanatory variables are toxic releases from the TRI, and all specifications include weather and economic controls. Variable definitions are in Appendix Table B-2. * significant at 10%; ** at 5%; *** at 1%. Standard errors clustered at the cell level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. var.				NDVI			
Sample	— Full —		TRI down	One plant		— Full —	
Tot. releases	-0.005***	-0.001**	-0.006*	-0.002**	-0.003**		
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)		
Tot. releases X RSEI above mean toxicity						-0.004***	
						(0.001)	
Tot. releases X RSEI below mean toxicity						-0.002	
						(0.001)	
Tot. on-site releases							-0.003**
							(0.002)
Tot. off-site releases							0.001
							(0.001)
rain	0.260***	0.057***	0.260***	0.057***	0.059***	0.059***	0.059***
	(0.018)	(0.004)	(0.021)	(0.004)	(0.002)	(0.002)	(0.002)
temperature	0.802***	0.367***	0.808***	0.363***	0.345***	0.345***	0.345***
	(0.015)	(0.004)	(0.017)	(0.005)	(0.004)	(0.004)	(0.004)
temperature sq.	-0.703***	-0.273***	-0.715***	-0.274***	-0.246***	-0.246***	-0.246***
	(0.017)	(0.004)	(0.019)	(0.004)	(0.004)	(0.004)	(0.004)
rain sq.	-0.140***	-0.027***	-0.139***	-0.027***	-0.033***	-0.033***	-0.033***
	(0.016)	(0.004)	(0.019)	(0.005)	(0.002)	(0.002)	(0.002)
Lights	-0.060***	-0.051***	-0.054***	-0.048***	-0.042***	-0.042***	-0.042***
	(0.005)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Population	-0.078**	-0.048***	-0.074**	-0.058***	-0.044***	-0.044***	-0.044***
	(0.031)	(0.018)	(0.032)	(0.022)	(0.016)	(0.016)	(0.016)
Build	0.149***	0.072***	0.164***	0.082***	0.064***	0.064***	0.064***
	(0.028)	(0.016)	(0.029)	(0.019)	(0.015)	(0.015)	(0.015)
Nb. facilities	0.006**	0.003*	0.007**	0.003*	0.004***	0.004***	0.004***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Cell FE	Yes	No	No	No	No	No	No
Cell X month FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No	No	No
Year X month FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year X agroclimatic FE	No	No	No	No	Yes	Yes	Yes
Frequency	Yearly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly
Observations	98029	2255922	1692631	1890168	2248494	2248494	2248494

Table D-5: NDVI and toxic releases - smaller or larger cells (0.05° or 0.5°). Results from OLS estimations with standardized variables. The dependent variable is NDVI, explanatory variables are toxic releases from the TRI, and all specifications include weather and economic controls. Variable definitions are in Appendix Table B-2. * significant at 10%; ** at 5%; *** at 1%. Standard errors clustered at the cell level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	——— NDVI ———					
Sample	— 0.05° x 0.05° grid cells —			— 0.5° x 0.5° grid cells —		
Tot. releases	-0.002*			-0.011***		
	(0.001)			(0.002)		
Tot. releases X RSEI above mean toxicity		-0.002***			-0.020***	
		(0.001)			(0.006)	
Tot. releases X RSEI below mean toxicity		-0.001			-0.011***	
		(0.001)			(0.002)	
Tot. on-site releases			-0.002*			-0.011***
			(0.001)			(0.002)
Tot. off-site releases			0.000			0.004
			(0.000)			(0.006)
Cell FE	No	No	No	No	No	No
Cell X month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
Year X month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year X agroclimatic FE	Yes	Yes	Yes	Yes	Yes	Yes
Frequency	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly
Observations	3750627	3750627	3750627	229873	229873	229873

