# Financial Frictions and Pollution Abatement Over the Life Cycle of Firms*


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**Abstract**

In the microdata and a quantitative heterogeneous firm general equilibrium model, we show a pecking order of capital investment and pollution abatement activities among U.S. public firms: Due to financial constraints, smaller and younger firms invest more in capital and engage less in pollution abatement activities; as they accumulate more net worth, their abatement activities accelerate, and their emission intensity reduces. Financial frictions make environmental regulation sub-optimal at any level by reducing the aggregate welfare gain by 40%. Counterfactuals show that green loan policies are considerably effective in reducing emission intensity even without monitoring because of the pecking order.



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# 1 Introduction

Economic activities often result in excessive corporate pollution, causing damage to human health, property, and nature. However, the 2005 Survey of Pollution Abatement Costs and Expenditures suggests that pollution abatement activities increased disproportionately slower than capital investment over time, and the majority of such abatement activities are in the form of operating costs rather than capital expenditures.[1] Further U.S. Census Bureau and Environmental Protection Agency (EPA) analyses show that such a gap is even more substantial across firms: smaller firms engage much less in pollution abatement activities than larger ones (Becker et al., 2013).

What is causing this pattern? Will it concern economists and policymakers? In this paper, we try to answer both questions empirically and quantitatively. We argue that such a pattern could be mainly attributed to the interplay of financial frictions and returns to scale on corporate policies regarding both capital investment, which increases firm growth, and pollution abatement activities, which reduce regulatory penalties along the life cycle of firm growth.

Our motivation starts with a simple trade-off in corporate decisions. A firm is self-interested and grows under financial constraints and environmental regulations. The firm chooses between capital investment to expand production scale and abatement activities to reduce environmental regulation penalties. The essential differences are that (1) abatement expenditures lack collateralizability compared to capital investment, and (2) the return to abatement expenditures scales with the production size, whereas the return to capital investment diminishes with the production size. When the firm is small and constrained, resources are particularly costly, and spending them on capital generates two returns: increased output and relaxed financial constraints through collateralizability. On the contrary, spending them on pollution abatement only helps to reduce environmental regulation penalties, and such a return is significantly smaller when the production size is small. Therefore, despite stringent environmental regulation and enforcement, the firm may still favor capital investment over abatement activities until it grows out of financial constraints.

We implement our investigation in three steps to demonstrate such a trade-off, explain the underlying mechanism, and explore potential policy implications. In the first step, we exploit rich microdata to examine how the cross-sectional variations in pollution abatement activities, total

[1] According to the Survey, U.S. manufacturing sectors spent \$20.7 billion in pollution abatement operating costs and invested \$5.9 billion in capital to reduce pollution. Also, pollution abatement expenditures even decreased from 1994 to 2005. Pollution abatement capital expenditures totaled \$5.9 billion in 2005 compared to \$10.0 billion in 1994, and pollution abatement operating costs totaled \$20.7 billion compared to \$24.7 billion in 1994, all in 2005 dollars. "In both years, pollution abatement operating costs are less than 1% of total output while pollution abatement capital expenditures are less than 7% and 5% of total new capital expenditures in 1994 and 2005, respectively." Link: www.epa.gov/environmental-economics/pollution-abatement-costs-and-expenditures-2005-survey

toxic emissions, emission intensity, and capital investment relate to financial frictions, illustrating the above trade-off. In the second step, we construct a heterogeneous firm model with financial frictions and life cycle dynamics, which clarifies the underlying mechanism. In the final step, we examine the effects of major environmental policies, including regulatory penalties and green loans, under the existence of financial frictions.

Our first step starts with combining several datasets. We first collect data from the Environmental Protection Agency's Pollution Prevention (P2) database for pollution abatement activities and the Toxic Release Inventory (TRI) database for emission data from 1991 to 2020. A firm's pollution abatement activities and total toxic emissions are measured by aggregating new source reduction activities reported in the P2 database and emissions listed in the TRI database for all facilities owned by a firm each year, respectively. We also find that the majority of reported pollution abatement activities are operating expenditures, which are non-collateralizable, and we focus on these activities in our empirical analyses. We scale a firm's total abatement activities and emissions by its revenue to calculate its abatement and emission intensities, respectively. We then collect financial data for public manufacturing firms from CRSP/Compustat. We assess a firm's financial constraints using size metrics, such as total assets, property, plant, and equipment, employment, etc, the firm's age measures, and other financial constraint indexes.

We find the following intriguing patterns related to financial frictions in the data. Larger, older, and less financially constrained firms disproportionately engage more in pollution abatement activities and exhibit lower emission intensity. In contrast, smaller, younger, and more financially constrained firms invest more in capital and emit more toxic releases, conditional on their production scale. Additional panel regression analysis confirms this pattern. We also estimate firm-level abatement expenditures and find consistent results. Our evidence suggests that firms prioritize expansion through capital investment when they are more financially constrained and then accelerate their pollution abatement to comply with regulations when their financial constraints ease. These findings underscore the significant impact of financial constraints on firms' trade-offs between capital investments and pollution abatement.

In the second step, we construct a heterogeneous firm model with financial frictions and life cycle dynamics that illustrate pollution abatement and capital investment trade-offs. We first analytically characterize the trade-off and graphically visualize the pecking order of capital investment and abatement activities. In the model, unconstrained firms always make the optimal capital and abatement choices by equalizing the marginal return of both decisions to unity, regardless of their net worth. However, constrained firms have limited resources to reach optimal capital and abatement choices. Thus, before they grow out of financial constraints, they always prefer capital investment over abatement activities because the marginal return of the former is higher, as it increases output and relaxes financial constraints through collateralizability.

We then take the model to US firm-level data to match firms' pollution emissions, borrowing, entry-exit dynamics, and pollution penalty in the microdata. The calibrated model reproduces results consistent with our empirical observations and reveals a range of heterogeneity in firm behaviors along with productivity and net worth dimensions. Furthermore, we validate the role of financial frictions using a quasi-natural experiment on relaxing financial frictions and confirm that heavy-polluting firms are subject to higher penalties from environmental litigation.

In the final step, we quantify the aggregate effects of financial frictions on environmental regulation outcomes. In equilibrium, less productive and more financially constrained firms invest less in pollution abatement and are less responsive to environmental regulations. These firms pollute the environment by emitting 13% more in the calibrated economy than a counterfactual frictionless economy. In an economy with financial frictions, increasing the regulatory penalty is less effective at reducing emission intensity. Moreover, financial frictions make regulatory penalties sub-optimal at all levels. Quantitatively, an optimal regulatory penalty would generate 1.8% welfare gain compared to 3% welfare gain in the frictionless economy, suggesting that financial frictions reduce the aggregate welfare gain from the current optimal environmental regulation by about 40%.

Finally, we examine the effects of green loan policies. By allowing firms to borrow green loans for their abatement activities, the government could support all abatement activities with green loans. The shortcoming is that the government cannot monitor the usage of green loans exactly for pollution abatement or other purposes, also known as "financial greenwashing." Nevertheless, even without monitoring, green loan policies could reduce emission intensity through two channels. They directly increase abatement activities and indirectly speed up the growth of constrained, dirty firms. Moreover, even a green loan policy that lends 100% of firms' costs of abatement activities will account for only 0.75% total loans in the economy.

**Related Literature.** This paper contributes to several strands of literature, most importantly the literature on corporate environmental policies with financing constraints and the broader literature on finance and macroeconomics on environmental issues. It also connects to the general literature on ESG. For brevity, we will only discuss the most relevant literature here.

*I. Corporate Environmental Policies with Financing Constraints.* Our paper relates to the large body of work on how financial frictions affect corporate environmental activities. Our major contributions to this literature are twofold. Our empirical evidence complements and extends earlier work focusing on the effects of various financial conditions on emission intensity and total emission (Masulis and Reza, 2015; Fernando et al., 2017; Akey and Appel, 2021a; Xu and Kim, 2022; Cheng et al., 2023; Hartzmark and Shue, 2023). In contrast, our empirical analysis focuses directly on firms' abatement activities and the life cycle perspectives regarding size and age. We also provide causal evidence showing that (1) financial frictions hinder corporate abatement activities, and (2) the return to abatement expenditures scales with the production size.

Our quantitative model is closely related to three recent papers. The first is Lanteri and Rampini (2023), which investigates clean technology adoption in a theoretical setting featuring old vs. new forms of capital and financial constraints. The second is Bellon and Boualam (2023), which predicts that financially distressed firms scale down their production while increasing pollution intensity in an endogenous default model. The third is Aghion et al. (2024), which shows how financial constraints disproportionately affect young firms' ability in green innovation. In these papers, firms choose between two types of capital or innovation to determine their emission intensity. In contrast, we focus on the operating abatement activities as a non-collateralizable corporate policy, highlight the change in choices between capital and operating abatement along the life cycle of firms, and validate such trade-off with microdata.

*II. Government Environmental Policies.* Second, our paper relates to the growing theoretical literature in environmental macroeconomics (Acemoglu et al., 2012; Golosov et al., 2014; Hassler et al., 2016; Acemoglu et al., 2016; Barrage, 2020; Iovino et al., 2021). This literature focuses on general equilibrium analyses of how to efficiently promote the economic transition from dirty inputs to cleaner inputs through the combination of taxes or subsidies; however, they do not account for firms' heterogeneity in financial constraints. We contribute to this literature by introducing a new framework with firms facing different financial constraints during their life cycle. We also show substantial efficiency loss of regulatory penalties due to financial frictions.

Our paper also highlights the conditional effectiveness of environmental policies and regulations and adds new insight into green credit policies. It is well documented that governments' environmental initiatives do not consistently deliver satisfactory outcomes (e.g., Cohen (1987), Baumol and Oates (1988), Magat and Viscusi (1990), and Eskeland and Jimenez (1992)). Our empirical evidence and model suggest that such ineffectiveness could be attributed to financial frictions. While recent literature (Sun et al., 2019; Fan et al., 2021; Dursun-de Neef et al., 2023) finds that the supply of green loans helps reduce pollution emissions, financial greenwashing (Kim et al., 2022; Du et al., 2023; Barbalau and Zeni, 2022), such that the green loan is used in non-abatement activities, is an essential concern on the efficacy of green loan policies in practice.[2] Our model suggests that despite financial greenwashing, green loan policies could still effectively reduce the emissions of financially constrained firms through firm growth.

[2]In another related paper, Li et al. (2024) shows that ex-post measures of financial mechanisms, such as carbon taxes, direct dirty capital towards financially constrained firms, potentially exacerbating emission.

*III. General Trade-offs of Corporate Policies.* Third, our paper contributes to the emerging corporate and macro-finance literature that examines the general trade-offs in corporate policies across multiple strategic dimensions—for example, acquisition vs. internal development (Lee and Lieberman, 2010), innovation vs. advertising (Cavenaile et al., 2025), and capital investment vs. innovation (Ottonello and Winberry, 2024). Our work is closely related to Ottonello and Winberry (2024), which studies how financial frictions influence the allocation between investment and innovation. They show a clear pecking order of investment over innovation before a firm becomes financially unconstrained. Like that paper, we show that most pollution abatement activities are operating expenditures, which are non-collateralizable, leading to a pecking order in which capital investment is prioritized over abatement activities. The key distinction in our analysis is that the return to abatement expenditures scales with the production size, which amplifies the welfare cost of financial frictions by introducing an additional source of inefficiency.

*IV. General CSR and ESG Practices.* Finally, our work contributes to the broad literature on the determinants of corporate social responsibility (CSR) and environmental, social, and governance (ESG) practices. Prior studies have focused on investors' preferences and their attention to environmental issues.[3] In contrast, our analysis examines the firms' optimization behavior under financial constraints and litigation concerns in a general equilibrium setting. Our model highlights that firms may rationally choose not to engage in pollution abatement activities due to financial frictions, leading to higher pollution emissions and potentially higher future litigation risks. Our study rationalizes the marginal investors' green preferences through the disutility of pollution from households that affects future magnitudes of environmental penalties and, therefore, pollution abatement (i.e., green investment) choices, contributing to the discourse on nonfinancial determinants of investment decisions.

**Layout.** The remainder of this paper is structured as follows. Section 2 presents our empirical findings, demonstrating that financially constrained firms are less likely to engage in pollution abatement and are associated with higher emission intensity. In Section 3, we develop a quantitative heterogeneous firm equilibrium model to interpret our findings further. In Sections 4, 5, and 6, we illustrate, validate, and quantify the financial friction mechanism in firm decisions and

[3]Such preferences may be due to social norms, reputation concerns, or liquidity issues. Hong and Kacperczyk (2009) argue that firms in "sin" industries are subject to funding constraints due to social norms. Krüger (2015) show that investors react negatively to negative CSR news. Hong et al. (2019) meanwhile show that food firms of drought-stricken countries underperformed those of countries that do not experience droughts in stock returns, which can be attributed to investors' inattention. Chen et al. (2019) find that investors' social sentiment and attention to CSR explain stock returns. Bansal et al. (2019) propose that households and institutional investors have stronger preferences for socially responsible investment. A growing body of literature documents that both retail and institutional investors are more willing to hold socially responsible firms and funds (Renneboog et al. (2008), Starks et al. (2017), Riedl and Smeets (2017), Dyck et al. (2019), Hartzmark and Sussman (2019), Cao et al. (2019), and Gibson et al. (2020)). Hsu et al. (2021) shows that state ownership enhances firms' environmental engagement.

the associated aggregate effects. Section 7 shows the policy implications of regulations and green loans. Finally, we conclude our paper in Section 8.

# 2 Data and Stylized Facts

In this section, we outline our data sources and examine how firms' pollution abatement and investment activities vary by different proxies of financial frictions. Our data analyses shed light on the determinants of corporate decisions in pollution abatement activities and motivate us to build a quantitative model aligned with these empirical findings.

## 2.1 Datasets

Our analysis utilizes a comprehensive dataset that includes firms listed in the TRI, P2, ECHO, NETS, and CRSP/Compustat databases, focusing specifically on those with TRI records.[4] Additionally, macroeconomic data is from the Federal Reserve Economic Data (FRED). We briefly discuss data sources and variable construction and leave all details to the Internet Appendix I.

**Toxic Release Inventory (TRI):** Our study utilizes the Toxic Release Inventory (TRI) database, managed by the U.S. Environmental Protection Agency (EPA). The TRI requires certain facilities to report their emissions of toxic chemicals to enhance public access to environmental data. We focus on toxic emissions reported by manufacturing facilities, starting in 1991, due to the limited coverage of earlier data. The TRI data provide detailed information on toxic emissions, including the type and quantity of TRI-listed chemicals released (production wastes, total releases, onsite releases, and land disposal), facility location, and the parent company.[5]

**Pollution Prevention (P2):** We then incorporate information from the EPA's P2 database, which documents facilities' efforts to reduce pollution at the source. Facilities report new source reduction activities in eight categories: raw material modifications, product modifications, cleaning and degreasing, surface preparation and finishing, process modifications, spill and leak preven-

[4]We link facility-level data from TRI, P2, and NETS to firm-level financial data in CRSP/Compustat using facility identifiers and a manual verification process, as outlined by Chen, Hsieh, Hsu, and Levine (2022) and Hsu, Li, and Tsou (2023), ensuring accurate matching across databases.

[5]It is important to note that while the TRI and P2 databases provide valuable information, they are not without limitations. One major limitation is that the data is self-reported by facilities, which may result in some reporting errors or failures to report. However, the EPA conducts quality checks and analyses to ensure report accuracy and correct mistakes. In fact, according to a quality check report by the EPA in 1998 (i.e., EPA (1998)), most industries reported errors within a 3% range. Furthermore, researchers such as Akey and Appel (2019, 2021b) and Kim and Kim (2020) suggest that the potential criminal or civil penalties, as well as reputation costs associated with misreporting to the EPA, incentivize facilities to provide accurate data and maintain strong data quality in the TRI database.

tion, inventory control, and good operating practices. There are 49 distinct activities across these eight categories. The Internet Appendix in Table IA.1 provides details on these activities.

**Enforcement and Compliance History Online (ECHO):** We extract data on environmental litigation from the Enforcement and Compliance History Online database, which records the EPA's administrative and judicial enforcement actions. Covering the period from 1991 to 2022, this database includes details on penalties and the frequency of civil cases related to environmental violations by firms. We use this database to validate our mechanism.

**National Establishment Time-Series (NETS):** We then leverage the National Establishment Time-Series (NETS) database, which offers a comprehensive record of U.S. establishments since 1990. This database provides detailed information about each facility, including location, size, and economic activity, and is crucial for tracing the operational history of firms without survivorship bias. The accuracy and breadth of NETS data support a robust analysis of production activities and facilitate the linkage of TRI and Compustat data.

**CRSP/Compustat Firm-level Data:** The CRSP/Compustat database includes a wide range of financial and operational details for publicly listed U.S. firms. It allows us to assess firms' financial positions, investment behaviors, and profitability. This dataset's extensive coverage and longitudinal nature enable us to control for firm-specific fixed effects, offering a nuanced understanding of the interplay between corporate finance and environmental policy.

## 2.2 Abatement Activity Measures

Our variables of focus are pollution abatement activities (from P2) and emissions (from TRI) at the facility/firm level. Unlike emissions that are well documented in the literature, abatement activities are barely directly studied in economics and finance. We classify each pollution abatement activity as an operating expense or a capital investment. In the P2 dataset, there are 49 distinct activities across these eight categories of facility-level new source reduction activities, among which most are non-collateralizable operating expenses. (See Table IA.1 in the Internet Appendix for detailed descriptions.) We use a score-based classification. We first assign a score from 10 to 1 based on an abatement activity's input requirements, process complexity, and infrastructure changes. A high score (10-9) indicates that the activity is an operating expense, as it is procedural, easy to implement, and requires little to no infrastructure changes (e.g., substituting materials or modifying operational practices.) A moderate score (8-7) suggests some minor capital investment (e.g., small equipment modifications or workflow adjustments), but does not require significant capital expenditures. A lower score implies that the abatement activity is more likely to be classified as a capital investment, requiring substantial capital commitment. Activities scoring 6-5 involve moderate investments and process changes, possibly including new machinery or upgrades that improve operational efficiency. A score of 4-3 represents activities that require significant infrastructure upgrades, such as modifying production layouts or integrating advanced monitoring systems, though not necessarily replacing entire systems. The lowest scores (2-1) are assigned to activities that demand full system replacements or high capital investment (e.g., installing new process equipment, overhauling production lines, or implementing major technological upgrades).

This scoring procedure ensures that each new abatement activity is systematically classified based on its implementation complexity, enabling us to distinguish between routine expenses and capital investments effectively. We then assign weights for each activity as follows: we assign a weight of 1 to abatement activities with scores above 7, 0.5 to those with scores between 4 and 6, and 0 to those with scores below 3. Finally, we aggregate the weighted new abatement activities across all facilities to the firm level, which is our measure for *operating* abatement activities (Abate) in annual frequency.

## 2.3 Sample and Summary Statistics

Table 1 reports pooled summary statistics with a total of 20, 518 firm-year observations with non-missing pollution abatement. We explore the impact of financial constraints on firms' pollution abatement efforts through detailed panel regressions and analysis of Abate as described in Section 2.1. We measure raw emissions (Emission) as the total pollutant releases, measured in pounds, across all of a firm's plants in a given year. Emission intensity (Emission/Sales) is then calculated by normalizing raw emissions by the firm's sales revenue, expressed in millions of dollars. We construct many proxies for financial constraints from Compustat, including net worth (N).[6]

## 2.4 The Pecking Order of Abatement and Capital

We first explore the heterogeneity of firm growth by examining how operating abatement activities and capital investment vary with a key metric used to proxy firm size and financial constraint: net worth (N). Additionally, we consider firm age and other financial constraint measures, as detailed in Section II of the Internet Appendix.

[6]Net worth (N) is the sum of sales revenue (SALE) and plant, property, and equipment (PPET) minus net debt issuance as in Eisfeldt and Muir (2016). Alternative variables used to proxy for financial constraints include total assets (AT), capital (K), and the number of employees (EMP). B/M is the ratio of book equity to market capitalization. I/K represents the investment rate and is calculated as capital expenditure (item CAPX) divided by property, plant, and equipment (item PPENT). ROA stands for return on assets and is calculated as operating income after depreciation (item OIADP) scaled by total assets. Book leverage is the ratio of total liability (item DLC + DLTT) to total assets.

**Table 1: Summary Statistics**

| | Mean | Std | P5 | P25 | Median | P75 | P95 | Observations |
|---|---|---|---|---|---|---|---|---|
| Abate | 3.70 | 13.06 | 0.00 | 0.00 | 0.00 | 2.50 | 16.50 | 20,518 |
| Emission | 1,764,524 | 10,707,621 | 0.00 | 2,526.9 | 40,311 | 365,699 | 7,284,471 | 20,518 |
| Emission/Sales | 1,736.02 | 30,059.55 | 0.00 | 2.14 | 32.56 | 226.59 | 2,439.21 | 20,039 |
| Net Worth | 13,232.92 | 39,512.55 | 83.64 | 615.53 | 2,645.71 | 10,136.93 | 53,436.94 | 10,387 |
| Total Asset | 8,803.51 | 33,566.03 | 57.62 | 349.70 | 1,327.27 | 5,269.51 | 36,865.67 | 20,055 |
| Capital | 2,871.07 | 10,407.94 | 12.21 | 83.75 | 331.67 | 1,478.71 | 12,970.55 | 20,055 |
| Employee | 18.60 | 68.51 | 0.30 | 1.57 | 4.90 | 14.4 | 73.53 | 20,438 |
| Book-to-market Ratio | 0.65 | 0.66 | 0.14 | 0.32 | 0.52 | 0.81 | 1.55 | 20,448 |
| Return on Asset | 0.18 | 0.12 | 0.05 | 0.11 | 0.16 | 0.22 | 0.40 | 20,401 |
| Investment Rate | 0.13 | 0.09 | 0.01 | 0.09 | 0.13 | 0.17 | 0.26 | 20,495 |
| Leverage | 0.26 | 0.16 | 0.00 | 0.14 | 0.25 | 0.37 | 0.54 | 20,473 |

Notes: This table presents summary statistics for the firm-year sample. We define pollution abatement activity as the total number of new source reduction projects implemented by a firm at the facility level within a given year. Specifically, Abate represents a firm's total pollution abatement activities, aggregated across all its facilities to the firm level, as defined by the weighting approach described in Section 2.1. We measure raw emissions (Emissions) as the total pollutant releases (measured in pounds) across all of a firm's plants in a given year. Emission intensity (Emission/Sales) is then calculated by normalizing raw emissions by the firm's sales revenue, expressed in millions of dollars. Net worth (N) is defined as the sum of sales revenue (SALE) and plant, property, and equipment (PPENT) minus net debt issuance (e.g., Eisfeldt and Muir (2016)) and is adjusted for inflation using the Consumer Price Index (CPI) and reported in 2009 million USD. Total assets (AT) are CPI-adjusted. Property, plant, and equipment (K) are also CPI-adjusted. Employee (EMP) is the number of employees. B/M is the ratio of book equity to market capitalization. I/K is capital expenditures (item CAPX) divided by property, plant, and equipment. Return on assets (ROA) is operating income after depreciation (item OIADP) scaled by total assets. Book leverage (Lev) is the summation of current liabilities (item DLC) and long-term debt (item DLTT) scaled by total assets. We report the pooled mean, standard deviation (Std), $5^{th}$ percentile (P5), $25^{th}$ percentile (P25), median, $75^{th}$ percentile (P75), and $95^{th}$ percentile (P95). Observations denote the valid number of observations for each variable. The sample period is 1991 to 2020 at an annual frequency.

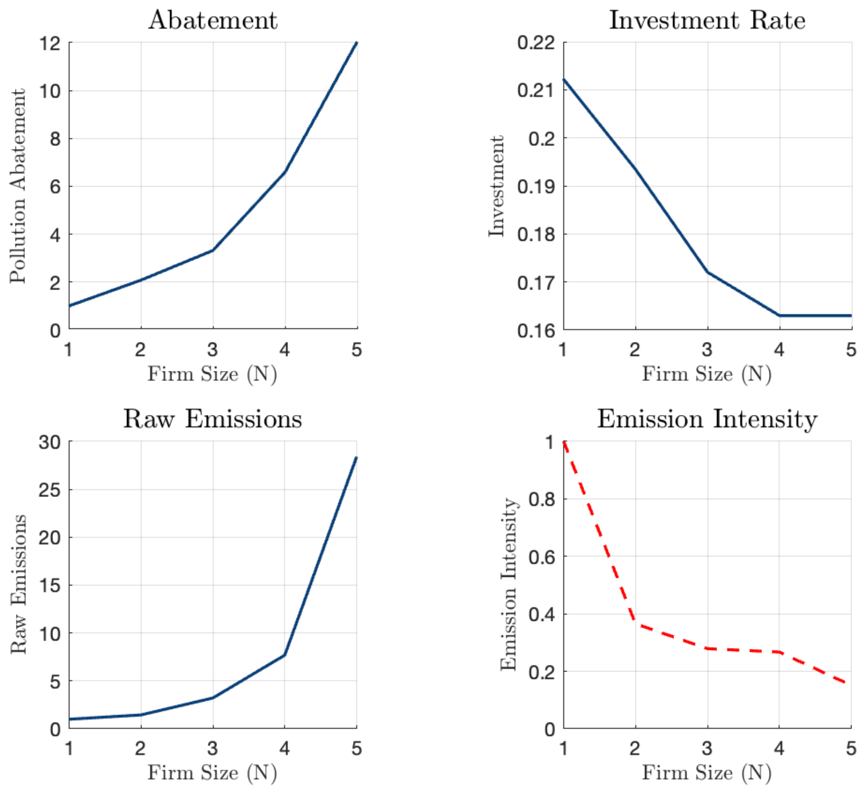
Our analysis is implemented in two ways. The first method categorizes firms into quintile groups based on their net worth and then compares the average characteristics of each group. The second method employs panel regressions to examine the relationship between net worth and pollution abatement, emission intensity, and physical capital investment.