Table D-6: NDVI and toxic releases- alternative clustering. Results from OLS estimations with standardized variables. The dependent variable is NDVI and explanatory variables are toxic releases from the TRI. Specifications include weather and economic controls. Standard errors are clustered at the levels indicated in the headings. Variable definitions are in Appendix Table B-2. * significant at 10%; ** at 5%; *** at 1%.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	——— NDVI ———					
Spatial cluster	— 1 degree —			— 10 degrees —		
Tot. releases	-0.003**			-0.003*		
	(0.002)			(0.002)		
Tot. releases X RSEI above mean toxicity		-0.004***			-0.004***	
		(0.001)			(0.001)	
Tot. releases X RSEI below mean toxicity		-0.002			-0.002	
		(0.001)			(0.001)	
Tot. on-site releases			-0.003**			-0.003*
			(0.002)			(0.002)
Tot. off-site releases			0.001			0.001
			(0.000)			(0.000)
Cell X month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year X month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year X agroclimatic FE	Yes	Yes	Yes	Yes	Yes	Yes
Frequency	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly
Observations	2248494	2248494	2248494	2248494	2248494	2248494

Table D-7: NDVI and toxic releases (lagged one year). Results from OLS estimations with standardized variables. The dependent variable is NDVI and the main explanatory variables are lagged toxic releases from the TRI. All specifications include weather and economic controls. Variable definitions are in Appendix Table B-2. * significant at 10%; ** at 5%; *** at 1%. Standard errors clustered at the cell level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. var.				——— NDVI ———			
Sample	— Full —		TRI down	One plant		— Full —	
l1totalreleases	-0.004**	-0.004**	-0.005**	-0.004***	-0.002		
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)		
l1releaseXhigh_toxicity						-0.003	
						(0.004)	
l1releaseXlow_toxicity						-0.000	
						(0.004)	
l1totalreleases_onsite							-0.002
							(0.004)
l1totalreleases_offsite							-0.000
							(0.001)
Cell FE	Yes	No	No	No	No	No	No
Cell X month FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No	No	No
Year X month FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year X agroclimatic FE	No	No	No	No	Yes	Yes	Yes
Frequency	Yearly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly
Observations	92697	2134231	1570124	1780834	2127216	2127216	2127216

Table D-8: NDVI and greenhouse gas emissions. Results from OLS estimations, controlling for CO_2 emissions from the EPA FLIGHT database. The dependent variable is NDVI. All specifications include weather and economic controls. Variable definitions are in Appendix Table B-2. * significant at 10%; ** at 5%; *** at 1%. Standard errors clustered at the cell level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. var.				——— NDVI ———			
Tot. releases	-0.003**		-0.003**				
	(0.002)		(0.002)				
Tot. CO2 emissions		0.001***	0.001***		0.001***		0.001***
		(0.000)	(0.000)		(0.000)		(0.000)
Tot. releases X RSEI above mean toxicity				-0.004***	-0.004***		
				(0.001)	(0.001)		
Tot. releases X RSEI below mean toxicity				-0.002	-0.002		
				(0.001)	(0.001)		
Tot. on-site releases						-0.003**	-0.003**
						(0.002)	(0.002)
Tot. off-site releases						0.001	0.000
						(0.001)	(0.001)
Cell FE	No	No	No	No	No	No	No
Cell X month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No
Year X month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X agroclimatic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Frequency	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly
Observations	2248494	2248494	2248494	2248494	2248494	2248494	2248494

E The NDVI Around Major Toxic Chemical Spills

In this section we further document the sensitivity of vegetation health to pollution around major toxic chemical spills. Spills are time-circumvented events, allowing us to asses the dynamics of vegetation health in an event-study setting. We retrieve data on toxic chemical spills from the U.S. Coast Guard's National Response Center (NRC). This database, used also in (Tian et al., 2023), compiles first-hand reports of oil, chemical, radiological, biological, or etiological discharges into the environment. Reports include details such as the incident's time, exact location and the number of evacuations. Between 2016 to 2020 the data records a total of 3,698 incidents across the United States (see Figure E-6), the vast majority of which did not result in serious consequences. To isolate serious incidents, we focus on the 90th percentiles value of number of evacuations among those events with at least one evacuation. This approach singles out 351 incidents which led to a minimum of 210 evacuations.

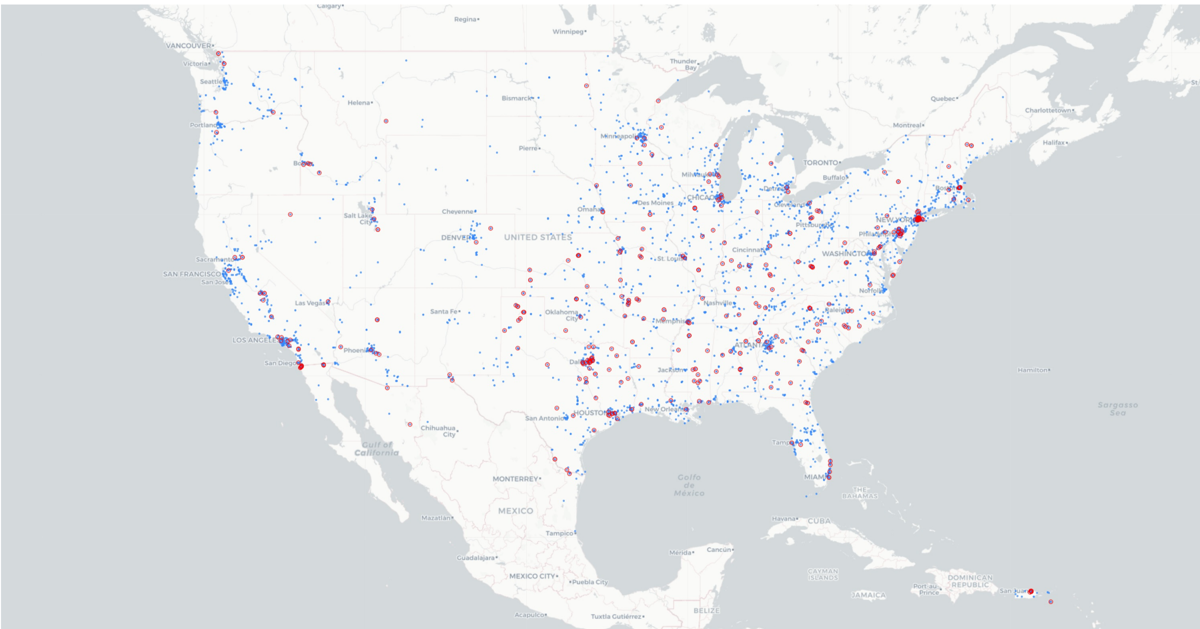


Figure E-6: Spatial distribution of toxic chemical spills. The map shows the spatial distribution of toxic chemical spills across the United States over the period 2016 to 2020, based on data from the U.S. Coast Guard's National Response Center (NRC). Each blue dot corresponds to a spill with at least one evacuation. Events that resulted in more than 210 evacuations (90th percentile) are highlighted with a red circle.

We estimate the impact of these short and acute pollution shocks on local vegetation health using a stacked regression difference-in-differences approach. For each event, the treated group consists in the cell where the incident is located. As control group we select all the neighboring cells up to 10 layers away, as long as they were never treated themselves. The first layer of neighbors consists of 8 cells, the second layer of 16 cells, etc., up until the tenth layer of 80 cells. A sub-experiment (or cohort) consists of one treated cell and its neighbors. For each sub-experiment, we build a panel of biweekly cell-level NDVI observations over a window of six month before and after the incident. We then create a stacked panel data set by pooling the data across sub-experiments. We estimate the average month-by-month treatment effect using the following dynamic regression model on the stacked panel data set:

$$Y_{i,e,t} = \sum_{l=0}^{9} \sum_{k=-6}^{6} (\beta_{k,l} \cdot D_{i,e,k,t} \cdot \mathrm{N}_{i,e,l}) + \mu_{e,i} + \mu_{e,t} + Weather'_{i,e,t-1} \cdot \delta + \epsilon_{i,e,t} \tag{1}$$

In the model above, i indicates the cell, e indexes the treatment-control sub-experiments, t denotes the date of the NDVI measurement. $D_{i,e,k,t}$ is a dummy variable equal to one for each cell i in cohort e if t is k-months away from the spill around which we build the treatment-control panel.[4] $N_{i,e,l}$ is a dummy variable equal to one for the l-th degree neighboring cells in cohort e. $l = 0$ corresponds to the treated cell. The omitted group is the 10-th degree neighbors, the estimated effect is relative to the most distant group. We include cohort-cell fixed effects ($\mu_{e,i}$) to control for unobserved heterogeneity across cells and spill events, and cohort-time fixed effects ($\mu_{e,t}$) to account for common time-varying factors. The model also includes cell-level weather controls. We cluster standard errors at the cell-cohort level.