### 2.4.1 The Pecking Order in Quintile Groups

We first discuss quintile groups' average characteristics. We first sort all sample firms into five groups by their net worth from low to high by each variable in each year. As a result, we construct breakpoints for quintile portfolios for each year. We then assign all firms in year $t$ into quintile groups. The low (high) quintile group contains firms with the lowest (highest) net worth in year $t$. After forming the five sorted groups (low to high), we calculate the time-series average of cross-sectional means of each firm characteristic in each group.

Figure 1 shows that larger firms are more active in pollution abatement (Abate). Meanwhile,

**Figure 1. Visualizing the Pecking Order in Firm Size**




Notes: These figures visualize the pecking order in firms' abatement activities, investment rate, raw emissions, and emission intensity. Raw values are presented for brevity, with the lowest quintile normalized to 1 in each panel, except for the investment rate panel.

larger firms are less active in capital investment (I/K), which is well-known in the literature.[7] However, although they have higher total emissions, their emission intensity (the red dashed line) is much lower than that of their smaller counterparts. These patterns are consistent across different measures of firm size, including total assets, capital stock, and number of employees, as detailed in Section II of the Internet Appendix. These patterns suggest a nuanced relationship between abatement activity and financial constraints, which will be furtehr examined in the next subsection.

[7] See the I/K ratio as in Ottonello and Winberry (2024). Smaller firms display higher investment rates (I/K), which is consistent with Almeida and Campello (2007, 2010). Conversely, the book-to-market ratio (B/M) and book leverage (Lev) show little variation across the groups sorted by net worth, total assets, capital, and employees.

### 2.4.2 The Pecking Order in Panel Regressions

We further validate the above pecking order of abatement activities and capital investment with panel regressions. Later in our model, net worth directly affects the shadow price of external finance – this concept is often approximated in corporate finance literature through various size-related metrics. Our analysis confirms this pecking order of firm growth, as demonstrated in Table 2, which presents the estimation results from the following regression:

$$o_{j,t} = \xi_j + \xi_t + b \log s_{j,t} + \varepsilon_{j,t}, \tag{1}$$

where $o_{j,t}$ represents outcomes such as abatement activity (Abate), emission, emission intensity, and investment levels of firm $j$ in year $t$; $\xi_j$ and $\xi_t$ denote firm- and year-fixed effects; $s_{j,t}$ denotes the size-related metric: net worth; and $\varepsilon_{j,t}$ captures residuals. The estimated coefficient $\hat{b}$ indicates how outcomes fluctuate with net worth, with each variable $\log s_{j,t}$ being standardized over the entire sample to make the units of the coefficient $\hat{b}$ easier to interpret. Our statistical inferences are based on standard errors clustered at the firm level.

We present the estimation results using net worth as a measure of $s_{j,t}$ in Panel A of Table 2. Column 1 indicates that a one-standard-deviation increase in net worth boosts pollution abatement by approximately 21%, highlighting the size-dependent relationship between net worth and pollution abatement. Additionally, the results show a contrast across specifications: Column 2 suggests that higher net worth is associated with increased emissions, whereas Column 3 indicates a substantial reduction in emission intensity. Specifically, a one-standard-deviation increase in net worth corresponds to a 93% increase in raw emissions (Emission) but an 86% decrease in emission intensity relative to production (Emission/Sales). This pattern is consistent with Figure 1. Finally, Column 4 suggests that increasing net worth corresponds to a lower investment rate, aligning with decreasing returns to scale in firm growth. This finding supports the idea that financially unconstrained firms experience lower returns on capital investment.

Consistent results are also found in Panels B to D based on total assets, capital (property, plant, and equipment, and the number of employees, respectively. Our regression results, in which firm- and time-specific factors have been controlled for, offer strong empirical evidence for the pecking order in abatement activities and capital investment.

## 2.5 Additional Results on the Pecking Order

We show additional evidence for the pecking order based on imputed abatement expenditures, various age measures, other financial indicators, capital-intensive abatement activities, and two-

**Table 2: The Peking Order by Various Size Measures**

| | (1) Log (1+Abate) | (2) Log (1+Emission) | (3) Log (1+Emission/S) | (4) Investment Rate |
|---|---|---|---|---|
| | | **Panel A: Net Worth** | | |
| Log N | 0.21*** | 0.93*** | -0.86*** | -0.02*** |
| [t] | [3.03] | [3.13] | [-4.85] | [-2.71] |
| Observations | 10,380 | 10,380 | 10,376 | 10,317 |
| R-squared | 0.73 | 0.85 | 0.86 | 0.56 |
| | | **Panel B: Total Assets** | | |
| Log AT | 0.13*** | 0.87*** | -0.66*** | -0.02*** |
| [t] | [2.95] | [4.60] | [-5.64] | [-2.97] |
| Observations | 20,055 | 20,055 | 20,039 | 19,938 |
| R-squared | 0.68 | 0.82 | 0.83 | 0.49 |
| | | **Panel C: Capital** | | |
| Log K | 0.13*** | 0.82*** | -0.57*** | -0.04*** |
| [t] | [2.92] | [4.49] | [-5.25] | [-6.53] |
| Observations | 20,052 | 20,052 | 20,039 | 19,938 |
| R-squared | 0.68 | 0.82 | 0.83 | 0.50 |
| | | **Panel D: Employee** | | |
| Log EMP | 0.18*** | 0.76*** | -0.54*** | -0.02*** |
| [t] | [4.43] | [4.44] | [-5.17] | [-4.05] |
| Observations | 20,438 | 20,438 | 19,963 | 20,323 |
| R-squared | 0.68 | 0.82 | 0.83 | 0.49 |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster SE | Yes | Yes | Yes | Yes |

Notes: This table reports univariate regressions of firms' pollution abatement, emission, emission intensity, and investment on the logarithm of the net worth (N) in Panel A, total assets (AT) in Panel B, capital (K) in Panel C, and employee (EMP) in Panel D, as well as firm and year fixed effects. All independent variables are normalized to zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. *t*-statistics based on standard errors clustered at the firm level are reported with ***, **, and * indicating significance at the 1, 5, and 10% levels. The sample period is from 1991 to 2020.

dimensional sorting considering productivity. All detailed results are available in Section II of the Internet Appendix.

**Pecking Order on Imputed Abatement Expenditures** We address additional concerns regarding the measures of abatement activities and their costs. Since no direct costs are reported in any datasets of each abatement activity, the only validation we could rely on is the imputation from the 2005 PACE survey. We then implement the empirical analysis to examine the relationship with firm size and find consistent results.

**Pecking Order on Age and Financial Indicators** We show additional pecking order evidence on firm age measures using founding/incorporation ages in Loughran and Ritter (2004), Jovanovic and Rousseau (2001), and WorldScope and Compustat age. The sorting patterns are noisier in firm age measures, but still qualitatively consistent with our main results. We also show the results for financially constrained indicators using both Whited and Wu (2006) and Hadlock and Pierce (2010). The pecking order between abatement activities and capital investment always holds.

**Pecking Order in Two Dimensions** We also show additional pecking order evidence in two dimensions: size/age/financial indicators and productivity. The pecking order between abatement activities and capital investment holds across all measures within each productivity group.

**Pecking Order on Capital Investment related to Abatement** We also show that such a pecking order exists for abatement activities that are more capital-related and less operational. To do so, we replace operating abatement activities with capital–related abatement activities as the dependent variable in equation (1). Section I.2 of the Internet Appendix provides details on the classification of capital-related abatement activities. We find that the coefficients on firm size remain significantly positive for this outcome variable; nevertheless, their economic magnitude is smaller than that based on operating abatement activities. Our results suggest that although capital-related abatement activities could be used as collateral, it could still be harder to finance, consistent with Lanteri and Rampini (2023).

# 3 The Model

We build a heterogeneous-firm general equilibrium model consisting of a production block with heterogeneous firms and a general equilibrium block with a representative family of households. Time is discrete and infinite.

## 3.1 Environment

**Production and Pollution** There is a unity mass of firms, indexed by $j$, that produce output $y_{jt} = z_{jt}k_{jt}^{\alpha}$, where $z_{jt}$ denotes firm $j$'s productivity at time $t$ and $\alpha < 1$ stands for a decreasing return to scale. Production creates a byproduct: pollution emission $e_{jt} = y_{jt} \times \bar{e}/(1+\gamma a_{jt})$, which is an increasing function of the production scale $y_{jt}$ and emission intensity $\bar{e}/(1+\gamma a_{jt})$. Emission intensity is a function of $\bar{e}$ that indicates the base emission intensity without any abatement activities, $a_{jt}$ which stands for abatement activities implemented in the prior period, and $\gamma$ as the transmission elasticity from abatement to emission reduction (Andreoni and Levinson, 2001).

**Firm Dynamics** Firms face two fundamental idiosyncratic shocks: (1) productivity shocks and (2) exit risk shocks. First, idiosyncratic productivity $z_{jt}$ follows a log-normal AR(1) process $logz_{jt+1} = \rho logz_{jt} + \epsilon_{jt+1}$. Second, at the beginning of each period, firms face a fixed probability of exit $\pi_d$. New entrants replace exiting firms with productivity, emission intensity, and net worth drawn from some distribution $\Phi^0(z, n)$ with the same $n_0$ and equilibrium distribution of $z$.

**Capital Investment and Abatement Activities** Firms that will continue into the next period spend resources on physical investment and abatement activities. Capital investment expenditures $i_{jt+1}$ accumulate into more capital in the next period $k_{jt+1} = (1-\delta_k)k_{jt} + i_{jt+1}$ which enlarges future production. Abatement activities $a_{jt+1}$ yield a lower emission intensity in the next period.

**Financial Frictions** Firms have two sources of finance for their physical investment and abatement activities, both subject to friction. First, firms can borrow externally subject to the collateral constraint $b_{jt+1} \leq \theta_k k_{jt+1}$ as in Khan and Thomas (2013). Second, firms can use their internal resources but not raise new equity through negative dividend payments ($d_{jt+1} \geq 0$).

**Pollution Regulation Penalties** Firms care about pollution emissions because they may cause implicit and explicit consequences once their externalities are visibly spotted. Implicitly, they may face penalties for losing the consumer base due to a bad reputation for social responsibility. Explicitly, they may face government regulations and litigation penalties. We model such penalties as an implicit tax $\tau_{jt}e_{jt}$, as in Shapiro and Walker (2018), but allow the pollution penalty to differ by firms with idiosyncratic shocks. Without loss of generality, we assume that $\tau_{jt}$ follows a log-normal distribution with the actual realized average penalty $\mu_\tau$ and volatility $\sigma_\tau$.

## 3.2 Recursive Problem and Equilibrium

**Recursive Problem for Firms** The firm's optimization problem is written recursively, where the state variables are the firm's total factor productivity $z_{jt}$ and net worth $n_{jt}$. The expression gives the net worth $n_{jt}$:

$$n_{jt} = z_{jt}k_{jt}^{\alpha} + (1-\delta)k_{jt} - \tau_{jt}e_{jt} - b_{jt}, \tag{2}$$

where $k_{jt}$, $b_{jt}$, and $e_{jt}$ are predetermined from the last period decision, but $\tau_{jt}$ represents the realized pollution penalty tax rate. The term $z_{jt}k_{jt}^{\alpha}$ represents the firm's production revenue, $(1-\delta)k_{jt}$ represents the depreciation-adjusted capital stock, $\tau_{jt}e_{jt}$ represents the pollution penalty, and $b_{jt}$ represents the cost of borrowing.

Let $v(z_{jt}, n_{jt})$ denote the equity value function before forced exiting; it can be expressed as:

$$v(z_{jt}, n_{jt}) = \max_{a_{jt+1}, k_{jt+1}, b_{jt+1}} d_{jt} + \frac{1}{1+r_t} \mathbf{E_t} \left[ \pi_d n_{jt+1} + (1-\pi_d) v(z_{jt+1}, n_{jt+1}) \right] \tag{3}$$

subject to

$$d_{jt} \equiv n_{jt} - k_{jt+1} - a_{jt+1} + \frac{b_{jt+1}}{1+r_t} \geq 0, \tag{4}$$

$$b_{jt+1} \leq \theta_k k_{jt+1}, \tag{5}$$

$$0 \leq a_{jt+1}, \tag{6}$$

$$n_{jt+1} \equiv z_{jt+1} k^{\alpha}_{jt+1} + (1-\delta) k_{jt+1} - \tau_{jt+1} e_{jt+1} - b_{jt+1}, \tag{7}$$

where $r_t$ is the real interest rate, $z_{jt+1}$ follows an AR(1) productivity process, $\tau_{jt+1}$ follows the log-normal i.i.d. process, and the expectation $\mathbf{E_t}$ is taken over the realization of $z_{jt+1}$ and $\tau_{jt+1}$.

**Representative Households** We assume a unit measure continuum of identical households that own all the firms with an expected utility given by

$$W = \mathbf{E_0} \sum_{t=0}^{\infty} \beta^t \Big( log(C_t) - \zeta log(E_t) \Big)$$

where $\beta$ is the time discount rate and $\zeta$ is a constant that captures the disutility of pollution emission (Hsu et al., 2023). The households face a budget constraint given $C_t + \frac{1}{1+r_t} B_t \leq B_{t-1} + \Pi_t + \Gamma_t$, where $r_t$ represents the risk-free interest rate during the period from $t$ to $t+1$. $B_t$ denotes the quantity of one-period risk-free bonds that households hold. Additionally, households receive capital income $\Pi_t$ from all the firms and $\Gamma_t$ pollution taxes from the government. Households bear the disutility of pollution by internalizing the negative externalities of it from the total pollution emission $E_t = \sum(e)$. The optimality of intertemporal saving decisions implies the Euler equation, which determines the real interest rate $\frac{1}{1+r_t} = \frac{\beta U_c(C_{t+1}, L_{t+1})}{U_c(C_t, L_t)} = \beta \left( \frac{C_{t+1}}{C_t} \right)^{-1}$.

**Equilibrium Definition** The equilibrium is a set of value functions $v_t(z, n)$; decision rules $k'_t(z, n)$, $b'_t(z, n)$, and $a'_t(z, n)$; a pollution penalty structure $\{\mu_\tau, \sigma_\tau\}$; the measure of firms $\mu_t(z, n, \tau, k, b)$; and real interest rate $r_t$ such that (i) all firms optimize, (ii) households optimize, (iii) the distribution of firms is consistent with decision rules, and (iv) the final good market clears, i.e., $Y = C + I + A$, where $A = \sum(a')$ and $I = \sum(k') - (1-\delta)\sum(k)$.

# 4 The Pecking Order in Our Model

We now show that our model generates a pecking order of firm investments in capital and abatement consistent with the data. We also discuss the key economic forces governing this pecking order, motivating how we calibrate the model in the quantitative part below.

## 4.1 Characterizing Decision Rules

**Key Differences Between Pollution Abatement Activities and Capital Investment** There are two key differences between the profit-generating capital investment choice $k'$ and the pollution-reducing abatement activity choice $a'$ in our model:

(1) *Collateralizability:* Capital investment could increase the collateralizability of firms to relax financial constraints, but investment in pollution abatement cannot.

(2) *Return-to-scale:* Capital investment exhibits decreasing return to scale in production, but investment in pollution abatement is increasing return to scale in production.

**Characterizing Decision Rules** To characterize the firm's decision rules, we first note that the marginal cost of spending resources on either capital or abatement is given by the firm's shadow value of net worth, $\frac{\partial v_t(z,n)}{\partial n} = 1 + \lambda_t(z,n)$, where $\lambda_t(z,n)$ is the Lagrange multiplier on the non-negative constraint on dividends and is also known as the financial wedge. It represents the marginal value of keeping resources inside the firm and is the opportunity cost of spending those resources on capital or abatement expenditures instead. First, the shadow price of issuing equity $\lambda_t(z,n) > 0$ when firms are not currently binding on borrowing constraint $b' < \theta_k k'$ but are potentially constrained and issuing zero dividends. Second, the shadow price of issuing equity $\lambda_t(z,n) = \mu_t(z,n)$, where $\mu_t(z,n)$ is the shadow price of additional borrowing when the collateral constraint is binding. Therefore, $\lambda_t(z,n)$ measures how financial frictions affect the marginal costs of both types of investments. We could derive the following Proposition 1, which extends a similar result from Sui (2020) and Ottonello and Winberry (2024) on the trade-off between investment and innovation of financially constrained firms.

**Proposition 1.** *Consider a firm at time $t$ that is eligible to continue into the next period and has idiosyncratic productivity $z$ and net worth $n$. For any given values of $\{z,n\}$, the firm's optimal decision can be characterized by one of the following cases.*

*(i)* ***Unconstrained:*** *If $n \geq \bar{n}_t(z)$, then the firm pays positive dividends $d > 0$ and the financial wedge on no-equity-issuance constraint $\lambda_t(z,n) = 0$.*

*(ii)* ***Constrained and binding:*** *If $n < \underline{n}_t(z)$, then the firm pays zero dividends $d = 0$, the collateral constraint is binding $b' = \theta_k k'$, and the financial wedge is positive $\lambda_t(z,n) > 0$.*

*(iii)* ***Constrained but not binding:*** *If $\underline{n}_t(z) < n < \bar{n}_t(z)$, then the firm pays zero dividends $d = 0$, the collateral constraint is not binding $b' < \theta_k k'$, and the financial wedge is positive $\lambda_t(z,n) > 0$.*

*In all three cases, the optimal choices for capital investment $k'_t(z,n)$, abatement activities $a'_t(z,n)$, and debt financing $b'_t(z,n)$ solve the following first-order conditions*

$$\begin{aligned}1 + \lambda_t(z,n) =& \theta_k \mu_t(z,n) + \frac{1}{1+r_t}\mathbf{E}_t\Big[ \big(\pi_d + (1-\pi_d)(1+\lambda_{t+1}(z',n'))\big) \times \\ & \left(\left(1 - \frac{\tau' \bar{e}}{1+\gamma a'}\right) MPK(z',k') + (1-\delta)\right)\Big]\end{aligned} \tag{8}$$

$$1 + \lambda_t(z,n) \geq \frac{1}{1+r_t}\mathbf{E}_t\Big[ \big(\pi_d + (1-\pi_d)(1+\lambda_{t+1}(z',n'))\big) \frac{\gamma \tau' \bar{e}}{(1+\gamma a')^2} z' k'^{\alpha} \Big] \tag{9}$$

$$k' + a' = n + \frac{b'}{1+r_t} \ \ if \, \lambda_t(z,n) > 0; otherwise, b'(z,n) = b^*_t(z), \tag{10}$$

*where $MPK(z',k') = \alpha z' k'^{\alpha-1}$ is the marginal product of capital, $\lambda_t(z,n)$ is the Lagrange multiplier, also known as the financial wedge, on the no equity issuance constraint $d \geq 0$, and $\mu_t(z,n)$ is the multiplier on the collateral constraint $b' \leq \theta_k k'$. The proof is in the Internet Appendix III.*

The first part of Proposition 1 describes three regimes of financial conditions, which are similar to Khan and Thomas (2013). Characterizing the three regimes simplifies the solution of the model numerically and also helps to illustrate the mechanism of the trade-off between capital and abatement expenditures through financial constraints more easily. The second part of Proposition 1 characterizes the capital investment and abatement decisions for any of these three types of firms. Equations (8) and (9) are the first-order conditions for capital and abatement expenditures, respectively. Both left-hand sides denote the unit cost of resources, including the financial wedge. Our focus is on the right-hand side of both equations. For capital investment, the marginal benefit is the discounted expected marginal product of capital in the future and the marginal collateral benefit provided by additional capital. For abatement expenditures, the marginal benefit is only the discounted expected marginal reduction in regulatory penalty. The first-order condition may not equal abatement expenditures due to the non-negative abatement $a' \geq 0$.

We have two observations in general. The first is that firm size already matters for abatement expenditures even without considering the financial wedges. Considering the abatement decision as given, the marginal benefit increases with firms' capital stock even without considering financial wedges. This is because firms' production scales the emission reduction benefit, making it more beneficial for larger firms to do abatement – a pattern that is fairly intuitive and fits the reality that larger firms face greater scrutiny and incur greater reputation costs. Second, when firms are financially constrained ($\lambda_t(z, n) > 0$), abatement expenditure is even less attractive because the marginal benefit of abatement investment decreases faster than the marginal benefit of capital investment in scale. Since capital and abatement expenditure must be financed from internal resources or new borrowing, constrained firms prefer more capital investment.

## 4.2 Visualization of the Pecking Order

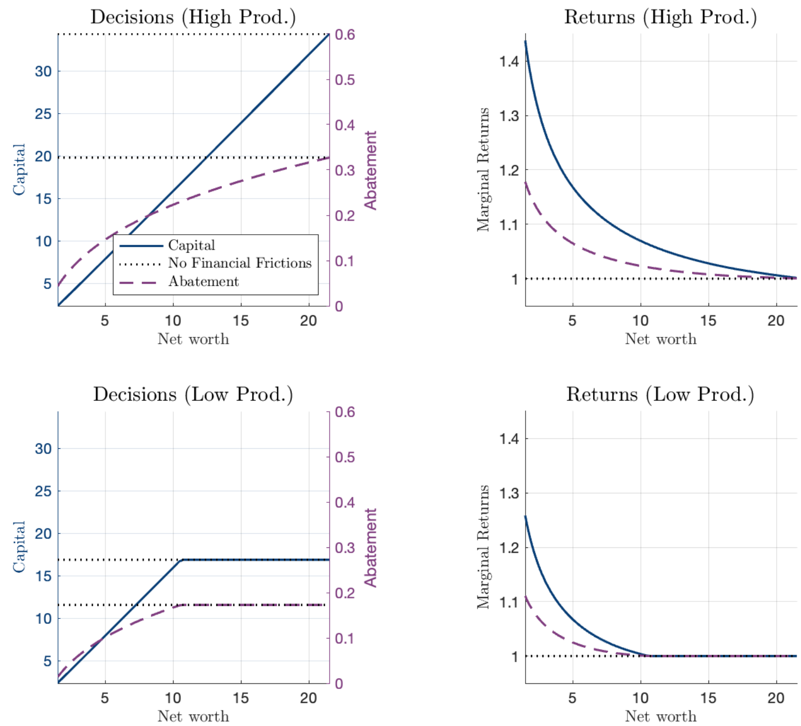
To illustrate the pecking order, we visualize the decision rules in Figure 2 and the realized total emission and emission intensity in Figure 3 to illustrate our model's key economic trade-offs and consequences. These plots are generated with our calibrated parameters in the following quantitative section, but the properties hold for a wide range of the parameter space.

The left panels of Figure 2 show the capital and abatement policies as a function of net worth for different productivity levels. The right panels plot the returns associated with both activities relative to unity, specifically the right-hand side of the respective first-order conditions (8) and (9). We show the pecking order in two dimensions to be consistent with our data. The productivity levels (*High Prod* for upper plots and *Low Prod* for lower plots) are fixed in these plots to illustrate how the decision rules depend on relative financial constraints reflected by net worth.

**The Pecking Order in the Model** Firms' pecking order in the model can be summarized in two regions of net worth for a given level of productivity $z$. The division of two areas is based on whether the firms are financially constrained. In our model, there are two indicators of when a firm is financially constrained (i.e., the first region): (1) the firm is below its optimal scale of capital given its productivity (in the left panels, any capital stock below the dotted black lines of "No Financial Frictions"), and (2) the firm has the marginal returns of capital investment and abatement expenditure above unity (in the right panels, marginal returns above the dotted black lines).

In the first region, the firm is below its optimal scale of capital, so it tends to spend more resources to build up capital stock and choose a lower abatement level, as shown in the left panels of Figure 2. Such a choice is optimal because the marginal return to capital lies strictly above the marginal return to abatement. As the firm keeps growing and accumulating more net worth, it can accumulate more capital. This has two effects on the returns of capital. First, it drives down capital's marginal return due to the diminishing marginal product of capital. Second, it improves the total value of collateral and lowers the shadow cost of collateral constraint, making the firm

**Figure 2. Abatement Activities and Capital Investment over Size and Productivity**



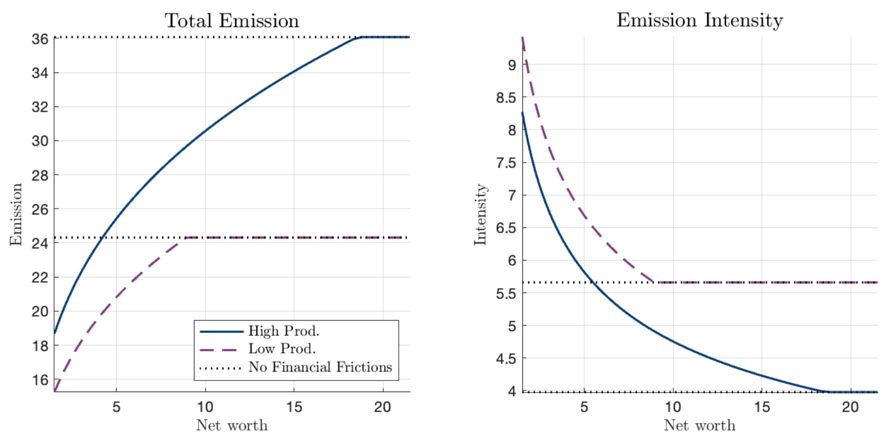

Notes: These figures plot firms' abatement activities and capital investment decisions over firms' size, measured in net worth. The blue solid line denotes capital, the purple dashed line denotes abatement, and the black dotted line denotes the case of "No Financial Frictions." The left panels plot capital expenditures $k_{t+1}(z,n)$ (left axis) and abatement expenditures $a_{t+1}(z,n)$ (right axis) of the calibrated model for fixed high $z^h$ and low $z^l$, respectively. The right panel plots the return to these activities, defined as the RHS of Euler Equations (8) and (9). "No financial frictions" refers to the model in which all firms follow the unconstrained policies $k'^*(z)$ and $a'^*(z)$ from Proposition 1.

less financially constrained. The firm, therefore, has started to engage in more abatement activities to avoid pollution regulation penalties for two reasons: a lower marginal cost of abatement and a larger production scale that increases the penalty. However, as shown in the right panels of Figure 2, the return to capital (in the solid line) is always higher than the return to abatement (in the dashed line) because the firm only grows its size by accumulating capital.