To account for seasonality in NDVI, the measure of vegetation health in the stacked panel data set is the abnormal NDVI, defined as the difference between the NDVI value in cell i at time t minus the average NDVI value in the cell in the same month computed over the full sample. The dependent variable is an indicator for whether the abnormal NDVI is negative. The estimated $\beta_{k,l}$ coefficients reported in Table E-9 are to be interpreted

[4] Given the biweekly frequency of the NDVI observations, we assign event-time $k = 0$ to measurements that take place within $[0, 32)$ days since the accidents. Similarly, $k = 1$ corresponds to measurements within $[32, 62)$ days, $k = -1$ to measurements within $[-32, 0)$ days, etc.

as estimated differences in the probability of observing abnormally low values of NDVI relative to the most distant neighbors.

Consistent with major toxic spills negatively affecting local vegetation, we find a statistically significant increase in the probability of negative abnormal NDVI coinciding with the month of the accident. The effect is stronger in the treated cell and in cells closer to the event. Moreover, the estimated effect decreases monotonically with the distance. The effect is still visible in the month after the accidents and it becomes undetectable after six months. In terms of magnitude, during the event month the probability of observing negative abnormal NDVI values is 4.6 percentage points higher in the treated cell than in the 10th layer neighbors. Unconditionally, the probability of abnormal NDVI being negative is 45%. While a few pre-event coefficients show marginal significance, the lack of consistent patterns before the incident supports the interpretation of a pollution-driven vegetation response.

Overall, the tests presented both in this and in the previous sub-section appear to support the idea that the NDVI reacts to industrial pollution. Two features, present in both subsection, are of particular interest of our subsequent analysis. First, the NDVI appears to react to both negative and positive changes in levels of pollution: NDVI values improve if pollution decreases or after some (short) time after a one-shot incident. Second, the NDVI reacts to local pollution, namely, reacting to on-site pollution, or magnified in the directly impacted cells of a toxic spill more than in their neighbors.

Table E-9: NDVI and environmental accidents. Results from stacked regressions following (Tian et al., 2023), estimating month-by-month effects of toxic chemical spills on NDVI in the affected cell and successive neighbor layers. Accidents are from the U.S. Coast Guard's NRC database (2016-2020), restricted to the top 10% of spills by evacuations. All specifications include weather controls. * significant at 10%; ** at 5%; *** at 1%. Standard errors clustered at the cohort-cell level.

Dependent variable	—— Prob(Negative Abnormal NDVI) ——									
	Distance from Treated Cell									
Months Since Event	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
-6	-0.011	-0.003	-0.004	-0.005	0.001	-0.000	0.002	0.002	0.004	-0.001
	(0.018)	(0.012)	(0.011)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.004)	(0.003)
-5	0.017	0.006	0.004	-0.003	0.001	0.000	0.004	0.001	0.004	0.004
	(0.020)	(0.013)	(0.012)	(0.010)	(0.008)	(0.008)	(0.007)	(0.005)	(0.005)	(0.003)
-4	0.020	0.020	0.018	0.021**	0.018**	0.013*	0.009	0.003	0.005	0.002
	(0.020)	(0.013)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
-3	0.018	0.033**	0.035***	0.024**	0.015*	0.007	0.004	0.001	0.001	-0.000
	(0.022)	(0.014)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
-2	-0.003	0.013	0.015	0.011	0.006	0.004	-0.001	-0.005	-0.009*	-0.001
	(0.021)	(0.014)	(0.012)	(0.011)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
-1	0.010	0.017	0.025**	0.019*	0.011	0.010	0.010	0.008	0.001	0.001
	(0.021)	(0.014)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
0	0.046**	0.045***	0.037***	0.029***	0.019**	0.015*	0.014*	0.007	0.005	0.001
	(0.022)	(0.015)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
1	0.031	0.035**	0.030**	0.030***	0.025***	0.019**	0.020***	0.016***	0.012**	0.005
	(0.022)	(0.015)	(0.013)	(0.011)	(0.010)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
2	0.020	0.021	0.020*	0.015	0.011	0.009	0.009	0.006	0.007	-0.000
	(0.021)	(0.014)	(0.012)	(0.011)	(0.009)	(0.009)	(0.007)	(0.006)	(0.005)	(0.003)
3	0.045**	0.030**	0.025**	0.015	0.019*	0.011	0.008	0.008	0.005	-0.001
	(0.021)	(0.015)	(0.012)	(0.011)	(0.010)	(0.009)	(0.008)	(0.006)	(0.005)	(0.003)
4	0.038*	0.028**	0.027**	0.017*	0.010	0.008	0.007	0.004	0.005	0.001
	(0.020)	(0.014)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
5	0.025	0.027*	0.025**	0.014	0.011	0.010	0.008	0.010	0.004	0.002
	(0.021)	(0.014)	(0.012)	(0.010)	(0.009)	(0.009)	(0.007)	(0.006)	(0.005)	(0.003)
6	0.001	-0.003	0.005	0.007	0.012	0.006	0.010	0.003	0.003	0.003
	(0.021)	(0.013)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)