When the firm accumulates sufficient net worth, it enters the second region and becomes financially unconstrained. Conditional on its specific productivity level, a firm in this region has reached its optimal scale of capital conditional on productivity. The shadow cost of finance $\lambda_t(z,n) = 0$, and the returns to capital investment and abatement expenditures both equal unity. This implies that the firm's abatement activities are finally unrelated to its financial conditions.

We show how the realization of total emission and emission intensity changes over firms' net

**Figure 3. Realized Pollution Measures over Size and Productivity**



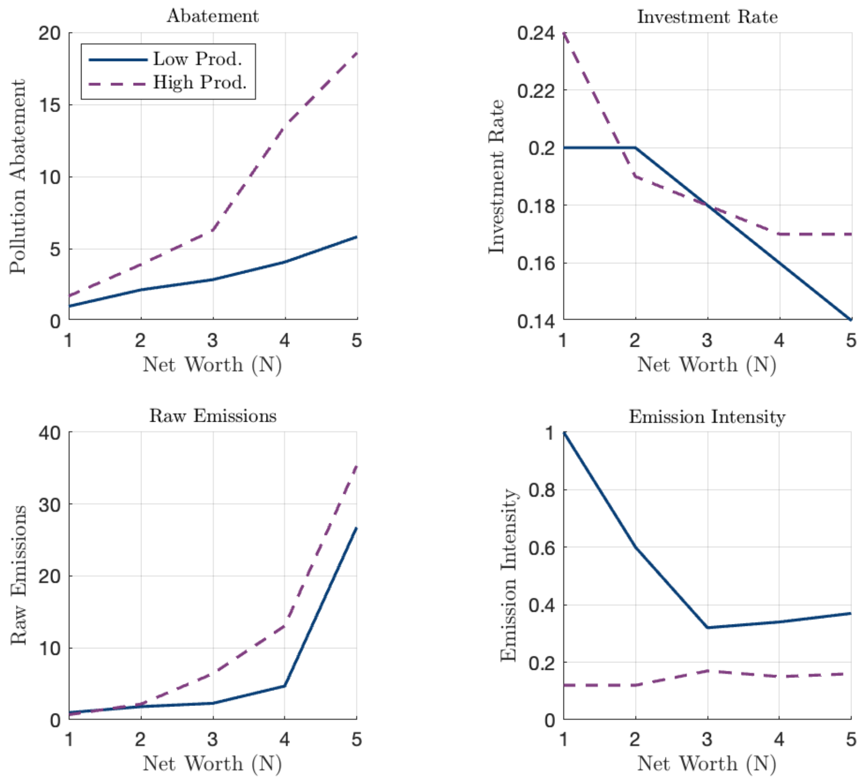

Notes: These figures plot firms' realized total emissions and emission intensity over firms' size measured in net worth. The left panel plots realized emission $e_{t+1}(z, n)$ of the calibrated model for fixed high $z^h$ and low $z^l$, respectively. The right panel plots the realized emission intensity $e_{t+1}(z, n)/y_{t+1}(z, n)$ of the calibrated model for fixed high $z^h$ and low $z^l$. "No financial frictions" refers to the model in which all firms follow the unconstrained policies $k'^*(z)$ and $a'^*(z)$ from Proposition 1.

worth in Figure 3 given the decision rules in Figure 2. As the firm keeps growing and accumulating more net worth, it can accumulate more capital and enlarge its production scale, implying a larger total emission. Meanwhile, the firm engages in more abatement activities and becomes cleaner. Therefore, the firm's total emission continuously increases, and emission intensity continuously decreases until it becomes financially unconstrained (i.e., the solid or dashed line hits the dotted line). More importantly, although high-productivity firms emit more as they grow, their engagements in abatement activities also grow faster than those of low-productivity firms. Their optimal emission intensity is also lower. As a result, the former's emission intensity is lower and drops faster than the latter's along the path of growth and accumulating net worth.

**Comparing to the Data** The discussion above illustrates how our model is consistent with empirical patterns of abatement activities and capital investment that we documented in Section 2.4. We provide visualization plots of the data in Figure 4. First, since most firms enter the economy as small and financially constrained, they start by growing through capital investment and pay less attention to environmental regulations, even though there are consequential penalties. Second, as these firms grow, abatement activities become more and more meaningful since the shadow cost of finance decreases and the production scale increases.

Figure 2 shows that, without financial frictions, the model would not have a pecking order; firms would immediately jump up to their optimal scale of capital investment and abatement

**Figure 4. The Pecking Order over Size and Productivity in Data**




Notes: These figures visualize the pecking order in two dimensions of net worth and productivity in Internet Appendix II. It depicts firm characteristics sorted by net worth (N) and productivity (z), including firms' abatement activities in the upper left panel, investment rate (I/K) in the upper right panel, raw emissions in the lower left panel, and emission intensity in the lower right panel. For brevity, the lowest quintile in the low productivity group is normalized to 1 in each panel, except for the investment rate in the upper right panel.

expenditures given current productivity. In such a case, abatement becomes independent of net worth, size, and age, which would be oddly inconsistent with the evidence presented in Section 2.4. Therefore, we argue that financial frictions are the key model ingredient when considering corporate abatement activities. Moreover, the model implies that, as they grow, high-productivity firms' abatement activities grow faster and their emission intensity drops faster than low-productivity ones. Meanwhile, since they are larger in sales and conditional on the same net worth, they still have higher raw emissions but lower emission intensity than low-productivity ones. All these patterns are consistent with the two-dimensional sorting in Figure 4.

# 5 Model Validation with Microdata

This section provides empirical validation to support testable implications in our model. First, we present direct evidence that relaxing financial frictions facilitates more abatement activities for financially constrained firms. Second, we demonstrate the presence of increasing returns to scale in abatement activities.

## 5.1 Decision Rules Regarding Collateralizability and Scale

In this subsection, we revisit the firm's optimal decisions regarding capital investment and abatement expenditures, where each decision is made by equating its marginal cost to its marginal benefit. Equations (8) denotes the optimal decision on capital investment $k'$:

$$\begin{aligned}\underbrace{1+\lambda_t(z,n)}_{\text{marginal cost}} \;=\; & \mathbf{E}_t\Bigg\{\Lambda'\Bigg[\Big(\pi_d+(1-\pi_d)(1+\lambda_{t+1}(z',n'))\Big)\\ & \times\underbrace{\left(\left(1-\frac{\tau'\bar{e}}{1+\gamma a'}\right)MPK(z',k')+(1-\delta)\right)}_{\text{marginal benefit from production}}\Bigg]\Bigg\}+\underbrace{\theta\mu_t(z,n),}_{\text{relax borrowing constraint}}\end{aligned}$$

And equation (9) denotes the the optimal decision on abatement expenditure $a'$:

$$\underbrace{1+\lambda_t(z,n)}_{\text{marginal cost}} \geq \mathbf{E}_t\left\{\Lambda'\left[\Big(\pi_d+(1-\pi_d)(1+\lambda_{t+1}(z',n'))\Big)\quad\underbrace{\frac{\gamma\tau'\bar{e}}{(1+\gamma a')^2}z'k'^{\alpha}}_{\text{marginal benefit of abatement}}\right]\right\}.$$

In equation (8), we show that the marginal benefit of a unit of capital investment consists of the marginal product of capital net of the emission penalty, plus the continuation value of capital net of depreciation. On top of that, capital is collateralizable, contributing an additional marginal value $\mu_t$ for financially constrained firms facing binding borrowing constraints (i.e., $\mu_t > 0$). In contrast, equation (9) presents the benefit of pollution abatement, which arises from mitigating the pollution penalty through reduced emissions. Both types of decisions on capital investment and pollution abatement draw on internal funding and may trigger the non-dividend payment constraint, resulting in a positive multiplier $\lambda_t > 0$. Consequently, the marginal cost of either capital investment or abatement expenditures is given by $1 + \lambda_t$.

Suppose there is an exogenous increase in the collateralizability parameter $\theta$, and the collateral constraint is binding (i.e., $\mu_t > 0$). In this case, the new equilibrium path of capital investment

$k'$ will rise, as firms can borrow more against their capital. As a result, the marginal product of capital (MPK) will decline due to the decreasing returns to scale in the production function, where $MPK = \alpha z k^{\alpha-1}$. Furthermore, since higher capital investment raises output, raw emissions will also increase, incentivizing firms to enhance their pollution abatement in response to the new equilibrium. Consequently, the relaxation of the collateralizability constraint (i.e., a higher $\theta$) leads to an increase in pollution abatement $a'$, especially among financially constrained firms with binding collateral constraints. This prediction will be empirically tested in Section 5.2.

On the other hand, following a positive innovation in productivity dynamics $z'$, the marginal product of capital scales up, while the Lagrange multiplier $\mu_t$ declines due to relaxed financial frictions. In the new equilibrium, capital investment $k'$ rises, which subsequently pushes down the marginal product of capital due to diminishing returns. According to equation (9), the optimal pollution abatement $a'$ increases in response to the rise in both productivity $z'$ and capital investment $k'$. Meanwhile, output $y'$ rises due to the increase in productivity and capital investment. Finally, emission intensity $e'/y'$ falls, recalling the emission function $e' = y' \times \bar{e}/(1 + \gamma a')$. In contrast, the offsetting effects of rising output and increased pollution abatement imply an ambiguous prediction for raw emissions. Taken together, a positive innovation in $z'$ drives higher output and lower emission intensity, but has an unclear effect on total emissions. This prediction will be empirically tested in Section 5.3.

Overall, our model further provides testable implications that guide subsequent empirical analyses. In the next subsection, we examine these predictions in the data, focusing on the role of financial frictions and increasing returns to scale.

## 5.2 The Role of Financial Frictions

Our first challenge is identifying exogenous variation in financial frictions to establish their causal effect on pollution abatement. It serves as the empirical counterpart to an increase in the collateralizability parameter $\theta$ in our model while controlling for other determinants. We address this by exploiting the exogenous variation provided by enacting anti-recharacterization laws as documented by Chu (2020), which alleviate firms' financial constraints by enhancing secured lenders' ability to repossess assets in bankruptcy.[8] Section I.5 of the Internet Appendix provides the institutional details. In a nutshell, anti-recharacterization laws, integral to secured transactions within U.S. Chapter 11 bankruptcy proceedings, ensure that secured debts maintain their priority status, protecting creditors from reclassifying their claims. These laws, enacted in states like

[8] While there is extensive literature on the effects of anti-recharacterization laws on corporate policies, a comprehensive review is beyond the scope of this paper. For reference, see Li, Whited, and Wu (2016), Chu (2020), Favara et al. (2021), and Fairhurst and Nam (2023) among others.

Texas, Louisiana, Alabama, and Delaware between 1997 and 2002, bolster lenders' confidence by legally safeguarding the terms of debt agreements, thus reducing lending risks. As a result, creditors are more willing to extend credit to borrowers incorporated in these states.

Since the anti-recharacterization laws are unrelated to firms' abatement operations, we can design an identification test by examining the abatement activities of firms in states with and without such laws. Considering the timing of law adoption, we limit our sample period from 1994 to 2004 and estimate the following difference-in-differences regressions:

$$\text{Log}(1 + \text{Abate}_{j,s,t}) = \xi_j + \xi_t + b \text{ Log } N_{j,s,t} \times \text{Treat}_{s,t} + c \text{ Controls}_{j,s,t} + \varepsilon_{j,s,t}, \tag{11}$$

where $\text{Log}(1 + \text{Abate}_{j,s,t})$ represents the logarithm of firm $j$'s pollution abatement, and $\text{Treat}_{s,t}$ is a dummy variable that equals 1 for firms incorporated in Texas or Louisiana starting in 1997, in Alabama from 2001, and in Delaware from 2002, up until 2004 when federal laws superseded the state-level laws (the end of our sample). We include firm- and year-fixed effects, $\xi_j$ and $\xi_t$, respectively. $\text{Controls}_{j,s,t}$ include firm-level fundamentals such as book-to-market ratio, investment rate, and ROA. All variables are winsorized at the 1st and 99th percentiles to minimize the impact of outliers, and independent variables are normalized to have zero mean and one standard deviation after winsorization. To focus on financially constrained firms, we interact the logarithm of firm $j$'s net worth with $\text{Treat}_{s,t}$. The interaction term allows us to examine whether more financially constrained firms (smaller $\text{Log } N_{j,s,t}$) display a more pronounced effect from the passage of the laws than their counterparts. Our theory predicts that enacting these laws improves such firms' borrowing capabilities, easing their financial constraints and increasing abatement activities, which means that the coefficient on the interaction term should be negative.

Table 3 reports estimation results of equation (11) for firms' abatement changes corresponding to the passage of anti-recharacterization laws. The first row shows that the negative coefficient on the interaction term indicates that enacting anti-recharacterization laws is associated with an increase in abatement activities among low net worth firms, compared to their counterparts in non-enacted states. This association remains robust in Columns 3 and 4 when controlling for other firm characteristics. As a validation of the model mechanism, our empirical evidence provides causal support for the financial friction mechanism that influences firms' pollution abatement strategies. Notably, the estimated coefficient for the interaction term $b$ is significantly negative, suggesting that financially constrained firms with lower net worth experience a more positive response to financial shocks following the passage of the laws. This finding is consistent with our theoretical prediction and underscores that the financial friction mechanism, rather than the size effect ($\text{Log } N_{j,s,t}$), is the primary driver of the endogenous choice of pollution abatement. These findings are consistent with Dang et al. (2022), which shows that financially constrained firms

**Table 3: The Effect of Anti-recharacterization Laws and Dynamics**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | | | | Abatement Activities | | | | |
| Log N x Treat | -0.09** | -0.09** | -0.10*** | -0.09** | | | | |
| [t] | [-2.23] | [-2.30] | [-2.66] | [-2.45] | | | | |
| Log N × $Treat_{-2}$ | | | | | -0.00 | -0.01 | 0.00 | -0.01 |
| [t] | | | | | [-0.13] | [-0.51] | [0.13] | [-0.31] |
| Log N × $Treat_{-1}$ | | | | | -0.00 | -0.02 | 0.00 | -0.01 |
| [t] | | | | | [-0.12] | [-0.53] | [0.05] | [-0.39] |
| Log N × $Treat_0$ | | | | | -0.05 | -0.07** | -0.05 | -0.07* |
| [t] | | | | | [-1.51] | [-2.01] | [-1.32] | [-1.84] |
| Log N × $Treat_1$ | | | | | -0.09** | -0.11*** | -0.08** | -0.10** |
| [t] | | | | | [-2.29] | [-2.67] | [-2.09] | [-2.49] |
| Log N × $Treat_2$ | | | | | -0.10*** | -0.12*** | -0.10** | -0.11*** |
| [t] | | | | | [-2.68] | [-3.01] | [-2.45] | [-2.81] |
| Log N × $Treat_3$ | | | | | -0.13*** | -0.15*** | -0.13*** | -0.14*** |
| [t] | | | | | [-2.94] | [-3.25] | [-2.81] | [-3.13] |
| Treat | -0.21*** | 0.11* | -0.17*** | 0.12* | | | | |
| [t] | [-5.49] | [1.78] | [-4.36] | [1.93] | | | | |
| Log N | -0.22** | 0.12 | -0.23** | 0.11 | -0.14 | -0.11 | -0.15 | -0.13 |
| [t] | [-2.54] | [1.25] | [-2.53] | [1.19] | [-1.22] | [-0.98] | [-1.24] | [-1.06] |
| B/M | | | 0.00 | -0.01 | | | -0.01 | -0.01 |
| [t] | | | [0.08] | [-0.44] | | | [-0.69] | [-0.39] |
| I/K | | | 0.04** | 0.01 | | | 0.01 | 0.01 |
| [t] | | | [2.29] | [0.46] | | | [0.53] | [0.55] |
| ROA | | | 0.05*** | -0.01 | | | -0.01 | -0.00 |
| [t] | | | [2.59] | [-0.37] | | | [-0.48] | [-0.08] |
| Observations | 4,530 | 4,530 | 4,459 | 4,459 | 2,565 | 2,565 | 2,508 | 2,508 |
| R-squared | 0.82 | 0.83 | 0.82 | 0.83 | 0.88 | 0.88 | 0.88 | 0.88 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Cluster SE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: This table reports changes in firms' pollution abatement following the adoption of anti-recharacterization laws. The independent variable, Treat, is a dummy that equals 1 for firms incorporated in Texas or Louisiana starting in 1997, in Alabama starting in 2001, and in Delaware starting in 2002, after the passage of these laws and before their preemption by federal laws in 2004. To capture the dynamic effect on the adoption of anti-recharacterization laws, the independent variables of interest include time-specific dummies: $Treat_{-2}$, $Treat_{-1}$, $Treat_0$, $Treat_1$, $Treat_2$, and $Treat_3$. These dummies indicate the status of the law two years before adoption ($Treat_{-2}$), one year before ($Treat_{-1}$), the year of adoption ($Treat_0$), one year after ($Treat_1$), two years after ($Treat_2$), and three years after ($Treat_3$) the law's implementation. Additional independent variables include net worth and control variables such as the book-to-market ratio, investment rate, and ROA. Detailed definitions of these variables are listed in Table 1. All regressions include firm and year fixed effects, and *t*-statistics based on standard errors clustered at the firm level are reported with ***, **, and * indicating significance at the 1%, 5%, and 10% levels, respectively. The analysis covers the sample period from 1994 to 2004, which corresponds to the timeline of the adoption of anti-recharacterization laws.

prioritize capital investments over abatement activities due to the collateralizability of capital assets using Chinese data on the Clean Air Act.

Another concern is that the results are driven by preexisting differences between treated and control firms before the passage of the anti-recharacterization laws. To mitigate this concern, we examine the dynamics of the law's effects on abatement activities. Specifically, we construct six variables related to the timing of the anti-recharacterization laws. The independent variables of interest are $\text{Treat}_{-2}$, which takes the value of 1 two years before the law's passage; $\text{Treat}_{-1}$, one year before; $\text{Treat}_{0}$, until $\text{Treat}_{3}$, three years after. We replace Treat in the baseline specification with these six newly constructed variables and interact them with the logarithm of net worth. If the baseline results were driven by preexisting differences between the treated and control firms, effects would likely appear in $\text{Treat}_{-2}$ and $\text{Treat}_{-1}$. However, the results presented in Columns 5 to 8 of Table 3 show that the coefficients on $\text{Treat}_{-2}$ and $\text{Treat}_{-1}$ are small and statistically insignificant, suggesting that the baseline results are unlikely to be driven by preexisting differences or reverse causality. In contrast, consistent with the baseline results, the coefficients on $\text{Treat}_{1}$ to $\text{Treat}_{3}$ are substantially negative and statistically significant. Our tests based on anti-recharacterization laws pinpoint the financial friction mechanism and support a causal interpretation of our baseline results.

### 5.3 The Role of Return to Scale

Our second challenge is identifying exogenous variations in return to scale to ascertain their causal effect on pollution emissions, controlling for other determinants. This task is particularly challenging since we need shocks that directly change firms' sales but not abatement activities. To do so, we test how firms' sales growth, emission growth, and emission intensity respond when exposed to exogenous demand shocks caused by natural disasters. Our empirical strategy is based on the idea that firms not directly affected by a natural disaster, but operating in industries where peer firms are hit, would experience an unexpected shift in demand for their production. These shocks are exogenous to the treated firms' prior decisions on pollution abatement and capital investment, but shift industry-wide demand and drive up sales for the unaffected firms. We interpret such events as exogenous industry-specific demand shocks.

To identify the exogenous demand shock, we use county-level disaster records from Spatial Hazard Events and Losses Database for the United States (SHELDUS), which provides data on the location, timing, and type of disaster events across U.S. counties.[9] We match SHELDUS disaster

[9]The SHELDUS Database is a county-level dataset that compiles information on natural hazard events and associated losses across the United States. Maintained by Arizona State University, SHELDUS includes detailed records on the location, timing, and type of disaster events, such as hurricanes, floods, earthquakes, and wildfires, along with

events to TRI-reporting facilities by county-year, identifying whether a given facility was directly affected by a disaster. Firms with facilities in disaster-hit counties are flagged as directly impacted. In contrast, those in the same industry but outside the disaster counties are indirectly exposed, where the industry classifications are based on Fama-French 48 (Fama and French, 1997). These indirectly exposed firms form our treatment group – we assume that they would experience an unexpected surge in demand but face no production disruption. As a result, we expect an increase in sales but a decline in emission intensity.

**Table 4: Effects of Demand Shocks on Sales and Emissions**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Sales Growth | | Emission Growth | | Emission Intensity | |
| Demand | 3.01* | 4.23*** | -0.13 | -0.09 | -0.42*** | -0.43*** |
| [t] | [1.92] | [2.62] | [-0.92] | [-0.62] | [-3.05] | [-3.19] |
| Log AT | | 10.73*** | | 0.03 | | 0.22*** |
| [t] | | [4.42] | | [0.19] | | [3.35] |
| Log (1+Abate) | | -0.27 | | 0.06 | | -0.70*** |
| [t] | | [-0.40] | | [1.14] | | [-2.80] |
| B/M | | -2.22*** | | -0.00 | | 0.09** |
| [t] | | [-4.11] | | [-0.06] | | [2.16] |
| I/K | | 1.45** | | 0.08* | | -0.00 |
| [t] | | [2.41] | | [1.87] | | [-0.05] |
| ROA | | 8.08*** | | 0.03 | | 0.00 |
| [t] | | [11.83] | | [0.59] | | [0.05] |
| Observations | 3,921 | 3,890 | 3,669 | 3,648 | 4,064 | 4,033 |
| R-squared | 0.30 | 0.40 | 0.13 | 0.13 | 0.86 | 0.87 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster SE | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: This table explores changes in firms' emission intensity following the realization of local demand shocks. The dependent variables include the firm-level sales growth and emission growth, as well as intensity. The key independent variable is the demand shock dummy ($\text{Demand}_{i,t}$), which equals 1 for firms not located in disaster-hit counties but operating in industries where peer firms were directly affected by natural disasters. These firms are assumed to experience a positive demand shock due to temporary production disruptions to their peers within their industry, where industry classifications are based on the Fama-French 48-industry classification. Additional independent variables include total assets and control variables such as the book-to-market ratio, investment rate, ROA, and abatement activity. Detailed definitions of these variables are listed in Table 1. All regressions include firm and year fixed effects, and $t$-statistics based on standard errors clustered at the firm level are reported with ***, **, and * indicating significance at the 1, 5, and 10% levels, respectively. The analysis covers the sample period from 1991 to 2020.

estimates of property and crop damages, injuries, and fatalities.

To verify the impact of demand shocks, we estimate the following panel regressions:

$$o_{j,i,t} = \xi_j + \xi_t + b \times \text{Demand}_{i,t} + c \times \text{Controls}_{j,i,t} + \varepsilon_{j,i,t}. \tag{12}$$

where the dependent variables include the firm-level sales growth, emission growth, and emission intensity. The key independent variable is a demand shock dummy ($\text{Demand}_{i,t}$), which equals 1 for firms not located in disaster-hit counties but operating in industries where peer firms were directly affected by natural disasters in year $t$. These firms are assumed to experience a positive demand shock due to temporary production disruptions to their peers within their industry. The control variables, $\text{Controls}_{j,i,t}$, include firm-level fundamentals such as total assets, the book-to-market ratio, investment-to-capital ratio, return on assets (ROA), and pollution abatement activity.[10] All regressions include firm fixed effects ($\xi_j$) and year fixed effects ($\xi_t$). All variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers, and the independent variables are standardized to have zero mean and unit variance following winsorization.

Table 4 presents the results. The first two columns show that firms that are hit by a positive demand shock experience a significant positive sales growth in the current year relative to the past year. This is consistent with our identification assumption that demand shifts from their peer firms, whose production was disrupted, to these firms, whose production was not disrupted. However, Columns 3 and 4 show that these firms do not experience significant emission growth, even after controlling for size and abatement. Finally, our last two columns show substantial reductions in the emission intensity of these firms, even after controlling for size and abatement. These results provide empirical support for abatement activities' increasing returns to scale, suggesting that larger firms naturally benefit more from abatement activities in reducing total emissions.

## 6 Quantitative Assessments

As the primary mechanism of this paper has been highlighted, we now apply the quantitative model to the data, quantify the mechanism, and show the aggregate effects. To do so, we first parameterize the model to match US firms' dynamic and cross-sectional moments. We then present the quantitative results on financial frictions' aggregate and cross-sectional effects.