F NDVI-PRI Additional Results

Table F-10: NDVI and PRI ownership - smaller or larger cells (0.05° or 0.5°). Results from OLS estimations of model (1). The unit of observation is either a 0.05° × 0.05° cell, or a 0.5° × 0.5° cell. The dependent variable is the Normalized Difference Vegetation Index (NDVI). The main explanatory variable is *PRI IO*, which measures socially responsible ownership of establishments in a cell in the previous quarter. Global firms are those with at least one facility outside the OECD. Controls variables are as in Table 3. Variable definitions and data sources are provided in Appendix Table B-2. * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cell level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	NDVI					
Split:	Full sample				One plant	Global firm
Panel A: 0.05° x 0.05° grid cells						
PRI IO	0.003***	0.003***	0.003***	0.003***	0.003**	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	6519432	6519432	5636081	5625624	3222655	4953499
Panel B: 0.5° x 0.5° grid cells						
PRI IO	0.007**	0.007**	0.012***	0.008***	-0.000	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1384970	1384970	1099422	1094249	298462	1043540
Cell-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Agroclimat FE	No	No	No	Yes	Yes	Yes

Table F-11: NDVI and PRI ownership - alternative clustering. Results from OLS estimations of the PRI-NDVI relationship with different clustering levels. Standard errors are clustered at the levels indicated in the headings. All specifications include fixed effects and controls for weather, built environment, population, and nighttime lights. * significant at 10%; ** at 5%; *** at 1%. Standard errors in parentheses.

	(1)	(2)	(3)
Dep. Variable		NDVI	
Spatial cluster	countries	agroclimatic	countries × agroclimatic
Lagged PRI IO	0.004*	0.004**	0.004**
	(0.002)	(0.002)	(0.002)
Lagged IO	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Builts	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
Population	-0.070	-0.070*	-0.070
	(0.049)	(0.036)	(0.042)
Lights	-0.450***	-0.450***	-0.450***
	(0.086)	(0.094)	(0.087)
Cell-month FE	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
Year-Agroclimat FE	Yes	Yes	Yes
Observations	3774182	3774182	3774182
Adjusted R^2	0.90	0.90	0.90

Table F-12: NDVI and PRI ownership - temporal dependence. Results from OLS estimations testing robustness to temporal dynamics. Column (1) reports the baseline specification, (2) adds an extra lag of PRI ownership, (3) includes twelve biweekly lags (FE-ADL(12)), and (4) estimates a quarterly first-difference model. Specifications include fixed effects and the standard weather and economic controls. * significant at 10%; ** at 5%; *** at 1%. Standard errors in parentheses.