[10]Sales and net worth are highly correlated, as net worth incorporates sales. To fix this problem, we use total assets to measure firm size to avoid multicollinearity. We have also tried other size measures and find consistent results.

## 6.1 Parameterization

Our parameterization proceeds in three steps. In the first step, we select a set of parameters to match standard cross-sectional and macroeconomic targets in the steady state. In the second step, we choose the remaining parameters so that the model can replicate additional cross-sectional moments observed in the data. Finally, we choose the pollution disutility parameter, assuming the current penalty schedule in the second step is already optimal.

**Fixed Parameters** The first part of Table 5 presents the parameters directly taken from the literature. The model operates at an annual frequency, and the time discount rate $\beta$ is set to 0.96 to match the average real risk-free rate of 4% per year. The capital share $\alpha$ is set to 0.65 to match a decreasing return to scale of two-thirds. The annual depreciation rate of capital $\delta_k$ is set to 0.10 to match the U.S.'s average nonresidential fixed investment rate.

**Table 5: Calibrated Parameter Values and Sources**

| Symbols | Descriptions | Values | Sources |
|---|---|---|---|
| **Fixed Parameters** | | | |
| $\beta$ | Discount factor | 0.96 | Annual Frequency |
| $\alpha$ | Capital share | 0.55 | DRS of Two-thirds |
| $\delta_k$ | Capital depreciation rate | 0.10 | BEA Data |
| $\zeta$ | Dis-utility of pollution emission | 0.17 | Uncalibrated |
| **Fitted Parameters** | | | |
| $\rho_z$ | Productivity persistence (fixed) | 0.90 | Targeted Moments |
| $\sigma_z$ | Productivity volatility | 0.05 | Targeted Moments |
| $\pi_d$ | Exogenous exit risk | 0.09 | Targeted Moments |
| $n_0$ | Net worth of entry | 2.50 | Targeted Moments |
| $\theta_k$ | Collateral constraint | 0.40 | Targeted Moments |
| $\bar{e}$ | Highest emission intensity | 10.0 | Targeted Moments |
| $\gamma$ | Elasticity of abatement into intensity | 5.0 | Targeted Moments |
| $\mu^\tau$ | Mean of pollution penalty | 0.01 | Targeted Moments |
| $\sigma^\tau$ | Volatility of pollution penalty | 0.01 | Targeted Moments |

Notes: This table presents the parameters used in the model, including both fixed and fitted parameters. The model operates at an annual frequency. The fixed parameters are based on existing literature and include the time discount rate ($\beta = 0.96$), chosen to match the average risk-free rate of 4% per year. On the firm side, the capital coefficient ($\alpha = 0.55$) is set to match an implied decreasing-return-to-scale of two-thirds, and capital is assumed to depreciate annually at a rate of 10% ($\delta_k = 0.10$), consistent with the average aggregate nonresidential fixed investment rate reported in Bachmann et al. (2013). The fitted parameters are chosen to match targeted moments from the firm-level data sample, which will be further discussed in Table 6.

**Fitted Parameters** The second part of Table 5 presents the parameters we calibrated to match the firm-level moments reported in Table 6. While all parameters are jointly determined, we outline the rough relations between the parameters and moments. The first set of parameters pertains to output and finance. We set the productivity persistence parameter, $\rho_z$, to 0.90 and the productivity volatility parameter, $\sigma_z$, to 0.05 to match the auto-correlations of output across different horizons. To match the annual exit risk of 8.7% and the size of entrants relative to average firms at about 30%, we choose the exogenous exit risk parameter, $\pi_d$, to be 0.09 and the net worth of the entry parameter, $n_0$, to be 2.50. Finally, we set the collateral constraint parameter, $\theta_k$, to 0.40, leading to an equilibrium average firm-level leverage of 34%

**Table 6: Targeted Moments: Model and Data**

| Moments | Data | Model |
|---|---|---|
| **Output and Finance** | | |
| 1-year autocorrelation of output | 0.89 | 0.90 |
| 3-year autocorrelation of output | 0.69 | 0.71 |
| 5-year autocorrelation of output | 0.53 | 0.56 |
| Size ratio of entrant relative to average | 0.28 | 0.28 |
| Annual exit rate of firms | 0.09 | 0.09 |
| Mean of debt/asset ratio | 0.34 | 0.34 |
| **Pollution and Abatement** | | |
| Mean of emission intensity | 5.38 | 4.16 |
| Median of emission intensity | 5.66 | 4.45 |
| Standard deviation of emission intensity | 3.05 | 1.82 |
| P75/P25 of emission intensity | 1.98 | 1.56 |
| Ratio of zero pollution penalty | 0.40 | 0.40 |
| Mean of pollution penalty | 0.01 | 0.01 |
| Standard deviation of pollution penalty | 0.01 | 0.01 |

Notes: This table presents the firm-level moments utilized to calibrate the fitted parameters of the model. The emission intensity is measured in pounds/millions and is normalized. We start by selecting a default pollution emission intensity of $\bar{e} = 10$ and an abatement technology of $\gamma = 5.0$ to simultaneously fit the emission intensity distribution, measured as the emission-to-sales ratio in the model. Next, we select the mean of pollution penalty as $\mu_\tau = 0.01$, the volatility of pollution penalty is $\sigma_\tau = 0.01$, to simultaneously fit the pollution penalty distribution, measured as the litigation-to-sales ratio. The fitted parameters chosen to match these targeted moments from the firm-level data sample are listed in Table 5.

The second set of fitted parameters is related to pollution and abatement. The default pollution emission intensity $\bar{e} = 10$ and the abatement to intensity elasticity $\gamma = 5.0$ are chosen to match the emission intensity distribution. The emission-to-sales ratio is defined as pounds of toxic emissions over millions of dollars of sales. Then, the mean of pollution penalty $\mu_\tau = 0.01$, the volatility of pollution penalty during normal periods $\sigma_\tau = 0.01$ are chosen to match the distribution of pollution penalty, which is measured as the litigation-to-sales ratio. Currently, the monetary value of the direct costs of litigation cases over the total sales of firms is used to measure the pollution penalty.[11]

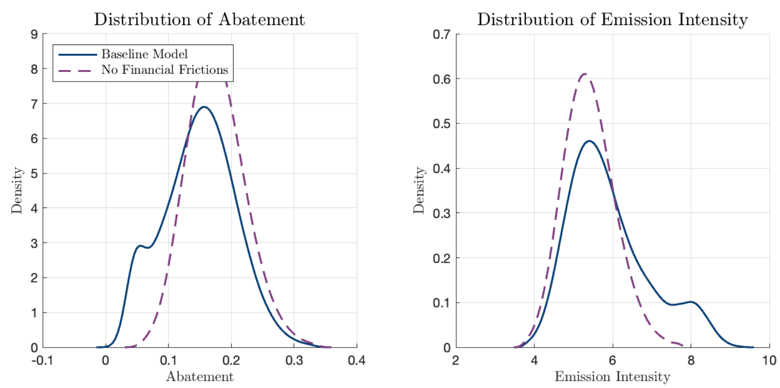
[11]The data source regarding the pollution penalty is available on the website of the EPA at this link here. We also

**Disutility of Pollution** While the disutility of pollution parameter $\zeta$ does not affect our current quantitative analysis on the firm side, it does have negative welfare effects on households, so we must have $\zeta > 0$. Our current data do not determine the exact value of $\zeta$. The value of $\zeta$ will impact the optimal degree of pollution penalty and the optimal level of abatement. We choose $\zeta$ in the baseline calibration, assuming the current penalty is optimal. We will further discuss the optimal regulation policy and the optimal level of abatement based on the value of $\zeta$.

## 6.2 The Effects of Financial Frictions

We now use our calibrated model to assess the aggregate implications of financial frictions. Since financial frictions delay constrained firms' incentive to abate pollution, aggregating across firms, this fact should imply that there will be fewer abatement activities in the aggregate level. Our goal in this subsection is to quantify these negative effects of financial frictions. To do so, we compare our calibrated baseline model to the frictionless model in which firms are not subject to financial constraints and follow the unconstrained policies $k'^{*}(z)$ and $a'^{*}(z)$.

**Figure 5. Environmental Distribution in Stationary Equilibrium**




Notes: These plots show the density distribution of abatement activities and emission intensity from our model-simulated firm sample. The dashed curve is the density of abatement and emission intensity in the frictionless model, while the solid blue curve is the corresponding density in the baseline model. The productivity distribution solely determines the densities in the frictionless model and, therefore, is perfectly normal-shaped. The densities in the baseline model are a combination of two firms: the unconstrained firms acting as firms in the frictionless model and the constrained firms that abate less. Therefore, the distributions are dual-peaked with lower abatement and higher emission intensity.

**Environmental Distributions in Equilibrium** First, we check how abatement activities are distributed across firms. Financial frictions depress abatement primarily in small, financially

collected data on the number of settlements for each case and found that the mean and median settlements for all cases are 8.27 and 0.8 million dollars, respectively.

constrained firms with relatively high returns to capital and low returns to abatement.

We illustrate this mechanism in Figure 5. These plots show the density distribution of abatement activities and emission intensity from our model-simulated firm sample. The dashed curve is the density of abatement activities and emission intensity in the frictionless model, while the solid blue curve is the corresponding densities in the baseline model. The productivity distribution solely determines the densities in the frictionless model and, therefore, is perfectly normal-shaped. The densities in the baseline model are a combination of two firms: the unconstrained firms acting as firms in the frictionless model and the constrained firms that spend less in abatement. Therefore, the distributions are dual-peaked with lower abatement and higher emission intensity. From this perspective, the emission intensity distribution in our full model has more mass in the right tails than the distribution without financial frictions. The thickness of the right tail reflects the essential outcome, which is that financial frictions hinder firms from being cleaner.

**Aggregate Effects of Financial Frictions** We then show the aggregate effects of financial frictions on the economy and the environment. Besides financial frictions hindering firms' growth (economy), we aim to find how financial frictions make firms dirtier (environment).

**Table 7: The Aggregate Effects of Financial Frictions**

| Outcomes | Output | Capital | Consump. | Abatement | Emission | E.Intensity |
|---|---|---|---|---|---|---|
| Frictionless | 4.78 | 17.05 | 2.90 | 0.172 | 25.37 | 5.43 |
| Baseline | 4.04 | 13.25 | 2.58 | 0.137 | 23.14 | 6.16 |
| % Changes | -15.5% | -22.3% | -11.0% | -20.3% | -8.8% | +14.8% |

Notes: This table shows the aggregate effects of financial frictions on the stationary economy calculated from aggregating the stationary equilibrium distributions of the frictionless economy and our baseline economy. We have two observations. First, financial frictions hinder firm growth over their life cycle, so total output and capital stock are lower in the baseline economy. More specifically, a 15.5% drop in output and a 22.3% drop in capital are both caused by financial frictions. Second, conditional on the 15.5% drop in output, emission only drops by 8.8%, but emission intensity goes up oppositely by 14.8%. This is because, under financial frictions, the more constrained, smaller, and younger firms choose to abate less optimally. Therefore, financial frictions amplify the pollution externality in the aggregate because of the distribution of financially constrained firms.

Table 7 shows the aggregate effects of financial frictions. We have two significant observations. First, financial frictions hinder firm growth over their life cycle, so total output and capital stock are lower in the baseline economy. More specifically, a 15.5% drop of the production and a 22.3% drop in capital are both caused by financial frictions. More importantly, we are able to quantify how financial frictions affect the economy's abatement activities and emission intensity. Conditional on the 15.5% drop in output, total emission only drops by 8.8%, but emission intensity goes up oppositely by 14.8%. This is because, under financial frictions, the more constrained, smaller, and younger firms choose to abate less optimally. In other words, financial frictions hurt economic growth and exacerbate the aggregate environmental externality.

# 7 Policy Implications

We now discuss policy implications after quantifying and validating the mechanism with data. To do so, we first show the effects of increasing the magnitude of regulatory penalties on the macroeconomy and the environment. We then present the results of combining regulatory penalties and credit interventions.

## 7.1 The Effects of Environmental Policy

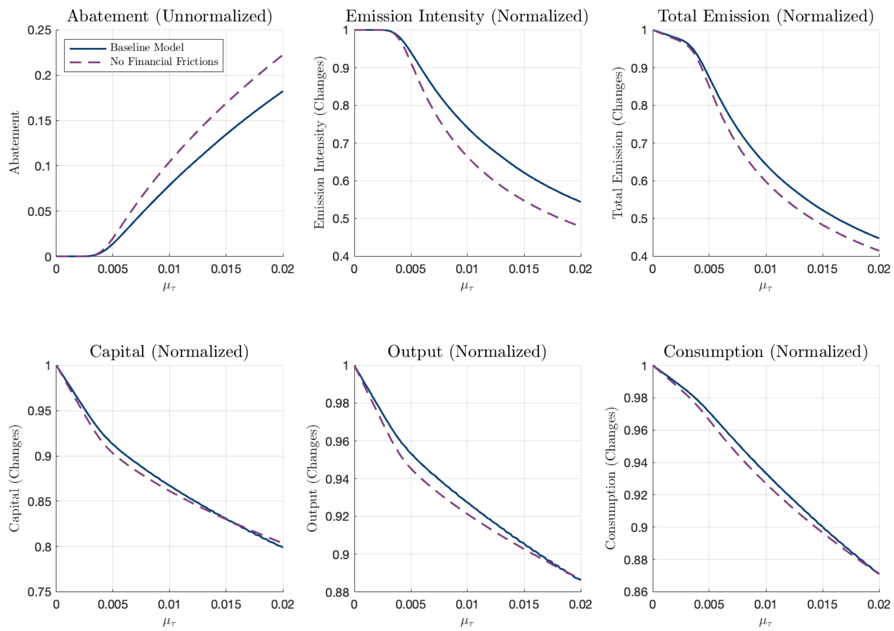
We first use our calibrated model to assess the aggregate effects of increasing environmental regulation penalties under financial frictions. Since financial frictions hinder firms' incentive to abate, the impact of regulation penalties depends on financial frictions.

**The Effects of Increasing Regulatory Penalty** We further investigate the effects of regulatory penalties by showing economies from zero penalty to a relatively high penalty using our model-simulated samples. Increasing regulatory penalties improves the environment (increased abatement, reduced emission intensity, and reduced emissions) but significantly reduces economic performance measured in capital, output, and consumption.

Figure 6 shows the results. We simulate 101 economies from zero penalty $\mu_\tau = 0.00$ to $\mu_\tau = 0.20$ with a step size $\Delta\mu_\tau = 0.005$ to generate the smooth changes. We normalize all variables $x$ by dividing by $x(\mu_\tau = 0.00)$, except abatement since it starts with zero. Therefore, we could directly observe the changes in the baseline economy relative to the frictionless economy without comparing the absolute values. We discuss the consequences in two parts: the economy and the environment. For the impact on the economy as shown in the lower three panels (Capital, Output, and Consumption), increasing the regulatory penalty monotonically leads to decreases in all variables; however, the differences between the baseline and frictionless models (denoted by solid and dashed lines, respectively) are negligible.

The key differences are in the perspective of the environment, as shown in the three upper panels (Abatement, Emission Intensity, and Total Emission). In the beginning, increasing the regulatory penalty does not increase abatement at all when the penalty is low, regardless of financial frictions. As a result, emission intensity stays at the highest level. Total emission decreases only because firms' optimal capital is smaller, and their output decreases. Then, as the regulatory

**Figure 6. The Effects of Increasing Regulatory Penalty**



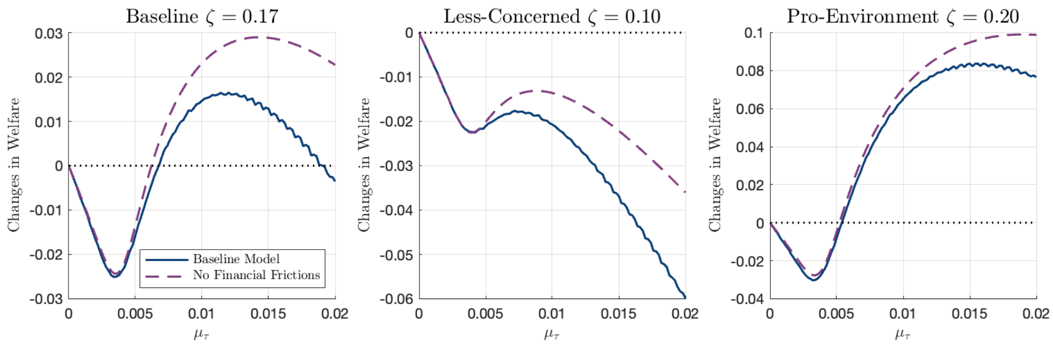

Notes: These plots show how the aggregate economy changes with increased regulatory penalties in our model-simulated firm samples. We simulate 101 economies from zero penalties $\mu_\tau = 0.00$ to $\mu_\tau = 0.20$ with a step size $\Delta\mu_\tau = 0.005$ to generate the smooth changes. We normalize all variables $x$ by dividing by $x(\mu_\tau = 0.00)$, except abatement since it starts with zero. Therefore, we could directly observe the changes in the baseline economy relative to the frictionless economy without comparing the absolute values.

penalty increases substantially, firms start to participate in abatement activities, and their emission intensity begins to decrease. Different from the perspective of the economy, the gap between the baseline and frictionless models is substantial, especially when penalties are considerable. For a realized $\mu_\tau = 0.01$, the emission intensity in a frictionless economy drops by 35% compared to while it only drops by 25% in the baseline economy.

**Welfare Implications Under Financial Frictions** We then explore the welfare implications by showing that the policy that directly increases the pollution penalty may be sub-optimal depending on the interaction of the penalties with financial frictions. The welfare in the stationary equilibrium is the trade-off between utility gain from consumption and utility loss from pollution, as in the following equation $W^*(\mu_\tau) = log(C^*(\mu_\tau)) - \zeta log(E^*(\mu_\tau))$. Therefore, the changes in consumption and pollution jointly govern the changes in total welfare.

We first show interesting results in Figure 7, how welfare changes with penalties in our baseline economy (left plot) compared to alternative economies in which households are less con-

**Figure 7. Welfare Implications Under Financial Frictions**



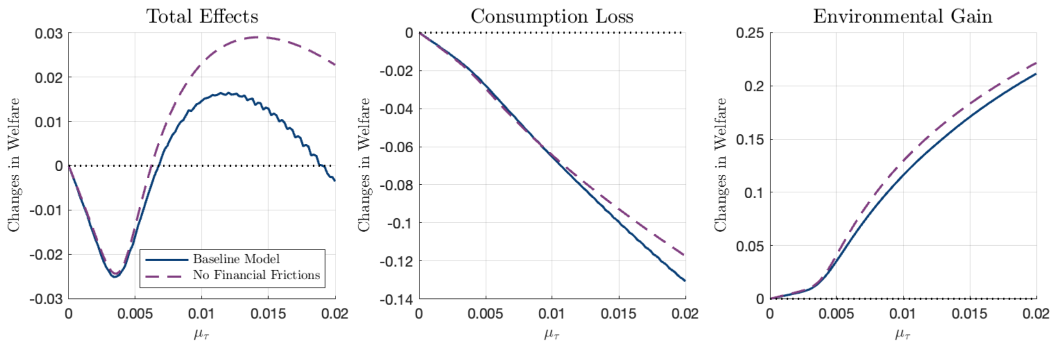

Notes: These plots show how welfare changes with increased regulatory penalties in our model-simulated firm samples. We simulate 101 counterfactuals from zero penalty $\mu_\tau = 0.00$ to $\mu_\tau = 0.20$ with a step size $\Delta\mu_\tau = 0.005$ to generate the smooth changes. We normalize the welfare by dividing by $welfare(\mu_\tau = 0.00)$ and then subtracting one. Therefore, we could directly observe the changes in the baseline economy relative to the frictionless economy without comparing the absolute values. We also show the results with different household preferences of the disutility of pollution parameters.

cerned about pollution (central plot) or households are more pro-environment (right plot). We normalize the welfare by dividing by $welfare(\mu_\tau = 0.00)$ and then subtracting one. Therefore, we could directly observe the changes in the baseline economy (solid line) relative to the frictionless economy (dashed line) without comparing the absolute values.

Figure 7 offers three patterns. First, welfare changes are not monotonic regarding regulatory penalties, regardless of financial frictions and household preferences under moderate parameter ranges. This is mainly due to firms' inaction in abatement when penalties are minor. In this region, increasing pollution penalties only reduce emissions through reduced production scale. Consequently, the economy generates welfare loss because households suffer from reduced consumption but gain only slowly from emission reduction. Figure 8 shows the decomposition, where the second panel shows the relative welfare loss caused by consumption reduction and the third panel shows the relative welfare gain from emission reduction.

Second, not surprisingly, welfare changes depend on the disutility of the pollution parameter $\zeta$. We calculate two alternative welfare, assuming a relatively lower disutility $\zeta = 0.10$ *(Less-Concerned)* economy and a relatively higher disutility $\zeta = 0.20$ *(Pro-Environment)* economy to show the differences. In the *Less-Concerned* economy, consumption losses dominate the environmental gains, and the optimal regulatory penalty is zero. In the *Pro-Environment* economy, the environmental gains dominate consumption losses when penalties are substantial, and the

**Figure 8. Welfare Implications Decomposition**




Notes: These plots show how welfare changes with increased regulatory penalties in our model-simulated firm sample for the baseline economy. We simulate 101 counterfactuals from zero penalty $\mu_\tau = 0.00$ to $\mu_\tau = 0.20$ with a step size $\Delta\mu_\tau = 0.005$ to generate the smooth changes. We normalize the welfare and welfare components by dividing by $welfare(\mu_\tau = 0.00)$ and then subtracting one. Therefore, we could directly observe the changes in the baseline economy relative to the frictionless economy without comparing the absolute values.

optimal regulatory penalty is about 1.5%, which leads to 10% consumption loss and 17% environmental gain. The decomposition is in the second and third panels in Figure 8 at $\mu_\tau = 0.015$.

Third, we discuss the role of financial frictions. Under all preferences, welfare changes in the frictionless economy (dashed line) are higher than in the baseline economy (solid line). More importantly, in a frictionless economy, the optimal penalty is larger because firms are more responsive to increases in regulatory penalties. If we check the decomposition in Figure 8, consumption losses are not increasing as fast in an economy without financial frictions, and environmental gains are growing faster with regulatory penalties. Quantitatively, an optimal regulatory penalty $\mu_\tau = 0.14$ in the frictionless economy would generate 3% welfare gain while an optimal regulatory penalty $\mu_\tau = 0.12$ in the baseline economy with financial frictions would generate 1.8% welfare gain, which is 1.2% lower in magnitude and 40% lower in percentage. In other words, the aggregate welfare gain from optimal environmental regulation is reduced by 40% due to financial frictions.

**Discussions on Investors' Green Preference** We do not explicitly model green preference from investors to motivate corporate inputs in abatement activities. Instead, shareholders are completely profit-driven; they only engage in abatement activities to prevent future environmental penalties (indirect forms of taxes, fines, litigation costs, or indirect forms of consumer and government relationships). These are reflected in households' disutility of pollution emissions $\zeta$ and, therefore, the general environmental penalties $\mu_\tau$. In other words, the marginal investors' green preferences are captured by the households' disutility of pollution, which affects future magnitudes of environmental penalties.

## 7.2 Effects of Green Loan Policies

We then use our calibrated model to assess the effects of combining environmental regulation penalties with alternative credit intervention policies such as green loan policies. A big concern about green loans is "financial greenwashing", which means that firms may use green loans partially or entirely for non-abatement activities, such as capital investment, due to imperfect monitoring technology. We present evidence for an interesting idea here that green finance could still be a good policy, along with moderate pollution penalties, even without monitoring.

**Implementation of Green Loan Policies** We implement the green loan interventions in an extension of our baseline model by modifying the collateral constraint. Firms can now use certificates of their pollution abatement costs as additional collateral to apply for a green loan from the government up to $\theta_a$.[12] The new collateral constraint would be:

$$b_{jt+1} \leq \theta_k k_{jt+1} + \theta_a a_{jt+1}, \tag{13}$$

The government cannot monitor the exact use of the funds raised for firms' abatement activities in a world without green loans. For instance, without getting a green loan, a company would implement abatement activities for one million; after getting a green loan of exactly one million, the company could still implement abatement activities for exactly one million and use the green loan for capital investment completely. The firms' optimization follows the same recursive problem as in Section 3.2 but now with the new collateral constraint as stated in equation (13) instead of equation (5). The solution method is in the Internet Appendix III.

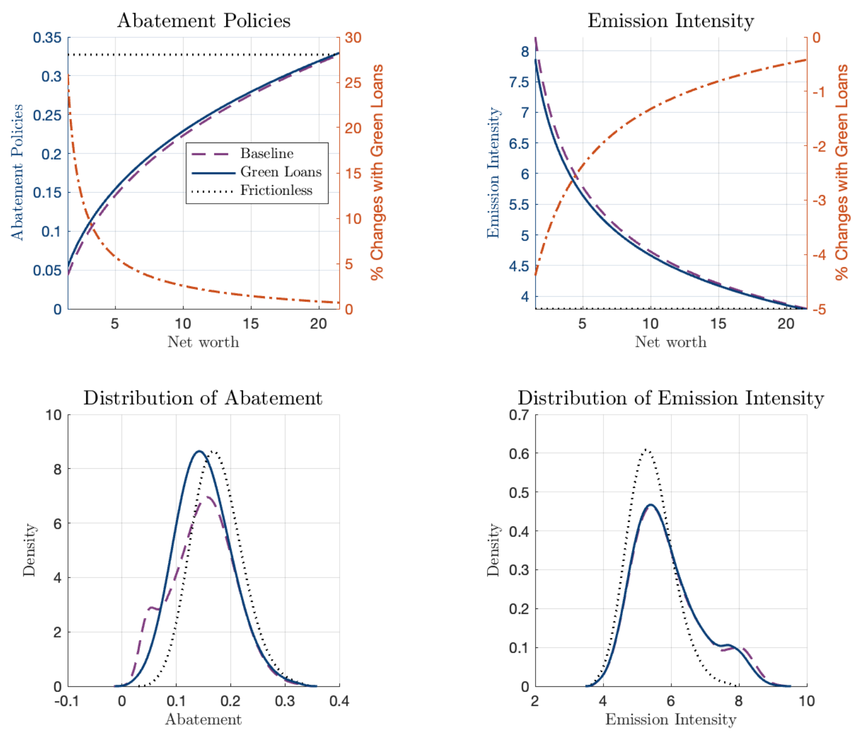
We choose a $\theta_a = 1$ to denote a 100% green loan support for any abatement activities for any firm. Though $\theta_a = 1$ is way larger than $\theta_k = 0.4$, given that total abatement activities are only about 1% of total capital stock, this policy is likely only injecting a tiny amount of green loans into the financial market. In our simulated counterfactual, the supply of green loans is only about 0.75% of total credit in the economy.

**Firm-level Effects of Green Loans** We first show which firms are affected more by green loan policies by examining their decision rules and the equilibrium distribution. Figure 9 shows the

[12]Using the certificates of pollution abatement costs as collateral is similar to the setup of patent collateral (Chen et al., 2023) or loan guarantee (Benhima et al., 2024). The essential idea is that firms' marginal finance costs of abatement are now relaxed, and they can get a green loan or bond based on such abatement expenditures.

firm-level effects. The upper-left panel shows the abatement policies of firms under green loans (blue solid line) compared to the baseline model (purple dashed line) and the frictionless model (black dotted line). We also show the percentage changes of abatement under green loans over the baseline model in the orange dashed-dotted line, which is the distance between the blue solid line and the purple dashed line. Smaller and more constrained firms significantly increase their abatement activities after receiving green loans. Therefore, as shown in the upper-right panel, their emission intensity also significantly decreases.

**Figure 9. Green Loan Effects on Decision Rules and Distributions**




Notes: Subplot 1 shows the abatement policies of firms (high productivity) under green loans compared to the baseline and frictionless models. Smaller and more constrained firms significantly increased their abatement activities. Therefore, as shown in Subplot 2, their emission intensity also significantly decreased. Subplots 3 and 4 show the density distribution of abatement activities and emission intensity from our model-simulated firm sample. The dotted curve is the density of abatement and emission intensity in the frictionless model, the dashed purple curve is the corresponding densities in the baseline model, and the solid blue curve is the corresponding densities in the green loan model. The densities in the baseline model are a combination of two firms: the unconstrained firms acting as firms in the frictionless model and the constrained firms that abate less. The distributions are dual-peaked, with lower abatement and higher emission intensity. The green loan model helps reduce the inefficient peak in the emission intensity distribution.

The lower panels show the density distribution of abatement activities and emission intensity from our model-simulated firm sample. The densities in the baseline model are a combination of two types of firms: the unconstrained firms acting as firms in the frictionless model and the constrained firms that abate less. The baseline model's abatement and emission intensity distribution are dual-peaked, with a second peak having lower abatement and higher emission intensity, respectively. In the counterfactual model with green loans, the second peak with lower abatement in the abatement distribution is wiped out, and the second peak with higher emission intensity is reduced. The green loan policies help reduce the inefficient emission intensity distribution peak.

**Table 8**: **The Allocation and Aggregate Effects of Green Loan Policies** ($\theta_a = 1$)

*Panel A: Allocation of Green Loans*

| Outcomes | Total $\sum b$ | Green $\sum b_g$ | Used $\frac{\sum \Delta a}{\sum b_g}$ | Washed $\frac{\sum \Delta k}{\sum b_g}$ | New $\sum \theta_k \Delta k$ |
|---|---|---|---|---|---|
| Baseline | 5.30 | 0.00 | – | – | – |
| Green Loan | 5.37 | 0.04 | 0.002 | 0.038 | 0.03 |
| % to Total $\sum b$ | +1.32% | +0.75% | +0.04% | +0.71% | +0.56% |
| % to Green $\sum b_g$ | – | – | 5% | 95% | 75% |

*Panel B: Aggregate Effects of Green Loan Policies*

| Outcomes | Output | Capital | Consump. | Abatement | Emission | E. Intensity |
|---|---|---|---|---|---|---|
| Baseline | 4.04 | 13.25 | 2.58 | 0.137 | 23.14 | 6.16 |
| Green Loan | 4.06 | 13.32 | 2.59 | 0.139 | 23.11 | 6.12 |
| % Changes | +0.5% | +0.5% | +0.4% | +1.5% | -0.1% | -0.6% |

Notes: Panel A shows the allocation of total credit and green loans. We have three observations. First, the green loans policy is a relatively small-scale credit intervention in the credit market. Firms, in total, use about 0.75% of green loans $\sum b_g$ relative to total credit $\sum b$ in the baseline model. Second, the supply of green loans also relaxes financial frictions in general. We see an accompanying growth in capital collateral credit $\sum \theta_k \Delta k$ of 0.56% because firms grow larger and have additional collateral. Both channels add up to a total of 1.32% growth in total credit $\sum b$. Third, financial greenwashing happens. Among the 0.75% usage of green loans $\sum b_g$, only 5% is indeed exactly used for increased abatement activities $\frac{\sum \Delta a}{\sum b_g}$. At the same time, the other 95% is greenwashed for increased capital investment $\frac{\sum \Delta k}{\sum b_g}$. Panel B shows the aggregate effects of green loan policies ($\theta_a = 1$) on the stationary economy calculated from aggregating the stationary equilibrium distributions of the green loans economy and its comparison to our baseline economy. First, the supply of green loans makes the economy cleaner by directly increasing abatement activities. More specifically, the injection of green loans of 0.75% of total credit directly increases abatement activities by 1.5% and lowers emission intensity. It also boosts the economy by increasing the output and capital stock by 0.5% and consumption by 0.4%. Such growth of the economy leads to a smaller reduction of total emissions of 0.1% compared to the 0.6% reduction in emission intensity. Second, the supply of green loans makes the economy cleaner by indirectly relaxing the financial frictions of dirtier firms and, therefore, making them cleaner. Although most green loans are used by firms for capital investment, the supply of green loans indirectly relaxes the financial burdens of smaller and constrained firms to do abatement and capital investment. Allowing the more constrained, smaller, and younger firms to grow faster also helps to reduce emission intensity. Therefore, both the direct and indirect channels lead to the total reduction of emission intensity of 0.6%.

**Allocation and Aggregate Effects of Green Loans** We finally show how the newly supplied green loans are allocated and their aggregate implications in Table 8. Panel A shows the allocation of total credit and green loans. We observe three patterns. First, when we compare the baseline economy with the economy with green loans in Panel A, the green loan policy is a relatively small-scale credit intervention in the credit market: Green loans used by firms ($\sum b_g$) only account for about 0.75% of total credit ($\sum b$). Second, financial greenwashing happens. Among the 0.75% usage of green loan $\sum b_g$, only 5% is indeed exactly used for increased abatement activities $\frac{\sum \Delta a}{\sum b_g}$. At the same time, the other 95% is greenwashed for increased capital investment $\frac{\sum \Delta k}{\sum b_g}$. Third, the supply of green loans also relaxes financial frictions in general. We see an accompanying growth in capital collateral credit $\sum \theta_k \Delta k$ of 0.56% because firms grow larger and have additional collateral. The two channels (the growth channel and the increased abatement channel) add up to a total of 1.32% growth in total credit $\sum b$.

Panel B shows the aggregate effects of green loan policies on the economy calculated by aggregating the distributions of firms in Panel A. First, the supply of green loans makes the economy cleaner by directly increasing abatement activities (i.e., the increased abatement channel). More specifically, the injection of green loans of 0.75% of total credit directly increases abatement activities by 1.5%. Second, the supply of green loans makes the economy cleaner by indirectly relaxing the financial frictions of dirtier firms and, therefore, making them cleaner (i.e., the growth channel). Although firms use most green loans for capital investment, the supply of green loans indirectly relaxes the financial burdens of smaller and constrained firms to do abatement and capital investment. Third, the green loans lead to economic growth. It also boosts the economy by increasing output and capital stock by 0.5% and consumption by 0.4%. Such growth of the economy leads to a 0.1% reduction in total emissions and a 0.6% reduction in emission intensity. In other words, allowing the more constrained, smaller, and younger firms to grow faster also helps to reduce emissions.

# 8 Conclusion

This paper explores the effects of financial frictions on firms' pollution abatement activities and their aggregate implications for the economy and the environment. At the center of our analysis is the role of financial frictions in the life cycle of firm growth. Using US firm-level data, we document significant differences in pollution abatement activities over the life cycle of firms. Smaller and younger firms are more constrained in financial indicators and have higher emission intensity. In addition, these firms invest more in physical capital and engage less in pollution abatement activities; interestingly, their abatement investment accelerates, and their emission intensity reduces as they accumulate more net worth and grow older.

Motivated by this evidence, we develop and quantify a heterogeneous firm model to study the relationship between financial frictions, physical investment, and pollution abatement activities. In the model, constrained, smaller, and younger firms prefer physical investment over pollution abatement because the returns from the former are higher than those from the latter. The model successfully replicates all the life cycle patterns in our empirical analysis. Taking the model to the data, we show that the aggregate welfare loss from the sub-optimal environmental regulation due to financial frictions is substantial. Finally, we show that even without monitoring, green loan policies are still considerably effective in reducing emission intensity through increasing abatement investment and enhancing firm growth.

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# Internet Appendix for "Financial Frictions and Pollution Abatement Over the Life Cycle of Firms"*

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## Contents



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# I Data Appendix

## I.1 The Toxic Release Inventory (TRI) Database

The Toxic Release Inventory (TRI) program and the resultant database are maintained by the United States Environmental Protection Agency (EPA). In 1986, the U.S. Congress passed the Community Right to Know Act (EPCRA) in response to public concerns over the release of toxic chemicals from several environmental accidents in the U.S. and overseas. The EPCRA entitles residents in their respective neighborhoods to know the source of detrimental substances, especially for their potential impacts on human health from routes of exposure.

In response to the EPCRA, the EPA established the TRI program to track and supervise certain classifications of toxic substances and chemical pollutants that endanger human health and the environment. The changes and updates to the list of these pollutants are provided on the EPA website (www.epa.gov/sites/production/files/2020-01/documents/tri_chemical_list_changes_01_21_2020.pdf). In particular, the EPA mandates a record of the amount of each TRI-listed toxic chemical being released to the environment through the air, water, or soil each year for every facility that meets the following criteria:

1. It manufactures, processes, or otherwise uses a TRI-listed chemical in quantities above threshold levels in a given year.
2. It has ten or more full-time equivalent employees.
3. It is in the mining, utility, manufacturing, publishing, hazardous waste, or federal industry.

When a facility meets all three criteria in a year, it must report to the EPA and thus enter into the TRI program. The EPA then publicizes the TRI database, which contains detailed information about the TRI program and is available for any interested third party to access. The EPA also provides annual data on pollutant density recorded by air monitors. A single air monitor records the density of multiple pollutants at a fixed location every hour.

To maintain the data quality of the information in the TRI program, the EPA first identifies if a TRI form submitted by a facility contains potential errors; if so, the EPA contacts the facility. Once the EPA confirms errors, the facility is requested to resubmit a corrected TRI report. In addition, the Office of Inspector General is an independent office within the EPA that performs audits, evaluations, and investigations of the agency and its contractors to prevent and detect fraud, waste, and abuse. The EPA then conducts an extensive quality analysis of the TRI reporting data and provides analytical support for enforcement efforts led by its Office of Enforcement and Compliance Assurance (OECA).

The annual emission data of all facilities reported to the EPA are updated on the webpage of the TRI program between July and September of the following year, as shown in Figure IA.1. It is worth noting that the TRI program has included approximately 98% of facility-level emission data of 2020 on July 20, 2022.

To calculate a facility's total emissions, we measure emissions across four key categories: total production emissions, total releases, onsite releases, and land disposal. As the EPA outlines, these categories enable a detailed emissions analysis, providing insights into a facility's environmental impact. For example, total production emissions include all emissions resulting from the facility's production processes within a specific timeframe, serving as a baseline for evaluating operational efficiency and environmental responsibility. Total releases compile all emissions discharged into the environment, offering a comprehensive view of the facility's overall impact.

On-site releases specifically focus on emissions directly released into the surrounding environment from the facility's location, highlighting areas for immediate pollution reduction. Land disposal measures the waste and emissions disposed of on land, indicating the facility's effect on land quality and the risk of soil contamination. This systematic categorization improves understanding of a facility's emission profile and supports identifying targeted strategies for mitigating environmental damage. Finally, we calculate the total emissions by adding the amounts of all chemicals the facility releases in pounds for a given year.

Thus, in our empirical tests, such as our portfolio analysis, we construct portfolios at the end of September of year $t$ to ensure that the information with respect to facility emissions in year $t-1$ is publicly available when we sort portfolios.

**[Place Figure IA.1 about here]**

We also notice that the TRI database may not be comprehensive before 1991, as we observe an abnormally high ratio of reported zeros in facilities' TRI-listed chemicals in pre-1991 years. We thus download and organize the facility-level TRI data from 1991 to 2020 as follows:

**Step 1:** We access the TRI program via the EPA website (https://www.epa.gov/toxics-release-inventory-tri-program)

**[Place Figure IA.2 about here]**

**Step 2:** We download the annual TRI data from 1991 to 2020.

**[Place Figure IA.3 about here]**

**Step 3:** For each facility in a year, we use the value "PROD._WASTE_(8.1_THRU_8.7)," which is the sum of the total released toxic pollutants (in pounds) across all chemical categories for each plant. Despite this, there are seven items reported in Section 8 of the TRI database, including item 8.1 (amount of total releases), 8.2 (energy recovery on-site), 8.3 (energy recovery off-site), 8.4 (recycling on-site), 8.5 (recycling off-site), 8.6 (treatment on-site), 8.7 (treatment off-site), and PROD._WASTE_(8.1_THRU_8.7) (the sum of the quantities in items 8.1 through 8.7). Details available in the TRI database (https://www.epa.gov/sites/production/files/2019-08/documents/basic_data_files_documentation_aug_2019_v2.pdf). Since 2003, item 8.1 (amount of total releases) has been separated into four sub-items and documented as item 8.1a (on-site contained releases), 8.1b (on-site other releases), 8.1c (off-site contained releases), and 8.1d (off-site other releases).

Three issues are worth discussing before we proceed. First, the TRI database provides a link table with the facility-level Dun & Bradstreet number. As a result, we exploit the identifier to bridge the TRI database to the NETS database and obtain additional facility-level information, including sales and employment. Second, the TRI database also includes a "parent name" that indicates the name of a company that owns the facility. Thus, we can further use the "parent name" to bridge the TRI database to the CRSP/Compustat database (e.g., Xiong and Png (2019)). Third, the TRI database has not changed the coverage of chemicals and pollutants to be disclosed.

## I.2 The Pollution Prevention (P2) Database

We obtain the facility-level abatement activities from the Pollution Prevention (P2) database to measure a facility's pollution abatement activities. Specifically, we sum up the number of new source reduction activities across all chemicals implemented by the facility in that year. For instance, Alcoa Corporation reported implementing 71 abatement activities across 28 states in the United States in 1993. For example, one of its facilities in Iowa State (TRI Facility ID: 52808LMNMCHIGHW) implemented two activities with code W58 to reduce other process modifications and one with code W81 to change product specifications. We download the facility-level P2 data from 1991 to 2020 as follows:

**Step 1:** We access the P2 program via the EPA website (`https://www.epa.gov/p2`)

**[Place Figure IA.4 about here]**

**Step 2:** We download the annual P2 data from 1991 to 2020.

**[Place Figure IA.5 about here]**

**Step 3:** For each facility in a year, we count the total number of abatement activities.

**[Place Figure IA.6 about here]**

We exploit the Pollution Prevention P2 database from the EPA to analyze abatement activities. As presented in Figure IA.6, EPA provides the waste management hierarchy starting from 1991. In addition, to release quantities for a released pollutant, plants reporting in the TRI database must document specific source reduction activities that mitigate the number of hazardous substances entering the waste stream: the quantities of the chemical recycled, used for energy recovery, or treated at the facility or elsewhere in addition to the original reporting requirements on releases emitted directly into the environment or transferred off-site to disposal, treatment, or storage facilities. Moreover, plants report optional waste minimization information on source reduction activities, such as process modifications and substituting raw materials, which were newly implemented during the reporting year. The rest, but the most common type of abatement activity, comprises several actions: modifications to equipment, layout, or piping. The list of various abatement activities is available in Table IA.1.

**[Place Table IA.1 about here]**

## I.3 Abatement Activity Measures: Capital Investment

Our analysis focuses on firm-level pollution abatement activities (from the P2 dataset) and emissions (from the TRI database). Following the classification method outlined in Section 2.2 of the main text, we first classify each abatement activity as either an operating expense or a capital investment based on its implementation characteristics, and then isolate those activities identified as capital investments for our analysis.

To classify pollution abatement activities from the P2 dataset, we assign each of the 49 distinct activities a score from 10 to 1 based on input requirements, process complexity, and infrastructure needs according to Table IA.1 in Section I.3. Higher scores (10 and 9) indicate low complexity and procedural changes that require minimal infrastructure modifications. These are characteristic of operating expenses, such as material substitution or adjustments to operational practices. Moderate scores (8–7) imply minor capital outlays (e.g., small equipment modifications), while lower scores denote increasing capital intensity: scores of 6–5 involve moderate investment (e.g., new machinery), 4–3 signal significant infrastructure upgrades, and 2–1 indicate full system replacements or major technological overhauls.

We then translate these scores into weights: 1 for scores below 3 (capital investment), 0.5 for scores between 4 and 6 (moderate), and 0 for scores above 7 (operating expenses). Aggregating the weighted activities at the firm-year level yields our measure of capital-intensive abatement activities.

## I.4 Civil Litigation Cases Against Pollution Dataset

**Pollution Penalty from Civil Litigation Cases Against Pollution** We collect data on civil cases against pollution to match the pollution penalty in our model. To collect the number and dollar amount of civil cases against pollution in the EPA record, we use the following procedures:

**Step 1:** We access the Enforcement and Compliance History Online (ECHO) system that contains information on civil cases provided by the EPA:
https://echo.epa.gov/tools/data-downloads/icis-fec-download-summary

**[Place Figure IA.7 about here]**

**Step 2:** We next download all cases from the "PENALTIES" file on the webpage. Different types of civil penalties are reported for each case, as well as the case identifier, the total federal penalty amount, the state or local penalty amount, the total supplemental environmental project amount, the total complying action amount, and the federal cost recovery awarded amount.

**Step 3:** Moreover, we access facility-case-level information from the "Facilities in Case" file, including the facility identifier, the case identifier, and detailed address information about the facility's location in each case. Finally, using this file, we trace back to the TRI database via the facility identifier and collect the number and dollar amount of civil litigation cases at the firm level for our empirical analysis.

**A Case Study of a Public Firm's Environmental Impact** Figure IA.8 illustrates a case of environmental contamination by Dow Chemical. In 2002, Dow Chemical agreed to settle a lawsuit in California by spending $3 million on wetlands restoration. In 2008, the federal government intervened and claimed damages to nearby residents' health from airborne contamination from Dow Chemical's nuclear weapon plant in Colorado. In 2011, Dow Chemical negotiated with the regulator about violations of the Clean Air Act, which caused the dioxin contamination in Michigan. See Corporate Research Project (http://www.corp-research.org/dowchemical). On November 9, 2019, Dow Inc., which merged with DuPont Co. in 2017, settled an environmental complaint at an estimated cost of $77 million in projects and funding for the restoration of injured fish, wildlife, and habitats after hazardous chemical pollutants were released over several decades from Dow's facility located in Midland, Michigan. See Dow's settlement (https://www.michigan.gov/ag/0,4534,7-359-92297_47203-511944--,00.html).

## I.5 Matching TRI (NETS) with CRSP/Compustat

We extract facilities' parental names in the TRI (NETS) database and then match these names in the TRI database to the names of U.S. public companies in the CRSP/Compustat database. We first clean parent firm names in the TRI (NETS) database and firm names in the CRSP/Compustat database following the approach of Chen, Hsieh, Hsu, and Levine (2022). Specifically, we remove punctuation and clean special characters. We then convert firm names into uppercase and standardize them. For example, we standardize "INDUSTRY" to "IND," "INCORPORATION" to "INC," and "COMPANY" to "COM."

To match facilities' parental firm names with firms in CRSP/Compustat based on standardized names, we use the fuzzy name-matching algorithm via SAS, which generates matching scores for all name pairs of parent names in TRI (NETS) and firms in CRSP/Compustat. The matching score measures the distance between the two firms' names. The index score ranges from 0 to infinity, with a score of zero being a perfect match. We obtain a pool of potential matches based on two criteria: (1) the matching score must be precisely 0 and thus the same as those of firms in the CRSP/Compustat database, and (2) the matching score must be below 500. We then hire research assistants to identify exact matches from all potential matches manually.

## I.6 Details on Anti-Recharacterization Laws Shocks

Anti-recharacterization laws are pivotal in secured transactions, especially pertinent in bankruptcy proceedings under Chapter 11 of the U.S. Bankruptcy Code, which facilitates business reorganization. These laws prevent reclassifying secured debt agreements as other forms of financial arrangements during bankruptcy. This distinction is crucial because the treatment of these agreements under Chapter 11 can significantly influence both the debtor's reorganization plan and the recovery strategy of secured creditors.

In regions where anti-recharacterization laws are robust, these statutes ensure that secured debts retain their status throughout the bankruptcy process. This is particularly important under Chapter 11, where the reclassification of debts can alter creditors' priority, potentially diminishing their rights to claim against the debtor's assets. By maintaining the integrity of the original contractual terms, these laws ensure that secured debts are not subject to recharacterization as unsecured, which can crucially affect the repayment hierarchy in bankruptcy.

The implications of anti-recharacterization laws on secured lending are as follows. The enactment of anti-recharacterization laws strengthens the position of secured creditors by safeguarding the terms of their agreements against judicial reinterpretation in bankruptcy cases. This legal certainty is instrumental for creditors, as it diminishes the risks associated with lending. Knowing that their claims and collateral are legally protected makes lenders more willing to extend credit to businesses, particularly in financially volatile environments.

For borrowers, particularly those in industries with higher operational risks, these laws can facilitate easier access to credit. Lenders, reassured by the legal protections these laws provide, may offer larger loans or more favorable terms. This is because the enhanced creditor protection minimizes the potential loss in the event of the borrower's bankruptcy, ensuring that the secured assets can be reclaimed or prioritized for repayment.

Ultimately, the stability brought by anti-recharacterization laws encourages a healthier credit market. Lenders are more likely to engage in secured lending when they can trust the enforceability of their agreements, leading to increased financial fluidity for businesses. This supports business expansion and stimulates economic growth by ensuring enterprises can access necessary capital under conditions that respect creditors' rights.

## I.7 Details on Natural Disaster Demand Shocks

To identify exogenous demand shocks, we utilize county-level disaster records from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), which provides detailed data on the location, timing, and type of natural disaster events across all U.S. counties. The SHELDUS Database, maintained by Arizona State University, is a comprehensive county-level dataset that tracks natural hazard events and associated losses across the United States. It includes information on the occurrence and severity of disasters such as hurricanes, floods, wildfires, and earthquakes, along with property damage, crop losses, injuries, and fatalities.

We begin by matching SHELDUS disaster events to facility-level data from the Toxics Release Inventory (TRI) based on the county-year in which each facility operates. A firm is considered indirectly affected—and thus part of the treatment group—if none of its TRI-reporting facilities is located in a county that experienced a disaster in a given year, but other firms in the same industry-year were directly affected. These treatment firms do not face production disruptions, operational delays, or physical damage, but may experience increased demand as a result of disasters impacting their industry peers. In contrast, firms with facilities located in disaster-affected counties are classified as directly impacted and excluded from the treatment group in order to avoid conflating supply-side disruptions with demand-driven effects. We focus on firms that were not directly affected by disasters but operate in the same industry-year as at least one firm that was. These firms are assumed to face a temporary surge in consumer demand, likely due to a substitution effect as supply disruptions reduce the output of disaster-affected peers. To define industries, we use the Fama-French 48 industry classification system (Fama and French, 1997).

This approach creates a quasi-experimental setup, allowing us to compare firms that are positively exposed demand shocks (but face no operational disruptions) to firms in unaffected industries. These demand shocks are exogenous to the firms' investment and pollution abatement decisions, which are assumed to be predetermined. Therefore, any observed difference in outcomes, such as emission intensity or sales growth, can be interpreted as a response to the exogenous shift in industry-specific demand pressure.

# II Empirical Appendix

In this section, we present additional empirical results and robustness tests.

## II.1 Details of Firm-level Productivity Estimation

**Firm-level Productivity Estimation** Data and firm-level productivity estimations are constructed as follows. We consider publicly traded companies on U.S. stock exchanges listed in both the annual Compustat and the CRSP (Center for Research in Security Prices) database. We assume that the production function at the firm level is Cobb-Douglas and allow the parameters of the production function to be industry-specific:

$$y_{i,j,t} = z_{i,j,t} k_{i,j,t}^{\alpha_{1,j}} n_{i,j,t}^{\alpha_{2,j}},$$

in which $z_{i,j,t}$ is the firm-specific productivity level at time $t$. This is consistent with our original specification because the observed physical capital stock, $k_{i,j,t}$, corresponds to the mass of production units owned by the firm.