	(1) Baseline	(2) Baseline + L1(NDVI)	(3) FE–ADL(12)	(4) Δ quarterly
Lagged PRI IO	0.005***	0.003***	0.003**	
	(0.001)	(0.001)	(0.002)	
Δ PRI IO (qtr)				0.533***
				(0.040)
NDVI lag 1		0.395***	0.357***	
		(0.002)	(0.015)	
NDVI lag 2			0.052***	
			(0.016)	
NDVI lag 3			0.047***	
			(0.012)	
NDVI lag 4			0.009	
			(0.010)	
NDVI lag 5			-0.004	
			(0.009)	
NDVI lag 6			0.003	
			(0.008)	
NDVI lag 7			-0.010*	
			(0.006)	
NDVI lag 8			-0.012**	
			(0.005)	
NDVI lag 9			-0.016***	
			(0.006)	
NDVI lag 10			-0.011**	
			(0.005)	
NDVI lag 11			-0.027***	
			(0.006)	
NDVI lag 12			-0.017***	
			(0.005)	
Controls	Yes	Yes	Yes	Yes
Cell–month(qtr) FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observations	Yes	Yes	Yes	Yes
N	3782638	3782082	3706651	43588

Table F-13: NDVI and PRI ownership - by regulatory quality. Results from OLS estimations. The unit of observation is a 0.1° × 0.1° cell. The dependent variable is the Normalized Difference Vegetation Index (NDVI). The main explanatory variable is *PRI IO*, which measures average PRI ownership of establishments in a cell in the previous quarter. *RQ* is the regulatory quality index from the World Bank's Worldwide Governance Indicators, which is available at country-year level. All specifications include weather controls (average temperature and its square, total precipitation and its square), economic controls (night-time lights, buildings in the cell, and population) and institutional ownership. Variable definitions and data sources are provided in Appendix Table B-2. * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cell level and reported in parentheses.

	(1)	(2)	(3)	(4)
Dep. Variable	NDVI			
Split:	Full sample		One plant	Global firm
PRI IO	-0.008**	-0.008**	-0.005	-0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
RQ Quintile=1	-0.001	0.003	0.005	0.003
	(0.002)	(0.003)	(0.003)	(0.003)
RQ Quintile=2	-0.007***	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
RQ Quintile=4	-0.019***	-0.018***	-0.014***	-0.017***
	(0.001)	(0.001)	(0.002)	(0.002)
RQ Quintile=5	-0.017***	-0.014***	-0.012***	-0.014***
	(0.001)	(0.001)	(0.002)	(0.002)
RQ Quintile=1 × PRI IO	-0.046***	-0.043***	-0.051***	-0.043***
	(0.011)	(0.011)	(0.013)	(0.011)
RQ Quintile=2 × PRI IO	0.002	0.004	0.002	0.004
	(0.004)	(0.004)	(0.005)	(0.004)
RQ Quintile=4 × PRI IO	0.018***	0.020***	0.013***	0.021***
	(0.003)	(0.004)	(0.004)	(0.004)
RQ Quintile=5 × PRI IO	0.011***	0.010***	0.007*	0.010***
	(0.003)	(0.003)	(0.004)	(0.004)
Controls	Yes	Yes	Yes	Yes
Cell-month FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Year-Agroclimat FE	No	Yes	Yes	Yes
Observations	3782638	3774182	1868951	3394504

G LLM Analysis of Open-Ended PRI Engagement Justifications

This appendix describes the methodology we use to extract common themes from open-ended responses provided by PRI signatories in module SG09 of the PRI Transparency Reports as motivation for their disclosed level of involvement with PRI. Although this field is optional, 63.5% of signatories provide an answer. This proportion is larger among Advanced signatories (91.1%), than Moderate (78.9%) or Basic (51.2%) institutions.

To extract and classify the content of these responses in a transparent and reproducible manner, we implement a two-step, model-agnostic procedure using large language models (LLM). First, we provide all justifications in the form of a list to ChatGPT-4 with the task of identifying the most common themes. Second, we feed each justification individually to the OpenAI API, prompting the model to evaluate whether a given theme is mentioned and returning a 0/1 indicator for each theme. Multiple themes can be assigned to a single justification. Our two-step design reduces errors that arise if one simply asks an LLM to report themes by engagement level: such prompts can yield inconsistent answers or reflect the model's priors about what *Advanced* or *Basic* investors should say, rather than the disclosures themselves.