We estimate the industry-specific capital share, $\alpha_{1,j}$, and labor share, $\alpha_{2,j}$, using the dynamic error component model adopted in Blundell and Bond (2000) to correct for endogeneity. Given the industry-level estimates for $\widehat{\alpha_{1,j}}$ and $\widehat{\alpha_{2,j}}$, the estimated log productivity of firm $i$ is computed as follows:

$$\ln \widehat{z_{i,j,t}} = \ln y_{i,j,t} - \widehat{\alpha_{1,j}} \cdot \ln k_{i,j,t} - \widehat{\alpha_{2,j}} \cdot \ln n_{i,j,t}.$$

We allow for $\widehat{\alpha_{1,j}} + \widehat{\alpha_{2,j}} \neq 1$, but our results also hold when we impose constant returns to scale in the estimation, that is, $\widehat{\alpha_{1,j}} + \widehat{\alpha_{2,j}} = 1$.

We use the multi-factor productivity index for the private non-farm business sector from the BLS as the measure of aggregate productivity.

**Endogeneity and the Dynamic Error Component Model** We follow Blundell and Bond (2000) and write the firm-level production function as follows:

$$\begin{aligned} \ln y_{i,t} &= \phi_i + w_t + \alpha_1 \ln k_{i,t} + \alpha_2 \ln n_{i,t} + v_{i,t} + u_{i,t} \\ v_{i,t} &= \rho v_{i,t-1} + e_{i,t}, \end{aligned} \tag{II.1}$$

in which $\phi_i$, $w_t$, and $v_{i,t}$ indicate a firm fixed effect, a time-specific intercept, and a possible autoregressive productivity shock, respectively. The residuals from the regression are denoted by

$u_{i,t}$ and $e_{i,t}$ and are assumed to be white noise processes. The model has the following dynamic representation:

$$\begin{aligned}\Delta \ln y_{i,j,t} &= \rho\Delta \ln y_{i,j,t-1} + \alpha_{1,j}\Delta \ln k_{i,j,t} - \rho\alpha_{1,j}\Delta \ln k_{i,j,t-1} + \alpha_2\Delta \ln n_{i,j,t} - \rho\alpha_2\Delta \ln n_{i,j,t-1} \\ &\quad +(\Delta w_t - \rho w_{t-1}) + \Delta\kappa_{i,t}, \end{aligned} \tag{II.2}$$

in which $\kappa_{i,t} = e_{i,t}+u_{i,t}-\rho u_{i,t-1}$. Let $x_{i,j,t} = \{\ln(k_{i,j,t}), \ln(n_{i,j,t}), \ln(y_{i,j,t})\}$. Assuming that $E[x_{i,j,t-l}e_{i,t}] = E[x_{i,j,t-l}u_{i,t}] = 0$ for $l > 0$ yields the following moment conditions:

$$\begin{aligned} E[x_{i,i,t-l}\Delta\kappa_{i,t}] &= 0 \text{ for } l \geq 3 \\ E[x_{i,j,t-l}\Delta\kappa_{i,t}] &= 0 \text{ for } l \geq 3. \end{aligned} \tag{II.3}$$

that are used to conduct a consistent GMM equation estimation (II.2). Given the estimates $\widehat{\alpha}_{1,j}$ and $\widehat{\alpha}_{2,j}$, log productivity of firm $i$ is computed as:

$$\ln \widehat{z}_{i,j,t} = \ln y_{i,j,t} - \widehat{\alpha}_{1,j} \ln k_{i,j,t} - \widehat{\alpha}_{2,j} \ln n_{i,j,t}, \tag{II.4}$$

in which $\widehat{z}_{i,j,t}$ is the productivity for firm $i$ in industry $j$.

**Endogeneity and Fixed Effects** An alternative way to estimate the production function, avoiding endogeneity issues, is to work with the following regression:

$$\ln y_{i,j,t} = v_j + \phi_{i,j} + w_{j,t} + \alpha_{1,j} \ln k_{i,j,t} + \alpha_{2,j} \ln n_{i,j,t} + u_{i,j,t}. \tag{II.5}$$

The parameters $v_j$, $\phi_{i,j}$, and $w_{j,t}$ indicate an industry dummy, a firm fixed effect, and an industry-specific time dummy, respectively. The residual from the regression is denoted by $u_{i,j,t}$. Given our point estimate of $\widehat{\alpha}_{1,j}$ and $\widehat{\alpha}_{2,j}$, we can use equation (II.4) to estimate $\widehat{z}_{i,j,t}$. Given this estimation of firms' productivity, we obtain an alternative estimation of firms' productivity.

## II.2 The Pecking Order in Two Dimensions

We further explore the pecking order of abatement and investment by jointly examining firm net worth and productivity. To do so, we double-sort firms along these two dimensions and report the results in Table IA.2. Productivity is defined as the Solow residual estimated from industry-specific Cobb-Douglas production functions, as detailed in Section II.1 of the Internet Appendix. We report Table IA.2 and visualize in Figure 4 in Section 4.2 of the main text to provide a nuanced understanding of how abatement activities, total raw emissions, emission intensity, and investment rates vary across different levels of net worth and productivity.

**[Place Table IA.2 about here]**

Panel A of Table IA.2 plots pollution abatement activities (Abate) against firm net worth, separating high- and low-productivity firms. Abatement activities rise monotonically with net worth for low-productivity firms, but the increase is steeper for high-productivity firms. This suggests that abatement decisions are shaped not only by firm size but also by productivity, which amplifies the effect of net worth. Notably, the gap in abatement between high- and low-productivity firms widens with net worth, highlighting the role of productivity in driving cross-firm variation in abatement activities.

Panel B shows that total raw emissions (Emission) also rise with net worth across both productivity groups. High-productivity firms emit more at any given net worth level, confirming a scaling effect due to greater output. Panel C examines emission intensity (Emission/Sales), which declines with net worth. This pattern aligns with the observed increase in abatement activities, suggesting that emissions per unit of output fall as firms grow. Furthermore, high-productivity firms exhibit lower emission intensity than their low-productivity counterparts at comparable net worth levels, indicating that productivity drives cross-firm heterogeneity.

Finally, Panel D focuses on investment rates (I/K), revealing an inverse relationship between investment rate and net worth, especially pronounced among high-productivity firms. This pattern may reflect diminishing marginal returns to capital as firms grow. Importantly, the investment rate is higher for more productive firms, underscoring the positive association between productivity and investment decisions. These results illustrate the interaction between net worth, productivity, and key firm characteristics, consistent with our model in Sections 4.2.

## II.3 The Pecking Order on Size Measures

Table IA.3 reports reports the time-series average of the cross-sectional means of firm characteristics for five groups sorted by firms' net worth in Panel A, total assets in Panel B, capital in Panel C, and the number of employees in Panel D. Pollution abatement is measured as the sum of new source reduction projects undertaken by facilities of a firm within a specific year. Raw emissions are derived by aggregating the pounds of total releases (Emission) from all plants owned by a firm within a year. Emission intensity (Emission/S) is calculated by aggregating the specified emission components across all of a firm's plants within a year for each group. This aggregate is then divided by aggregating firms' sales for each respective group to normalize the measure. This process yields the emission intensity. Net worth, total assets, and capital are adjusted for inflation using the Consumer Price Index (CPI) and reported in 2009 million USD. I/K is capital expenditures (item CAPX) divided by property, plant, and equipment (PPENT). B/M is the ratio of book equity to market capitalization. Return on assets (ROA) is operating income after depreciation (item OIADP) scaled by total assets. Book leverage (Lev) is the summation of current liabilities (item DLC) and long-term debt (item DLTT) scaled by total assets. Firm characteristics are described in Table 1. The sample period is 1991 to 2020.

**[Place Table IA.3 about here]**

## II.4 The Pecking Order on Age Measures

Table IA.4 reports the time-series average of the cross-sectional means of firm characteristics for five groups sorted by age according to Compustat in Panel A, World Scope in Panel B, incorporation year in Panel C, and founding year in Panel D.

**[Place Table IA.4 about here]**

Table IA.5 presents the time-series average of the cross-sectional means of firm characteristics, categorized into five groups double-sorted by those measures for firm ages and two groups by firm-level productivity. The estimation for firm-level productivity is discussed in Section II.1 of the Internet Appendix. The sample period covers from 1991 to 2020.

**[Place Table IA.5 about here]**

Table IA.6 reports univariate regressions of firms' pollution abatement, emission intensity, and investment rate on age according to Compustat in Panel A, World Scope in Panel B, incorporation year in Panel C, and founding year in Panel D, as well as firm and year fixed effects. All independent variables are normalized to zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. $t$-statistics based on standard errors clustered at the firm level are reported with ***, **, and * indicating significance at the 1, 5, and 10% levels. The sample period is from 1991 to 2020.

**[Place Table IA.6 about here]**

## II.5 The Pecking Order on Financial Constrained Indicators

Table IA.7 reports the time-series average of the cross-sectional means of firm characteristics for five groups sorted by SA index in Panel A and WW index in Panel B.

**[Place Table IA.7 about here]**

Table IA.8 presents the time-series average of cross-sectional means of firm characteristics, categorized into five groups double-sorted by financial constraint measures, SA index in Panel A and WW index in Panel B, and two groups based on firm-level productivity.

**[Place Table IA.8 about here]**

Table IA.9 reports univariate regressions of firms' pollution abatement, raw emissions, emission intensity, and investment on the SA index in Panel A and the WW in Panel B, as well as firm and year fixed effects. All independent variables are normalized to zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. $t$-statistics based on standard errors clustered at the firm level are reported with ***, **, and * indicating significance at the 1, 5, and 10% levels. The sample period is from 1991 to 2020.

**[Place Table IA.9 about here]**

## II.6 The Pecking Order on Abatement Capital Investment

We further examine whether the pecking order observed for operating-related abatement also holds for capital investment–intensive abatement activities; for instance, green capital versus brown capital. To do so, we re-estimate equation (1) using only capital-related abatement as the outcome variable. The results are presented in Table IA.10.

**[Place Table IA.10 about here]**

Table IA.10 shows that firm size, as measured through various proxies such as net worth, total assets, capital stock, and employment, is positively associated with the level of capital-intensive abatement. For example, a one-standard-deviation increase in net worth is associated with a 14% increase in capital-related abatement activities. Moreover, the age and financial constraint proxies indicate that older and less financially constrained firms also undertake more abatement activity. This finding is consistent with the idea that such abatement investments may still be more complex to finance, although potentially pledgeable due to their long-term and illiquid nature, in line with insights from Lanteri and Rampini (2023). Overall, the evidence reinforces the existence of a pecking order in firms' abatement activities.

## II.7 Details on Abatement Costs Imputation

To estimate the expenditure burden of operating pollution abatement activities at the firm level, we develop a method that integrates detailed source reduction activity data from the Toxics Release Inventory (TRI) with industry-level cost information from the 2005 Pollution Abatement Costs and Expenditures (PACE) survey. We aim to assign a cost estimate to each reported W-code activity, reflecting its implementation type (operating cost vs. capital investment) and its intensity in dollar terms relative to industry output.

**Step 1: Classifying W-codes by Cost Type.** Each W-code in the TRI P2 dataset represents a distinct type of source reduction activity. We begin by assigning a score to each W-code on a scale from 1 to 10, based on its expected input requirement, complexity, and infrastructure changes. Higher scores indicate lower implementation complexity and are more likely to reflect operating costs than capital investments. For example, W84 (substituting materials in products) is a low-complexity, procedural change and receives a high score, while W66 (installing new rinse systems) involves equipment upgrades and gets a lower score.

We then classify codes with scores above seven as operating costs, while those with scores seven or below are treated as capital investments. This binary categorization allows us to link each W-code to the appropriate category of abatement spending reported in the PACE survey.

**Step 2: Measuring Abatement Cost Intensity by Industry.** The PACE survey reports total industry-level expenditures on pollution prevention, broken down into operating costs and capital investments. These are expressed in nominal 2005 U.S. dollars. To normalize for differences in industry size, we divide each cost component by total industry output (from BEA gross output data) to derive operating cost intensity and capital investment intensity, measured in dollars per $1 of production, for each 3-digit NAICS manufacturing sector, where $\omega_i^{\text{op}}$ and $\omega_i^{\text{cap}}$ denote the operating cost and capital investment intensity, respectively, for industry $i$.

**Step 3: Allocating Cost to W-codes within Each Industry** Next, we compute the relative frequency of each W-code within its category (capital or operating) in a given industry. For example, if industry $i$ has 200 capital W-code entries, and W66 accounts for 50, its frequency weight is 0.25 in the operating cost or capital investment category. We then allocate the corresponding cost intensity to each W-code in a given industry based on this frequency weight:

$$\text{Cost Intensity}_{h,i} = \begin{cases} \left(\frac{\text{Count}_{h,i}}{\sum_{h' \in \text{capital}} \text{Count}_{h',i}}\right) \times \omega_i^{\text{op}}, & \text{if } h \text{ is the operating cost} \\ \left(\frac{\text{Count}_{h,i}}{\sum_{h' \in \text{operating}} \text{Count}_{h',i}}\right) \times \omega_i^{\text{cap}}, & \text{if } h \text{ is the capital investment.} \end{cases} \tag{II.6}$$

This yields a *W-code-specific abatement cost intensity* by industry, which can be interpreted as the average cost intensity (in dollars per $1 of output) associated with each activity.

**Step 4: Estimating Firm-Level Abatement Costs** Using firm-year observations from the TRI dataset, we calculate the share of each W-code activity reported by a firm in a given year. Let $\text{Share}_{h,j,t}$ be the share of firm $j$ reports W-code $h$ in year $t$, and let $S_{j,t}$ be the firm's total sales. We compute the estimated firm-level abatement cost as:

$$\text{Abatement Cost}_{j,t} = \sum_{h} \text{Share}_{h,j,t} \times \text{Cost Intensity}_{h,i} \times S_{j,t} \tag{II.7}$$

This method produces a cost-weighted abatement metric for each firm-year, reflecting the scale and composition of its reported pollution prevention activities and adjusted for industry-specific cost norms.

**Step 5: Link to Firm Size and Empirical Validation** We use this dollar-adjusted measure to examine how abatement costs vary with firm size. Specifically, we test whether larger firms incur higher abatement costs or benefit from economies of scale in abatement investment. We regress firm-level abatement costs on size-related metrics to do so, as described in Section 2.4.

## II.8 The Pecking Order on Imputed Abatement Expenditures

We further examine whether the pecking order observed also holds for imputed abatement expenditures in the above subsection. To do so, we re-estimate equation (1) using the imputed abatement expenditures as the outcome variable. The results are presented in Table IA.11.

**[Place Table IA.11 about here]**

Table IA.11 shows that firm size, as measured through various proxies such as net worth, total assets, capital stock, and employment, is positively associated with the level of imputed abatement expenditures. For example, a one-standard-deviation increase in net worth is associated with a 51% increase in imputed abatement expenditures. Moreover, the age and financial constraint proxies indicate that older and less financially constrained firms also undertake more abatement activity. This finding is consistent with our main results in the paper. Overall, the evidence reinforces the existence of a pecking order in firms' abatement activities.

## II.9 Pollution Abatement Activities and Emission Reduction

According to Xu and Kim (2022), the higher release of toxic emissions is driven by insufficient investment in pollution abatement among firms subject to financial frictions. We provide direct evidence by examining the joint relationship between firm-level operating- or capital-intensive abatement activities and emission reduction. The Pollution Prevention database includes information on how much an abatement activity has reduced releases of each toxic chemical to the environment by which pollution prevention each year and compare how different facilities have managed their toxic releases. We sum up these reductions at the firm level each year.

**[Place Table IA.12 about here]**

We examine the relation between firm-level operating- or capital-intensive abatement activities and emission reduction more formally by estimating OLS regressions,

$$\Delta \text{Emission}_{j,t} = \xi_j + \xi_t + b \text{ Log}\left(1 + a_{j,t}\right) + c \text{ Controls}_{j,t} + \varepsilon_{j,t}, \tag{II.8}$$

for which we control a list of firm-level control variables, including size, book-to-market ratio, investment rate, and profitability, as well as facility and year fixed effects. Standard errors are clustered at the firm level. As presented in Table IA.12, all specifications indicate that estimated coefficients on operating- or capital-intensive abatement activities are statistically significantly negative at the 1% level, suggesting that pollution abatement activities effectively reduces toxic emissions. More importantly, evidence in this subsection provides us with a micro-foundation of a negative relation between emission and pollution abatement investment and calls for more theoretical work.

# III Quantitative Appendix

## III.1 Proof of Proposition 1

Following closely to Ottonello and Winberry (2024) with modifications to abatement activities.

**Lagrangian** The Lagrangian of the firm's optimization equation (3) is

$$\begin{aligned}\mathcal{L} =&(1+\lambda_t(z,n))\left(n-k'-a'+\frac{b'}{1+r_t}\right)+\mu_t(z,n)(\theta_k k'-b')\\ &+\chi_t(z,n)a'+\frac{1}{1+r_t}\mathbf{E}_t[\pi_d n'+(1-\pi_d)v_{t+1}(z',n')]\end{aligned} \tag{III.1}$$

where $\lambda_t(z,n)$ is the multiplier on the non-negative dividend constraint $d \geq 0$, $\mu_t(z,n)$ is the multiplier on the collateral constraint $b' \leq \theta_k k'$, and $\chi_t(z,n)$ is the multiplier on the non-negative constraint on abatement investment $a' \geq 0$.

The first-order condition for borrowing $b'$ is

$$(1+\lambda_t(z,n))\frac{1}{1+r_t}=\mu_t(z,n)-\frac{1}{1+r_t}\mathbf{E}_t\left[\pi_d\frac{\partial n'}{\partial b'}+(1-\pi_d)\frac{\partial v_{t+1}(z',n')}{\partial n'}\frac{\partial n'}{\partial b'}\right]$$

From the envelope condition, we have $\frac{\partial v_{t+1}(z',n')}{\partial n'}=1+\lambda_{t+1}(z,n)$, together with $\frac{\partial n'}{\partial b'}=-1$, we get

$$(1+\lambda_t(z,n))\frac{1}{1+r_t}=\mu_t(z,n)+\frac{1}{1+r_t}\mathbf{E}_t\left[\pi_d+(1-\pi_d)(1+\lambda_{t+1}(z,n))\right]$$

Reorganize we get

$$\lambda_t(z,n)=(1+r_t)\mu_t(z,n)+(1-\pi_d)\mathbf{E}_t\left[\lambda_{t+1}(z',n')\right] \tag{III.2}$$

This is the same as in Ottonello and Winberry (2024). The financial wedge here $\lambda_t(z,n)$ is the expected value of current and all future Lagrange multipliers on the collateral constraint $\mu_t(z,n)$, discounted by the exit risk.

The first-order condition for future capital $k'$ is

$$1+\lambda_t(z,n)=\theta_k\mu_t(z,n)+\frac{1}{1+r_t}\mathbf{E}_t\left[\pi_d\frac{\partial n'}{\partial k'}+(1-\pi_d)\frac{\partial v_{t+1}(z',n')}{\partial n'}\frac{\partial n'}{\partial k'}\right]$$

Given that $\frac{\partial n'}{\partial k'}=\alpha z'k'^{\alpha-1}+(1-\delta)-\frac{\tau'\bar{e}}{(1+\gamma a')}\alpha z'k'^{\alpha-1}=\left(1-\frac{\tau'\bar{e}}{(1+\gamma a')}\right)MPK(z',k')+(1-\delta)$, where

$MPK(z', k') = \alpha z' k'^{\alpha-1}$, we could rewrite the FOC as

$$1 + \lambda_t(z, n) = \theta_k \mu_t(z, n) + \frac{1}{1 + r_t} \mathbf{E}_t \Big[ \left( \pi_d + (1 - \pi_d)(1 + \lambda_{t+1}(z', n') \right) \times \\ \left( \left( 1 - \frac{\tau' \bar{e}}{(1 + \gamma a')} \right) MPK(z', k') + (1 - \delta) \right) \Big] \tag{III.3}$$

The first-order condition for abatement $a'$ is

$$1 + \lambda_t(z, n) = \chi_t(z, n) + \frac{1}{1 + r_t} \mathbf{E}_t \left[ \pi_d \frac{\partial n'}{\partial a'} + (1 - \pi_d) \frac{\partial v_{t+1}(z', n')}{\partial n'} \frac{\partial n'}{\partial a'} \right] \tag{III.4}$$

Given that $\frac{\partial n'}{\partial a'} = \frac{\gamma \tau' \bar{e}}{(1+\gamma a')^2} z' k'^{\alpha}$, we have

$$1 + \lambda_t(z, n) \geq \frac{1}{1 + r_t} \mathbf{E}_t \left[ (\pi_d + (1 - \pi_d)(1 + \lambda_{t+1}(z, n)) \frac{\gamma \tau' \bar{e}}{(1 + \gamma a')^2} z' k'^{\alpha} \right] \tag{III.5}$$

with equality if $a' > 0$.

To summarize, the firm's optimal decisions are characterized by the first-order conditions (III.2), (III.3), and (III.5) together with the complementary slackness conditions:

$$\mu_t(z, n) \left( \theta_k k' - b' \right) = 0 \text{ with } \mu_t(z, n) \geq 0, \text{ and}$$
$$\lambda_t(z, n) d = 0 \text{ with } \lambda_t(z, n) \geq 0.$$

**Partition of State Space** The first-order conditions derive very nice properties of partition of state space. This would also benefit the solution of the model quantitatively, as in Ottonello and Winberry (2024). We briefly describe our understanding and proof below.

***Unconstrained Firms:*** A financially unconstrained firm pays positive dividends and is not binding on borrowing constraint, so their financial wedges $\lambda_t(z, n) = 0$ and $\mu_t(z, n) = 0$. Also, from the first-order condition of borrowing (III.2), $\lambda_t(z, n) = 0$ today means that the firm expects $\lambda_{t+1}(z', n') = 0$ for any possible states of $\{z', \tau'\}$ (or further, as in Ottonello and Winberry (2024), $\mu_{jt+s} = \lambda_{jt+s} = 0$ for all $s \geq 0$; being unconstrained is an absorbing state.)

Since these firms are unconstrained at all today and in the future, their net worth $n_t$ should not be a factor affecting their optimal decisions. These decisions could be characterized by a set of policy functions $b_t'^*(z)$, $k_t'^*(z)$, $a_t'^*(z)$, and a separable value function $v_t^*(z)$.

First, we determine the optimal borrowing $b_t'^*(z)$ since unconstrained firms are indifferent over any combination of $b'$ and $d$ which leaves them financially unconstrained. We follow Khan and Thomas (2013)'s *minimum savings policy* by assuming the firms accumulate the most debt (or, if $b' < 0$, do the least amount of savings) which leaves them financially unconstrained. The optimal borrowing $b_t'^*(z)$ would then be for any $z'$, $d_{t+1}(z') \geq 0$ holds, which is

$$d_{t+1}(z') = z' \left(k_t'^*(z)\right)^\alpha + (1-\delta)k_t'^*(z) - \frac{\tau' \bar{e} z' \left(k_t'^*(z)\right)^\alpha}{1 + a_t'^*(z)} - b_t'^*(z) - k_{t+1}'^*(z') - a_{t+1}'^*(z') + \frac{b_{t+1}'^*(z')}{1 + r_{t+1}} \geq 0$$

The minimum savings policy $b_t'^*(z)$ is the largest level of debt to satisfy this constraint certainly:

$$\begin{aligned} b_t'^*(z) = \min_{z',\tau'} \Big\{ & z' \left(k_t'^*(z)\right)^\alpha + (1-\delta)k_t'^*(z) \\ & - \frac{\tau' \bar{e}}{1 + \gamma a_t'^*(z)} z' \left(k_t'^*(z)\right)^\alpha - k_{t+1}'^*(z') - a_{t+1}'^*(z') + \frac{b_{t+1}'^*(z')}{1 + r_{t+1}} \Big\} \end{aligned} \tag{III.6}$$

The above policy implies dividends are zero at the minimizer $z'$ of the right-hand side of (III.6) and strictly positive otherwise. Computationally, we could iterate (III.6) to solve the minimum savings policy $b_t'^*(z)$ after solving the optimal policies $k_t'^*(z)$ and $a_t'^*(z)$.

Second, we solve for the unconstrained optimal separable value function $v_t^*(z)$ given the optimal policies as follows:

$$v_t^*(z) = -k_t'^*(z) - a_t'^*(z) + \frac{-b_t'^*(z)}{1 + r_t} + \frac{1}{1 + r_t} \mathbb{E}_t[\pi_d n' + (1 - \pi_d) v_{t+1}^*(z')] \tag{III.7}$$

where $n' = z' \left(k_t'^*(z)\right)^\alpha + (1-\delta)k_t'^*(z) - \frac{\tau' \bar{e} z' \left(k_t'^*(z)\right)^\alpha}{1 + a_t'^*(z)} - b_t'^*(z)$ is independent of net worth $n$ today. Therefore, for unconstrained firms, $v_t(z, n) = n + v_t^*(z)$. Given the value function, the first-order conditions for capital and innovation are reduced to

$$1 = \frac{1}{1 + r_t} \mathbf{E}_t \Big[ \left(1 - \frac{\tau' \bar{e}}{1 + \gamma a'}\right) MPK(z', k') + (1 - \delta) \Big] \tag{III.8}$$

$$1 \geq \frac{1}{1 + r_t} \mathbf{E}_t \left[ \frac{\gamma \tau' \bar{e}}{(1 + \gamma a')^2} z' k'^\alpha \right] \tag{III.9}$$

Finally, we could determine the lower bound of net worth $\bar{n}_t(z)$ that firms are considered financially unconstrained. If the firms do not violate the no-equity issuance constraint, they are considered financially unconstrained if they can follow these policies. Therefore,

$$n - k_t'^*(z) - a_t'^*(z) + \frac{b_t'^*(z)}{1 + r_t} \geq 0$$

We can now define

$$\bar{n}_t(z) \equiv k_t'^*(z) + a_t'^*(z) - \frac{b_t'^*(z)}{1 + r_t}. \tag{III.10}$$

***Constrained Firms:*** Financially constrained as those for whom $\lambda_t(z,n) > 0$. These firms issue zero dividends $d_t(z,n) = 0$. They solve the first-order conditions (III.2), (III.3), and (III.5) together to get optimal policies $b_t^{'C}(z,n)$, $k_t^{'C}(z,n)$, and $a_t^{'C}(z,n)$.

## III.2 Solution Method

***Unconstrained Firms' Policies:*** We first solve for the decisions of the unconstrained firms.

Step 1: Guess unconstrained policies $k^{'*}_{(\text{it})}(z)$, $a^{'*}_{(\text{it})}(z)$, and $b^{'*}_{(\text{it})}(z)$, where (it) indexes the iteration, we start with $it = 0$ since it is the initial guess; Given an interest rate $r_t = r^*$.

Step 2: Update $k^{'*}_{(\text{it+1})}(z)$ using equation (III.8, restated below) taken $r_t = r^*$ and $a' = a^{'*}_{(\text{it})}(z)$.

$$k^{'*}(z) = \left(\frac{\alpha}{r^* - \delta}\mathbf{E}_t\left[z'\left(1 - \frac{\tau'\bar{e}}{1+\gamma a^{'*}(z)}\right)\right]\right)^{\frac{1}{1-\alpha}}$$

Step 3: Update $a^{'*}_{(\text{it+1})}(z)$ using equation (III.13 with equality, restated below) taken $r_t = r^*$ and the new iteration of the capital policy $k^{'*}_{(\text{it+1})}(z)$. Suppose the solution of equation (III.13) with equality is $\widetilde{a^{'*}_{(\text{it+1})}(z)}$, then $a^{'*}_{(\text{it+1})}(z) = max\{0, \widetilde{a^{'*}_{(\text{it+1})}(z)}\}$.

$$a^{'*}(z) = \max\left\{0, \left(\frac{\mathbf{E}_t[\tau'\bar{e}z'(k^{'*}(z))^{\alpha}]}{\gamma(1+r^*)}\right)^{\frac{1}{2}} - \frac{1}{\gamma}\right\}$$

Step 4: Repeat Steps 2 and 3 until the convergence of $k^{'*}_{(*)}(z)$ and $a^{'*}_{(*)}(z)$.

Step 5: Iterate on equation (III.6, restated below) until the convergence of $b^{'*}_{(*)}(z)$ with the borrowing constraints applied for the optimal capital choice $k^{'*}_{(*)}(z)$.

$$\widetilde{b}_t^{\prime*}(z) = \min_{z',\tau'}\left\{z'\left(k_t^{\prime*}(z)\right)^{\alpha} + (1-\delta)k_t^{\prime*}(z) - \frac{\tau'\bar{e}z'\left(k_t^{\prime*}(z)\right)^{\alpha}}{1+\gamma a_t^{\prime*}(z)} - k^{'*}_{t+1}(z') - a^{'*}_{t+1}(z') + \frac{b^{'*}_{t+1}(z')}{1+r_{t+1}}\right\}$$

$$b^{\prime*}_{(*)}(z) = \min\left(\theta_k k^{\prime*}_{(*)}(z), \widetilde{b}_t^{\prime*}(z)\right)$$

Step 6: Calculate the unconstrained net worth cutoff from equation (III.10, restated below).

$$\bar{n}_t(z) \equiv k_t^{'*}(z) + a_t^{'*}(z) - \frac{b_t^{\prime*}(z)}{1+r_t}.$$

Output: A collection of vectors $k^{'*}_{(*)}(z)$, $a^{'*}_{(*)}(z)$, $b^{'*}_{(*)}(z)$, and $\bar{n}_t(z)$.

***Constrained Firms' Policies:*** With these unconstrained policies in hand, we can then solve the decision rules for all firms over the entire state space $(z, n)$. We iterate on $k'_{(\text{it})}(z, n)$, $b'_{(\text{it})}(z, n)$, $a_{(\text{it})}(z, n)$, $\lambda_{(\text{it})}(z, n)$, and $v_{(\text{it})}(z, n)$.

Step 1: Guess constrained policies $k'_{(\text{it})}(z, n)$, $b'_{(\text{it})}(z, n)$, $a'_{(\text{it})}(z, n)$, $\lambda_{(\text{it})}(z, n)$, and $v_{(\text{it})}(z, n)$, where (it) indexes the iteration, we start with $it = 0$; Given an interest rate $r_t = r^*$.

Step 2: For any state $(z, n)$ that satisfies $n > \bar{n}(z)$, use the unconstrained policies and value function for $k'_{(\text{it})}(z, n)$, $b'_{(\text{it})}(z, n)$, $a'_{(\text{it})}(z, n)$, and $v_{(\text{it})}(z, n)$. Make $\lambda_{(\text{it})}(z, n) = 0$ and $\mu_t(z, n) = 0$.

Step 3: Solve for the policy assuming the collateral constraint is not binding:

Step 3.1: Update $k'_{(\text{it}+1)}(z, n)$ using equation (III.3, restated below) with $\mu_t(z, n) = 0$. We compute the law of motion for net worth $n'$ and the expectation using the current iteration (it) of the policy rules.

$$k'_{(\text{it}+1)}(z, n) = \left( \frac{\alpha \mathbf{E_t} \left[ (1 + (1 - \pi_d)\lambda_{t+1}(z', n')) \left( 1 - \frac{\tau' \bar{e}}{(1+\gamma a')} \right) z' \right]}{(1 + r_t)(1 + \lambda_t(z, n)) - (1 - \delta)\mathbf{E_t} \left[ (1 + (1 - \pi_d)\lambda_{t+1}(z', n')) \right]} \right)^{\frac{1}{1-\alpha}}$$

Step 3.2: Update $b'_{(\text{it}+1)}(z, n)$ from $d_t = 0$ constraint:

$$b'_{(\text{it}+1)}(z, n) = (1 + r^*)(k'_{(\text{it}+1)}(z, n) + a'_{(\text{it})}(z, n) - n).$$

Step 4: Solve for the policy where the collateral constraint is binding, that is, for the state space $(z, n)$ such that $b'_{(\text{it}+1)}(z, n) > \theta_k k'_{(\text{it}+1)}(z, n)$ from the last step:

Step 4.1: Update $k'_{(\text{it}+1)}(z, n)$ from $d = 0$ and $b' = \theta_k k'$:

$$k'_{(\text{it}+1)}(z, n) = \frac{n - a'_{(\text{it})}(z, n)}{1 - \theta_k/(1 + r^*)}$$

Step 4.2: Set $b'_{(\text{it}+1)}(z, n) = \theta_k k'_{(\text{it}+1)}(z, n)$.

Step 4.3: Recover $\mu_{(it+1)}(z, n)$ from equation (III.3).

$$\mu_t(z, n) = \frac{1}{\theta_k} \Bigg( 1 + \lambda_t(z, n) - \frac{1}{1 + r_t} \mathbf{E}_t \Bigg[ \Big( 1 + (1 - \pi_d)\lambda_{t+1}(z', n') \Big) \times \\ \left( \left( 1 - \frac{\tau' \bar{e}}{(1 + \gamma a')} \right) MPK(z', k') + (1 - \delta) \right) \Bigg] \Bigg)$$

Step 5: Update $a'_{(\text{it}+1)}(z, n)$ from equation (III.5 with equality, restated below). Suppose the solution of equation (III.5) with equality is $\widetilde{a'_{(\text{it}+1)}(z,n)}$, then $a'_{(\text{it}+1)}(z,n) = max\{0, \widetilde{a'_{(\text{it}+1)}(z,n)}\}$.

$$\widetilde{a'_{(\text{it}+1)}(z,n)} = \left(\frac{\mathbf{E}_t[(1(1-\pi_d)\lambda_{t+1}(z,n))\,\tau'\bar{e}z'(k'(z))^{\alpha}]}{\gamma(1+r^*)(1+\lambda_t(z,n))}\right)^{\frac{1}{2}} - \frac{1}{\gamma}$$

Step 6: Update the financial wedge $\lambda_{(\text{it})}(z,n)$ with equation (III.2).

$$\lambda_t(z,n) = (1+r_t)\mu_t(z,n) + (1-\pi_d)\mathbf{E}_t\left[\lambda_{t+1}(z',n')\right]$$

Output: Iterate Steps 1 to 6 until the convergence of $k'_{(\text{it})}(z,n)$, $b'_{(\text{it})}(z,n)$, $a'_{(\text{it})}(z,n)$, $\lambda_{(\text{it})}(z,n)$, and $\mu_{(\text{it})}(z,n)$.

## III.3 Solution Method for Green Loan Policies

***Lagrangian for Green Loan Extension*** The Lagrangian of the firm's optimization (3) is

$$\begin{aligned}\mathcal{L} =&(1+\lambda_t(z,n))\left(n - k' - a' + \frac{b'}{1+r_t}\right) + \mu_t(z,n)(\theta_k k' + \theta_a a' - b') \\ &+ \chi_t(z,n)a' + \frac{1}{1+r_t}\mathbf{E}_t[\pi_d n' + (1-\pi_d)v_{t+1}(z',n')]\end{aligned} \tag{III.11}$$

where $\lambda_t(z,n)$ is the multiplier on the non-negative dividend constraint $d \geq 0$, $\mu_t(z,n)$ is the multiplier on the collateral constraint $b' \leq \theta_k k'$, and $\chi_t(z,n)$ is the multiplier on the non-negative constraint on abatement investment $a' \geq 0$.

The first-order condition for borrowing $b'$ is the same as equation (III.2).

The first-order condition for future capital $k'$ is the same as equation (III.3).

The first-order condition for abatement $a'$ is now different as:

$$1 + \lambda_t(z,n) = \theta_a\mu_t(z,n) + \chi_t(z,n) + \frac{1}{1+r_t}\mathbf{E}_t\left[\pi_d\frac{\partial n'}{\partial a'} + (1-\pi_d)\frac{\partial v_{t+1}(z',n')}{\partial n'}\frac{\partial n'}{\partial a'}\right] \tag{III.12}$$

Given that $\frac{\partial n'}{\partial a'} = \frac{\gamma\tau'\bar{e}}{(1+\gamma a')^2}z'k'^{\alpha}$, we have

$$1 + \lambda_t(z,n) \geq \theta_a\mu_t(z,n) + \frac{1}{1+r_t}\mathbf{E}_t\left[(\pi_d + (1-\pi_d)(1+\lambda_{t+1}(z,n))\,\frac{\gamma\tau'\bar{e}}{(1+\gamma a')^2}z'k'^{\alpha}\right] \tag{III.13}$$

with equality if $a' > 0$.

To summarize, the firm's optimal decisions are characterized by the first-order conditions

(III.2), (III.3), and (III.13) together with the complementary slackness conditions:

$$\mu_t(z,n)\left(\theta_k k' + \theta_a a' - b'\right) = 0 \text{ with } \mu_t(z,n) \geq 0, \text{ and}$$
$$\lambda_t(z,n)d = 0 \text{ with } \lambda_t(z,n) \geq 0.$$

***Unconstrained Firms' Policies:*** Same as in Section III.2.

***Constrained Firms' Policies:*** With these unconstrained policies in hand, we can then solve the decision rules for all firms over the entire state space $(z,n)$. We iterate on $k'_{(\text{it})}(z,n)$, $b'_{(\text{it})}(z,n)$, $a_{(\text{it})}(z,n)$, $\lambda_{(\text{it})}(z,n)$, and $v_{(\text{it})}(z,n)$.

Step 1: Guess constrained policies $k'_{(\text{it})}(z,n)$, $b'_{(\text{it})}(z,n)$, $a'_{(\text{it})}(z,n)$, $\lambda_{(\text{it})}(z,n)$, and $v_{(\text{it})}(z,n)$, where (it) indexes the iteration, we start with $it = 0$; Given an interest rate $r_t = r^*$.

Step 2: For any state $(z,n)$ that satisfies $n > \bar{n}(z)$, use the unconstrained policies and value function for $k'_{(\text{it})}(z,n)$, $b'_{(\text{it})}(z,n)$, $a'_{(\text{it})}(z,n)$, and $v_{(\text{it})}(z,n)$. Make $\lambda_{(\text{it})}(z,n) = 0$ and $\mu_t(z,n) = 0$.

Step 3: Solve for the policy assuming the collateral constraint is not binding:

Step 3.1: Update $k'_{(\text{it+1})}(z,n)$ using equation (III.3, restated below) with $\mu_t(z,n) = 0$. We compute the law of motion for net worth $n'$ and the expectation using the current iteration (it) of the policy rules.

$$k'_{(\text{it+1})}(z,n) = \left(\frac{\alpha \mathbf{E}_t\left[(1+(1-\pi_d)\lambda_{t+1}(z',n'))\left(1-\frac{\tau'\bar{e}}{(1+\gamma a')}\right)z'\right]}{(1+r_t)(1+\lambda_t(z,n)) - (1-\delta)\mathbf{E}_t\left[(1+(1-\pi_d)\lambda_{t+1}(z',n'))\right]}\right)^{\frac{1}{1-\alpha}}$$

Step 3.2: Update $b'_{(\text{it+1})}(z,n)$ from $d_t = 0$ constraint:

$$b'_{(\text{it+1})}(z,n) = (1+r^*)(k'_{(\text{it+1})}(z,n) + a'_{(\text{it})}(z,n) - n).$$

Step 4: Solve for the policy where the collateral constraint is binding, that is, for the state space $(z,n)$ such that $b'_{(\text{it+1})}(z,n) > \theta_k k'_{(\text{it+1})}(z,n) + \theta_a a'_{(\text{it+1})}(z,n)$ from the last step:

Step 4.1: Update $k'_{(\text{it+1})}(z,n)$ from $d = 0$ and $b' = \theta_k k' + \theta_a a'$:

$$k'_{(\text{it+1})}(z,n) = \frac{n - (1+r^* - \theta_a)/(1+r^*)a'_{(\text{it})}(z,n)}{1 - \theta_k/(1+r^*)}$$

Step 4.2: Set $b'_{(\text{it+1})}(z,n) = \theta_k k'_{(\text{it+1})}(z,n) + \theta_a a'_{(\text{it+1})}(z,n)$.

Step 4.3: Recover $\mu_{(it+1)}(z,n)$ from equation (III.3).

$$\mu_t(z,n) = \frac{1}{\theta_k}\Bigg(1 + \lambda_t(z,n) - \frac{1}{1+r_t}\mathbf{E}_t\Big[\left(1 + (1-\pi_d)\lambda_{t+1}(z',n')\right) \times \\ \left(\left(1 - \frac{\tau'\bar{e}}{(1+\gamma a')}\right) MPK(z',k') + (1-\delta)\right)\Big]\Bigg)$$

Step 5: Update $a'_{(\text{it}+1)}(z,n)$ from equation (III.13 with equality, restated below). Suppose the solution of equation (III.13) with equality is $\widetilde{a'_{(\text{it}+1)}(z,n)}$, then $a'_{(\text{it}+1)}(z,n) = max\{0, \widetilde{a'_{(\text{it}+1)}(z,n)}\}$.

$$\widetilde{a'_{(\text{it}+1)}(z,n)} = \left(\frac{\mathbf{E}_t[(1(1-\pi_d)\lambda_{t+1}(z,n))\,\tau'\bar{e}z'(k'(z))^{\alpha}]}{\gamma(1+r^*)(1+\lambda_t(z,n)-\theta_a\mu_t(z,n))}\right)^{\frac{1}{2}} - \frac{1}{\gamma}$$

Step 6: Update the financial wedge $\lambda_{(\text{it})}(z,n)$ with equation (III.2).

$$\lambda_t(z,n) = (1+r_t)\mu_t(z,n) + (1-\pi_d)\mathbf{E}_t\left[\lambda_{t+1}(z',n')\right]$$

Output: Iterate Steps 1 to 6 until the convergence of $k'_{(\text{it})}(z,n)$, $b'_{(\text{it})}(z,n)$, $a'_{(\text{it})}(z,n)$, $\lambda_{(\text{it})}(z,n)$, and $\mu_{(\text{it})}(z,n)$.

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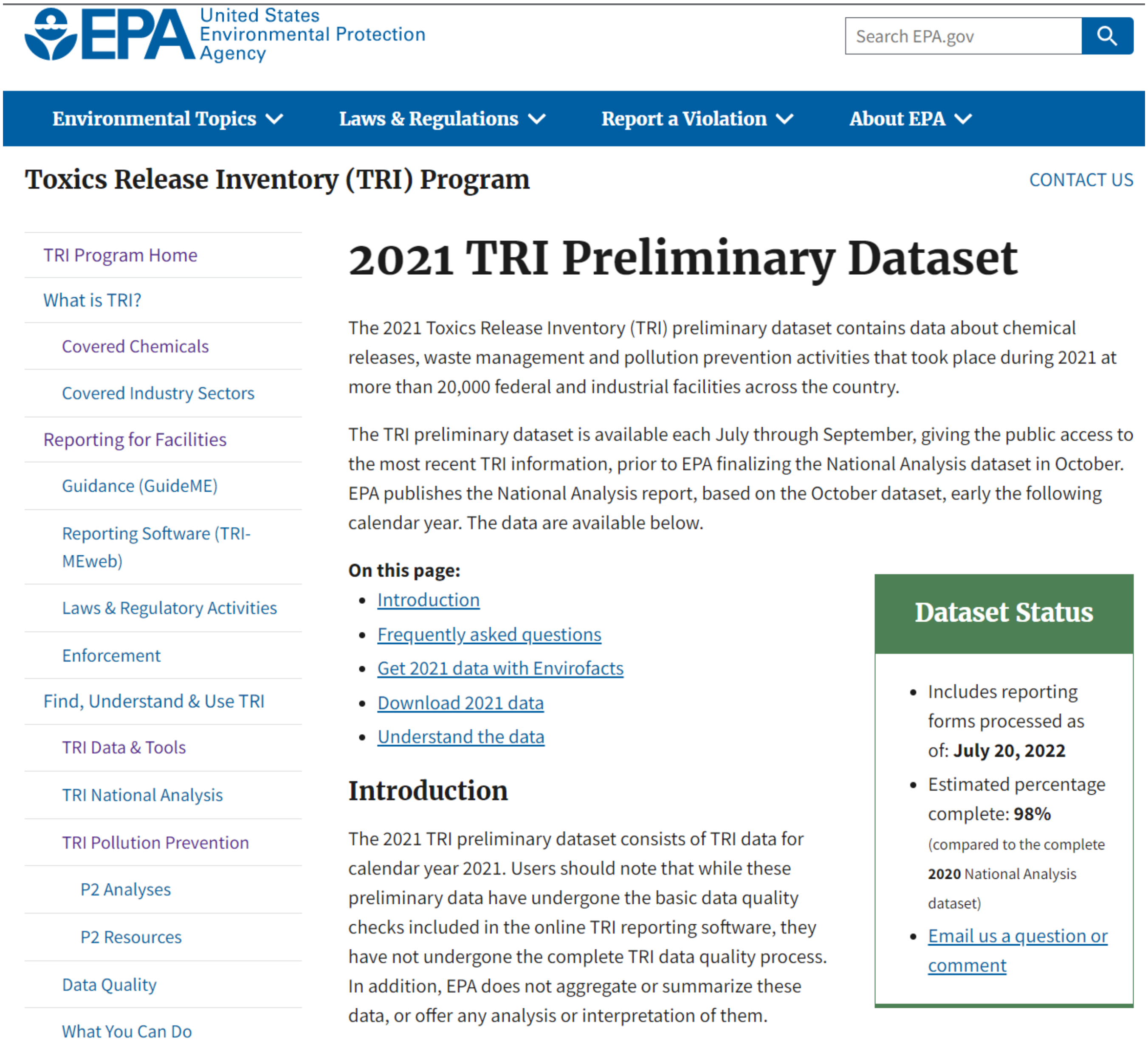
**Figure IA.1. The Annual Updates of the TRI Program**



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# 2021 TRI Preliminary Dataset

The 2021 Toxics Release Inventory (TRI) preliminary dataset contains data about chemical releases, waste management and pollution prevention activities that took place during 2021 at more than 20,000 federal and industrial facilities across the country.

The TRI preliminary dataset is available each July through September, giving the public access to the most recent TRI information, prior to EPA finalizing the National Analysis dataset in October. EPA publishes the National Analysis report, based on the October dataset, early the following calendar year. The data are available below.

**On this page:**

- Introduction
- Frequently asked questions
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**Dataset Status**

- Includes reporting forms processed as of: **July 20, 2022**
- Estimated percentage complete: **98%** (compared to the complete **2020** National Analysis dataset)
- Email us a question or comment

## Introduction

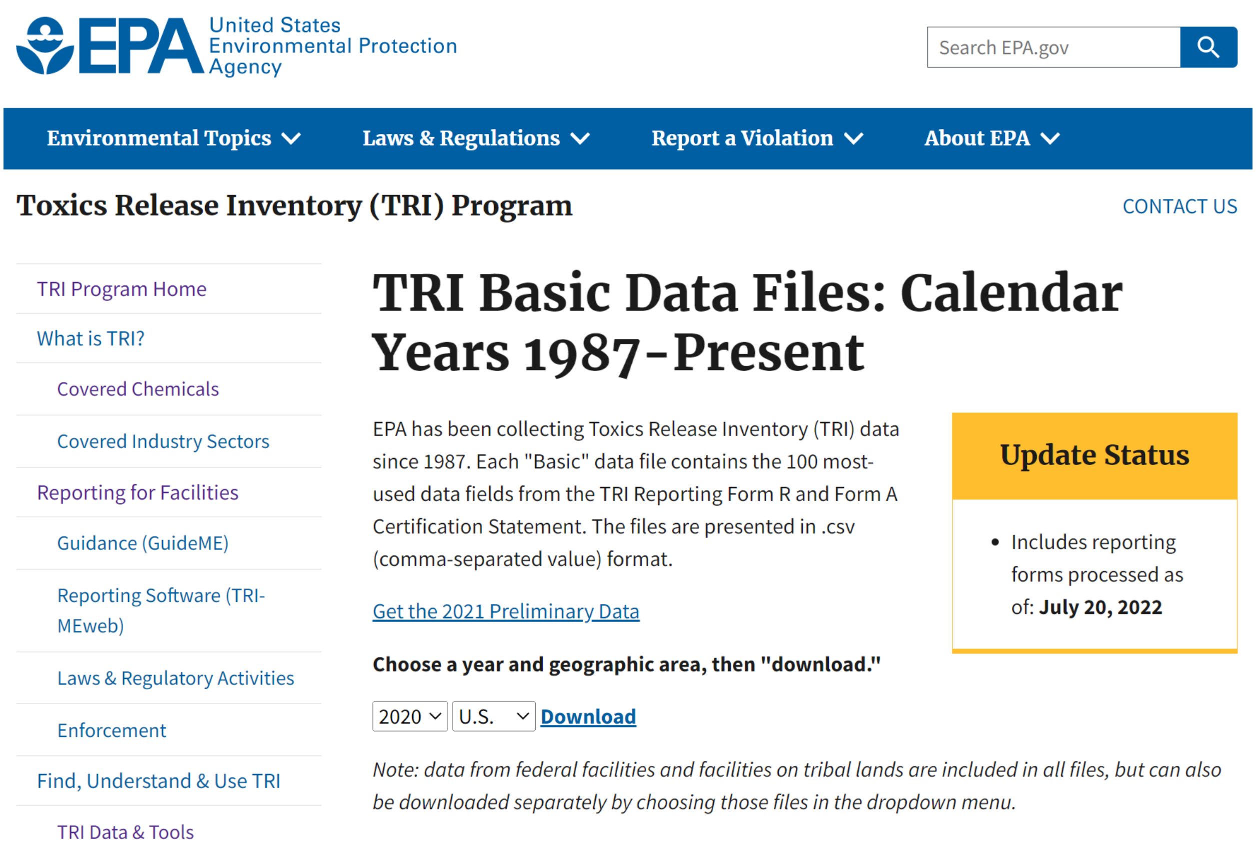
The 2021 TRI preliminary dataset consists of TRI data for calendar year 2021. Users should note that while these preliminary data have undergone the basic data quality checks included in the online TRI reporting software, they have not undergone the complete TRI data quality process. In addition, EPA does not aggregate or summarize these data, or offer any analysis or interpretation of them.