The LLM model identified seven main themes that signatories mention most frequently in their open-ended responses:

1. Mentions of being a signatory only (e.g. *We are a signatory to the PRI.*, *Joined initiative and its meetings but not actively involved in its work.*);

2. Event participation (e.g. *We participated in some working group meetings arranged by PRI Japan Network and exchanged opinions on ESG issues with participants*, *We participated in our local PRI network on many occasions.*)

3. Involvement in PRI collaborative engagements (e.g. *active member of two collaborative engagements*, *Comgest participated in engagement initiatives through the UN PRI Clearinghouse.*),

4. taking a leadership role in one or several PRI initiatives (e.g. *Participated in a number of collaborative engagements led by the PRI, including as a leading investor on some.*)
5. Integration of PRI / ESG principles into investment policies (e.g. *The UN PRI set of principles provides an overarching framework for Hastings' approach to responsible investment*, *We apply the PRI principles*),
6. Fulfillment of mandatory PRI reporting requirements (e.g. *Since joining PRI, The Drapac Group have reported a moderate level of information on a regular basis*),
7. Promotion of PRI efforts through media or public advocacy (e.g. *We have been consistently talking about and disseminating information on the UNPRI within the investment community and during various meetings.*, *Presented research at PRI Academic Conference, Paris, November 2013.*).

From running the second step we find that the average response mentions 1.7 themes; 5% do not reference any of these topics. Figure G-8 shows the frequency of each theme by engagement level.

Promoting responsible investment

SG 09	Mandatory	Public	Core Assessed	PRI 4,5

SG 09.1	Select the collaborative organisation and/or initiatives of which your organisation is a member or in which it participated during the reporting year, and the role you played.

Select all that apply

☑ Principles for Responsible Investment

Your organisation's role in the initiative during the reporting period (see definitions)

☐ Basic

☑ Moderate

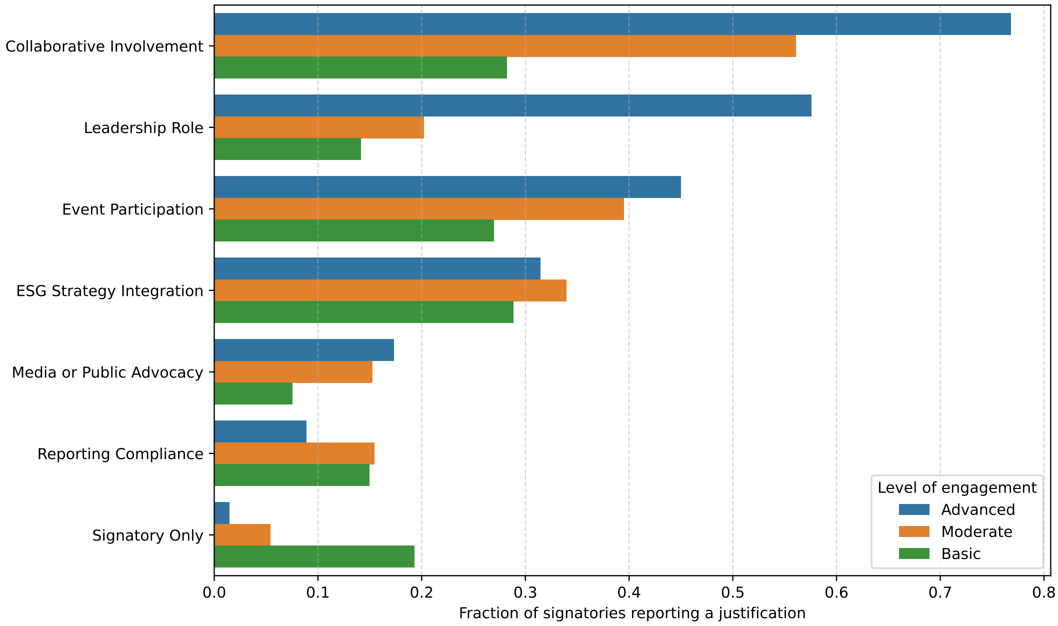
☐ Advanced

Provide a brief commentary on the level of your organisation's involvement in the initiative. [Optional]

Our organization participates in the PRI-led collaborative engagements, in addition to upholding the PRI and educating our clients and internal employees about the mission of the PRI.

Figure G-7: Example of 2020 PRI Transparency Report, Section SG 09. This figure reports an example of Section SG 09 of the PRI transparency report, which we parse to classify signatories based on their self-reported level of involvement with PRI (Basic, Moderate, Advanced). The figure also displays the optional field where organizations may provide comments on their response.

Figure G-8: Self-reported justifications by level of PRI engagement. This figure shows the fraction of signatories reporting a given justification for their level of engagement with the PRI initiative. Signatories are classified as Basic, Moderate, or Advanced based on their self-reported engagement level in module SG09 of the Public Transparency Reports. Common themes in the justifications were agnostically extracted from all optional open-ended follow-up responses using GPT-4. The bars indicate the share of signatories, by engagement level, who mentioned each theme in their justification. Appendix G describes the data preparation process.



References

Dyck, Alexander, Karl V Lins, Lukas Roth, and Hannes F Wagner, 2019, Do institutional investors drive corporate social responsibility? international evidence, *Journal of financial economics* 131, 693–714.

Appendix References

Alfani, A, D Baldantoni, G Maisto, G Bartoli, and A Virzo De Santo, 2000, Temporal and spatial variation in c, n, s and trace element contents in the leaves of quercus ilex within the urban area of naples, *Environmental Pollution* 109, 119–129.

Aragón, Fernando M, and Juan Pablo Rud, 2016, Polluting industries and agricultural productivity: Evidence from mining in ghana, *The Economic Journal* 126, 1980–2011.

Bi, Xiang, 2017, "cleansing the air at the expense of waterways?" empirical evidence from the toxic releases of coal-fired power plants in the united states, *Journal of Regulatory Economics* 51, 18–40.

Colella, Fabrizio, Rafael Lalive, Seyhun Orcan Sakalli, and Mathias Thoenig, 2019, Inference with arbitrary clustering .

Donaldson, Dave, and Adam Storeygard, 2016, The view from above: Applications of satellite data in economics, *Journal of Economic Perspectives* 30, 171–198.

Gheorghe, Iuliana Florentina, and Barbu Ion, 2011, The effects of air pollutants on vegetation and the role of vegetation in reducing atmospheric pollution, *The impact of air pollution on health, economy, environment and agricultural sources* 29, 241–80.

Gibson, Matthew, 2019, Regulation-induced pollution substitution, *Review of Economics and Statistics* 101, 827–840.

Greenstone, Michael, 2003, Estimating regulation-induced substitution: The effect of the clean air act on water and ground pollution, *American Economic Review* 93, 442–448.

Kondo, Keisuke, 2021, Moransi: Stata module to compute moran's i .

Louwagie, Geertrui, Stephan Hubertus Gay, F Sammeth, and T Ratinger, 2011, The potential of european union policies to address soil degradation in agriculture, *Land degradation & development* 22, 5–17.

Moraes, Regina Maria de, Welington Braz Carvalho Delitti, and José Antonio Proença Vieira de Moraes, 2003, Gas exchange, growth, and chemical parameters in a native atlantic forest tree species in polluted areas of cubatao, brazil, *Ecotoxicology and environmental safety* 54, 339–345.

Moran, Patrick AP, 1950, Notes on continuous stochastic phenomena, *Biometrika* 37, 17–23.

Rai, Prabhat Kumar, 2016, Impacts of particulate matter pollution on plants: Implications for environmental biomonitoring, *Ecotoxicology and environmental safety* 129, 120–136.

Resende Vieira, Fabianna, and Cristiano Christofaro, 2024, Contributions of the vegetation index (ndvi) in water quality prediction models in a semi-arid tropical watershed, *Journal of Arid Environments* 220, 105122.

Tian, George Zhe, Buvaneshwaran Venugopal, and Vijay Yerramilli, 2023, Environmental pollution and business activity: Evidence from toxic chemical spills .

Vashold, Lukas, Gustav Pirich, Maximilian Heinze, and Nikolas Kuschnig, 2025, Downstream impacts of mines on agriculture in africa, *Journal of Development Economics* 103671.

Xiao, Xiangming, Bobby Braswell, Qingyuan Zhang, Stephen Boles, Stephen Frolking, and Berrien Moore III, 2003, Sensitivity of vegetation indices to atmospheric aerosols: continental-scale observations in northern asia, *Remote sensing of Environment* 84, 385–392.

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