Source:
https://www.epa.gov/toxics-release-inventory-tri-program/2021-tri-preliminary-dataset

**Figure IA.2. Access to the TRI Database**


Source: https://www.epa.gov/toxics-release-inventory-tri-program

**Figure IA.3. The TRI Database by Years**

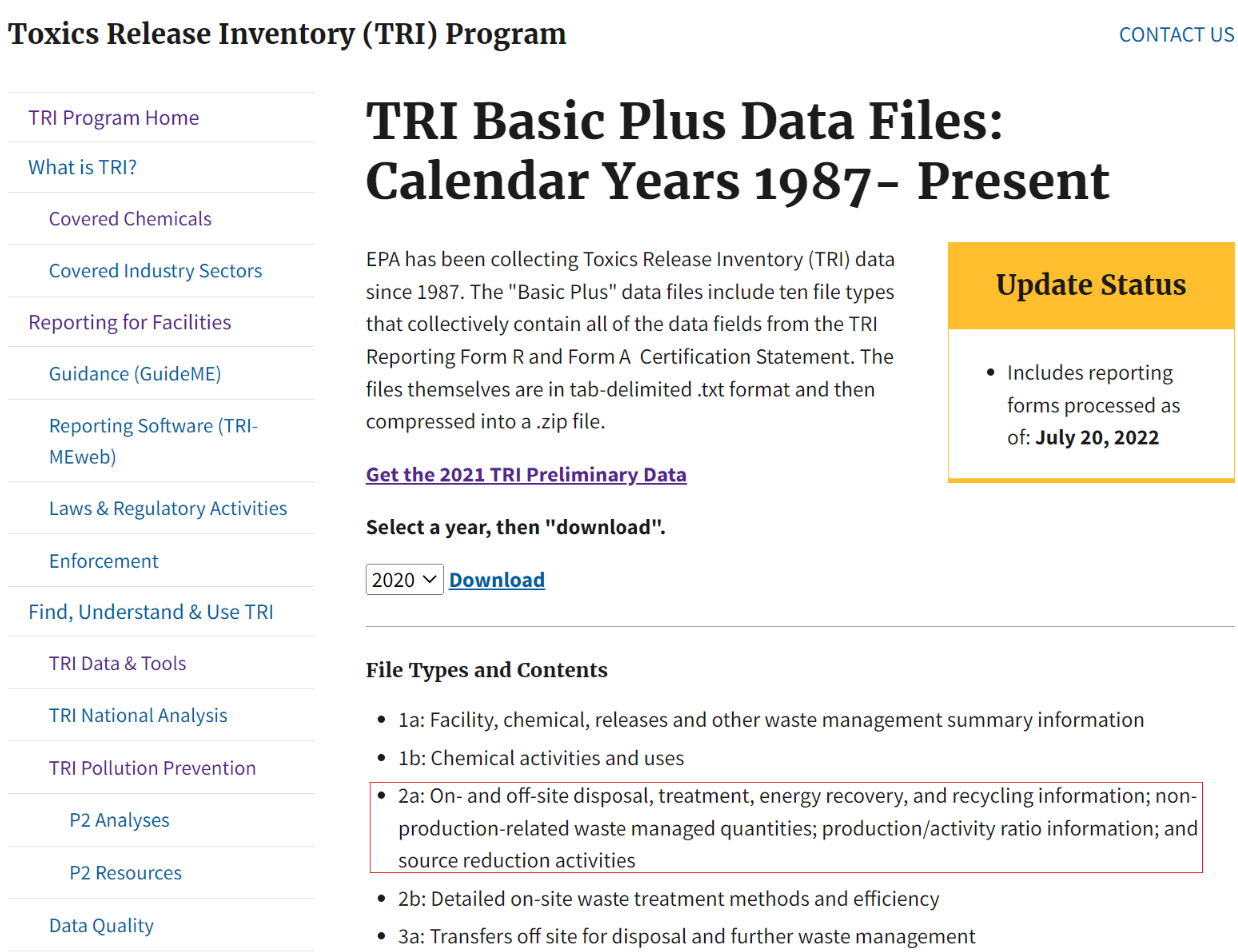



Source: https://www.epa.gov/toxics-release-inventory-tri-program/tri-basic-data-files-calendar-years-1987-present

**Figure IA.4. Access to the P2 Database**


Source: `https://www.epa.gov/p2`

## Figure IA.5. The P2 Database by Years



Toxics Release Inventory (TRI) Program

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  - Data Quality

# TRI Basic Plus Data Files: Calendar Years 1987- Present

EPA has been collecting Toxics Release Inventory (TRI) data since 1987. The "Basic Plus" data files include ten file types that collectively contain all of the data fields from the TRI Reporting Form R and Form A Certification Statement. The files themselves are in tab-delimited .txt format and then compressed into a .zip file.

**Update Status**

- Includes reporting forms processed as of: **July 20, 2022**

**Get the 2021 TRI Preliminary Data**

**Select a year, then "download".**

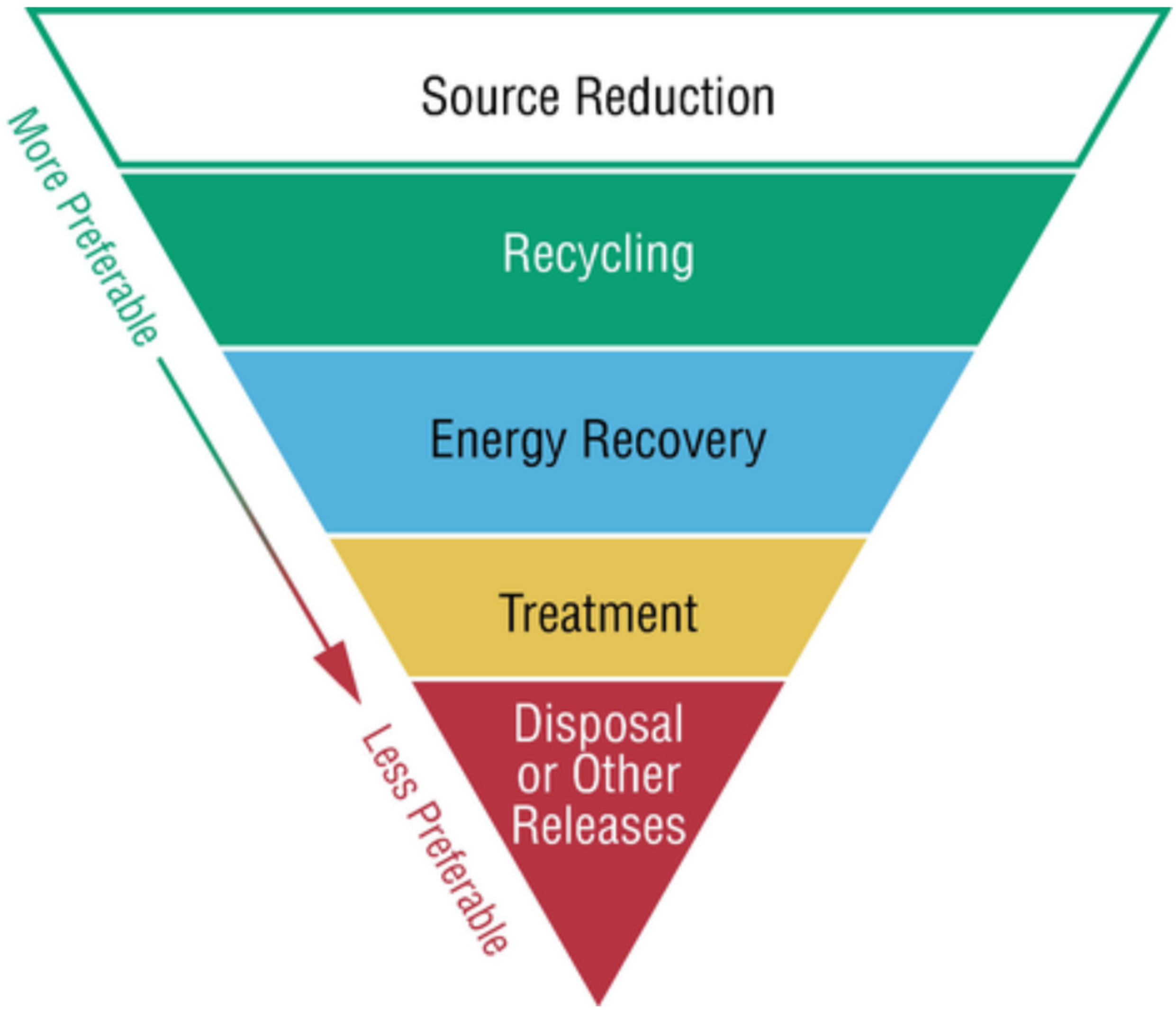
2020 **Download**

**File Types and Contents**

- 1a: Facility, chemical, releases and other waste management summary information
- 1b: Chemical activities and uses
- 2a: On- and off-site disposal, treatment, energy recovery, and recycling information; non-production-related waste managed quantities; production/activity ratio information; and source reduction activities
- 2b: Detailed on-site waste treatment methods and efficiency
- 3a: Transfers off site for disposal and further waste management

Source: https://www.epa.gov/toxics-release-inventory-tri-program/tri-basic-plus-data-files-calendar-years-1987-present

**Figure IA.6. Waste Management Hierarchy**




Source: https://www.epa.gov/smm/sustainable-materials-management-non-hazardous-materials-and-waste-management-hierarchy

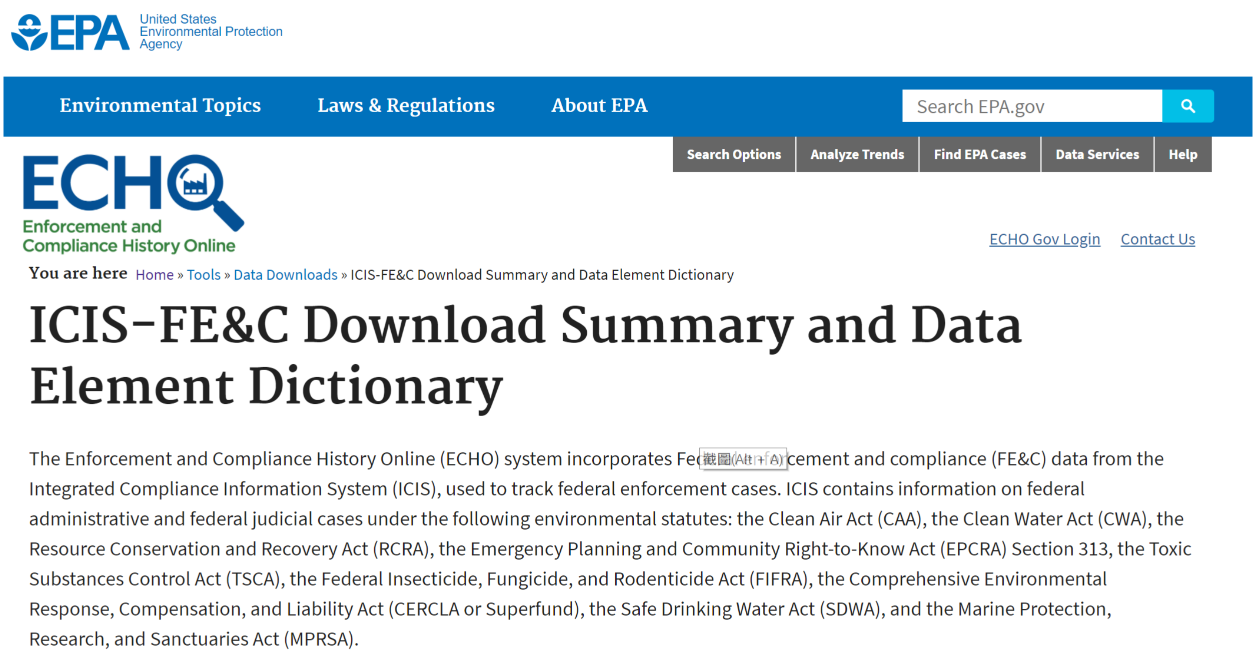



**Figure IA.7.** Civil cases and settlements.
Source: https://echo.epa.gov/tools/data-downloads/icis-fec-download-summary



**Figure IA.8.** Dow's environmental settlement.

Source: https://intercontinentalcry.org/dow-chemical-agrees-to-77-million-environmental-restoration-settlement/ and https://www.michiganradio.org/post/why-does-it-take-40-years-clean-polluted-river.

## Table IA.1: The List of Reported Abatement Activities

| W Code | Catecgory | Abatement Activities | Score |
|---|---|---|---|
| W41 | Raw Material Modifications | Increased purity of raw materials | 9 |
| W42 | Raw Material Modifications | Substituted raw materials | 10 |
| W43 | Raw Material Modifications | Substituted a feedstock or reagent chemical with adifferent chemical | 9 |
| W49 | Raw Material Modifications | Other raw material modifications made | 6 |
| W81 | Product Modifications | Changed product specifications | 8 |
| W82 | Product Modifications | Modified design or composition of product | 8 |
| W83 | Product Modifications | Modified packaging | 10 |
| W84 | Product Modifications | Developed a new chemical product to replace a previous chemical product | 4 |
| W89 | Product Modifications | Other product modifications made | 7 |
| W59 | Cleaning and Degreasing | Modified stripping/cleaning equipment | 3 |
| W60 | Cleaning and Degreasing | Changed to mechanical stripping/cleaning devices | 2 |
| W61 | Cleaning and Degreasing | Changed to aqueous cleaners | 10 |
| W63 | Cleaning and Degreasing | Modified containment procedures for cleaning units | 9 |
| W64 | Cleaning and Degreasing | Improved draining procedures | 10 |
| W65 | Cleaning and Degreasing | Redesigned parts racks to reduce drag out | 7 |
| W66 | Cleaning and Degreasing | Modified or installed rinse systems | 2 |
| W67 | Cleaning and Degreasing | Improved rinse equipment design | 3 |
| W68 | Cleaning and Degreasing | Improved rinse equipment operation | 8 |
| W71 | Cleaning and Degreasing | Other cleaning and degreasing modifications made | 9 |
| W72 | Surface Preparation and Finishing | Modified spray systems or equipment | 3 |
| W73 | Surface Preparation and Finishing | Substituted coating materials used | 10 |
| W74 | Surface Preparation and Finishing | Improved application techniques | 9 |
| W75 | Surface Preparation and Finishing | Changed from spray to other system | 2 |
| W78 | Surface Preparation and Finishing | Other surface preparation and finishing modifications made | 6 |
| W50 | Process Modifications | Optimized reaction conditions or otherwise increased efficiency of synthesis | 5 |
| W51 | Process Modifications | Instituted re-circulation within a process | 3 |
| W52 | Process Modifications | Modified equipment, layout, or piping | 2 |
| W53 | Process Modifications | Used a different process catalyst | 8 |
| W54 | Process Modifications | Instituted better controls on operating bulk containers tominimize discarding of empty containers | 10 |
| W55 | Process Modifications | Changed from small volume containers to bulk containersto minimize discarding of empty containers | 9 |
| W56 | Process Modifications | Reduced or eliminated use of an organic solvent | 10 |
| W57 | Process Modifications | Used biotechnology in manufacturing process | 3 |
| W58 | Process Modifications | Other process modifications made | 7 |
| W31 | Spill and Leak Prevention | Improved storage or stacking procedures | 10 |
| W32 | Spill and Leak Prevention | Improved procedures for loading, unloading, and transferoperations | 9 |
| W33 | Spill and Leak Prevention | Installed overflow alarms or automatic shut-off valves | 2 |
| W35 | Spill and Leak Prevention | Installed vapor recovery systems | 1 |
| W36 | Spill and Leak Prevention | Implemented inspection or monitoring program ofpotential spill or leak sources | 3 |
| W39 | Spill and Leak Prevention | Other changes made in spill and leak prevention | 8 |
| W21 | Inventory Control | Instituted procedures to ensure that materials do not stay in inventory beyond shelf-life | 10 |
| W22 | Inventory Control | Began to test outdated material—continue to use if stilleffective | 10 |
| W23 | Inventory Control | Eliminated shelf-life requirements for stable materials | 10 |
| W24 | Inventory Control | Instituted better labeling procedures | 10 |
| W25 | Inventory Control | Instituted clearinghouse to exchange materials that wouldotherwise be discarded | 10 |
| W29 | Inventory Control | Other changes made in inventory control | 9 |
| W13 | Good Operating Practices | Improved maintenance scheduling, record keeping, orprocedures | 10 |
| W14 | Good Operating Practices | Changed production schedule to minimize equipment and feedstock changeovers | 9 |
| W15 | Good Operating Practices | Introduced in-line product quality monitoring or otherprocess analysis system | 4 |
| W19 | Good Operating Practices | Other changes made in operating practices | 9 |

## Table IA.2: Double Sort on Net Worth and Productivity

This table presents the time-series average of the cross-sectional means of firm characteristics, categorized into five groups double-sorted by net worth and two groups by firm-level productivity. The estimation for firm-level productivity is discussed in Section II.1 of the Internet Appendix. We report firm characteristics, including pollution abatement (Abate) in Panel A, raw emissions (Emission) in Panel B, emission intensity (Emission/Sales) in Panel C, and investment rate (I/K) in Panel D, for these double sorts. Detailed descriptions of firm characteristics are provided in Table 1. The sample period covers from 1991 to 2020.

| | **L** | **2** | **3** | **4** | **H** |
|---|---|---|---|---|---|
| | | | **Panel A: Abate** | | |
| **L** | 0.67 | 1.42 | 1.89 | 2.71 | 3.87 |
| **H** | 1.14 | 2.59 | 4.17 | 8.98 | 12.36 |
| | | | **Panel B: Log Emission** | | |
| **L** | 12.06 | 12.66 | 12.89 | 13.61 | 15.35 |
| **H** | 11.72 | 12.84 | 13.92 | 14.63 | 15.63 |
| | | | **Panel C: Log Emission/Sales** | | |
| **L** | 7.54 | 7.03 | 6.39 | 6.45 | 6.55 |
| **H** | 5.39 | 5.42 | 5.75 | 5.64 | 5.68 |
| | | | **Panel D: I/K** | | |
| **L** | 0.21 | 0.20 | 0.18 | 0.16 | 0.14 |
| **H** | 0.24 | 0.19 | 0.18 | 0.17 | 0.17 |

## Table IA.3: Firm Characteristics

This table reports the time-series average of the cross-sectional means of firm characteristics for five groups sorted by net worth (N) in Panel A, total assets (AT) in Panel B, capital (K) in Panel C, and employee (EMP) in Panel D. Abate represents a firm's total pollution abatement activities, aggregated across all its facilities to the firm level. We measure raw emissions (emissions) as the total pollutant releases (measured in pounds) across all of a firm's plants in a given year. Emission intensity (Emission/Sales) is then calculated by normalizing raw emissions by the firm's sales revenue, expressed in millions of dollars. Net worth, total assets, and capital are adjusted for inflation using the Consumer Price Index (CPI) and reported in 2009 million USD. I/K is capital expenditures (item CAPX) divided by property, plant, and equipment (PPENT). B/M is the ratio of book equity to market capitalization. Return on assets (ROA) is operating income after depreciation (item OIADP) scaled by total assets. Book leverage (Lev) is the summation of current liabilities (item DLC) and long-term debt (item DLTT) scaled by total assets. Firm characteristics are described in Table 1. The sample period is 1991 to 2020.

| | **L** | **2** | **3** | **4** | **H** | **L** | **2** | **3** | **4** | **H** |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Panel A: Net Worth** | | | | | **Panel B: Total Assets** | | | | |
| Abate | 0.84 | 1.75 | 2.79 | 5.53 | 10.11 | 1.01 | 1.52 | 2.98 | 4.45 | 7.74 |
| Log Emission | 12.21 | 12.58 | 13.38 | 14.25 | 15.55 | 12.85 | 13.22 | 13.62 | 14.36 | 15.51 |
| Log Emission/Sales | 7.85 | 6.14 | 5.96 | 5.95 | 5.90 | 8.46 | 7.40 | 6.68 | 6.28 | 6.26 |
| Log AT | 5.54 | 6.90 | 7.96 | 9.03 | 10.93 | 5.19 | 6.51 | 7.45 | 8.50 | 10.58 |
| Log K | 3.93 | 5.53 | 6.64 | 7.93 | 9.83 | 3.87 | 5.23 | 6.18 | 7.34 | 9.48 |
| Log N | 5.52 | 7.02 | 8.05 | 9.09 | 10.95 | 5.62 | 6.86 | 7.76 | 8.71 | 10.71 |
| Log EMP | 0.02 | 1.35 | 2.30 | 3.08 | 4.53 | 0.01 | 1.16 | 1.99 | 2.79 | 4.22 |
| I/K | 0.21 | 0.19 | 0.17 | 0.16 | 0.17 | 0.20 | 0.19 | 0.18 | 0.17 | 0.16 |
| B/M | 0.77 | 0.64 | 0.60 | 0.58 | 0.55 | 0.81 | 0.67 | 0.64 | 0.58 | 0.57 |
| ROA | 0.10 | 0.14 | 0.14 | 0.14 | 0.14 | 0.10 | 0.13 | 0.14 | 0.14 | 0.13 |
| Lev | 0.14 | 0.23 | 0.27 | 0.30 | 0.29 | 0.17 | 0.24 | 0.28 | 0.29 | 0.30 |
| Num | 70 | 69 | 69 | 69 | 69 | 134 | 134 | 134 | 134 | 133 |
| | **Panel C: Capital** | | | | | **Panel D: Employee** | | | | |
| Abate | 0.82 | 1.64 | 2.90 | 5.23 | 7.12 | 0.95 | 1.73 | 2.52 | 3.46 | 9.09 |
| Log Emission | 12.29 | 12.99 | 13.13 | 14.12 | 15.67 | 13.75 | 13.53 | 13.58 | 14.74 | 15.18 |
| Log Emission/Sales | 8.23 | 7.56 | 6.64 | 6.92 | 6.69 | 8.71 | 6.82 | 5.91 | 6.43 | 5.53 |
| Log AT | 5.56 | 6.73 | 7.63 | 8.66 | 10.54 | 5.93 | 7.18 | 8.03 | 8.96 | 10.45 |
| Log K | 3.61 | 4.95 | 6.00 | 7.17 | 9.51 | 5.17 | 6.39 | 7.12 | 8.19 | 9.18 |
| Log N | 5.73 | 6.84 | 7.83 | 8.88 | 10.68 | 6.17 | 7.49 | 8.22 | 9.21 | 10.64 |
| Log EMP | 0.23 | 1.30 | 2.12 | 2.93 | 4.15 | -0.40 | 0.85 | 1.69 | 2.50 | 4.32 |
| I/K | 0.21 | 0.19 | 0.18 | 0.17 | 0.15 | 0.20 | 0.18 | 0.18 | 0.17 | 0.18 |
| B/M | 0.76 | 0.67 | 0.62 | 0.60 | 0.62 | 0.79 | 0.73 | 0.64 | 0.60 | 0.50 |
| ROA | 0.09 | 0.13 | 0.14 | 0.14 | 0.13 | 0.09 | 0.13 | 0.14 | 0.14 | 0.14 |
| Lev | 0.17 | 0.23 | 0.28 | 0.29 | 0.31 | 0.19 | 0.25 | 0.28 | 0.28 | 0.28 |
| Num | 134 | 134 | 134 | 134 | 133 | 134 | 133 | 133 | 133 | 132 |

## Table IA.4: Firm Characteristics Sorted by Age

This table reports the time-series average of the cross-sectional means of firm characteristics for five groups sorted by age according to Compustat in Panel A, World Scope in Panel B, incorporation year in Panel C, and founding year in Panel D. Abate represents a firm's total pollution abatement activities, aggregated across all its facilities to the firm level. We measure raw emissions (Emission) as the total pollutant releases (measured in pounds) across all of a firm's plants in a given year. Emission intensity (Emission/Sales) is then calculated by normalizing raw emissions by the firm's sales revenue, expressed in millions of dollars. Net worth, total assets, and capital are adjusted for inflation using the Consumer Price Index (CPI) and reported in 2009 million USD. I/K is capital expenditures (item CAPX) divided by property, plant, and equipment (PPENT). B/M is the ratio of book equity to market capitalization. Return on assets (ROA) is operating income after depreciation (item OIADP) scaled by total assets. Book leverage (Lev) is the summation of current liabilities (item DLC) and long-term debt (item DLTT) scaled by total assets. Firm characteristics are described in Table 1. The sample period is 1991 to 2020.

| | **L** | **2** | **3** | **4** | **H** | **L** | **2** | **3** | **4** | **H** |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Panel A: Compustat** | | | | | **Panel B: World Scope** | | | | |
| Abate | 1.81 | 2.21 | 2.55 | 4.36 | 7.53 | 2.54 | 2.60 | 2.31 | 4.49 | 7.24 |
| Log Emission | 13.74 | 14.18 | 14.24 | 14.40 | 15.09 | 14.63 | 14.48 | 13.94 | 14.26 | 14.37 |
| Log Emission/Sales | 7.28 | 6.73 | 8.07 | 7.59 | 6.11 | 7.75 | 6.72 | 6.22 | 6.05 | 5.72 |
| Log AT | 8.00 | 7.96 | 8.62 | 8.84 | 10.41 | 8.67 | 8.65 | 8.92 | 8.92 | 9.66 |
| Log K | 6.82 | 6.87 | 7.48 | 7.85 | 9.27 | 7.67 | 7.73 | 7.91 | 7.79 | 8.59 |
| Log N | 8.21 | 8.06 | 9.25 | 9.06 | 10.5 | 9.06 | 9.04 | 9.29 | 9.45 | 10.10 |
| Log EMP | 1.94 | 2.23 | 2.86 | 2.76 | 3.95 | 2.45 | 2.65 | 2.73 | 3.18 | 3.42 |
| I/K | 0.20 | 0.19 | 0.18 | 0.18 | 0.16 | 0.18 | 0.19 | 0.19 | 0.18 | 0.16 |
| B/M | 0.69 | 0.71 | 0.67 | 0.61 | 0.56 | 0.69 | 0.64 | 0.64 | 0.65 | 0.56 |
| ROA | 0.11 | 0.12 | 0.14 | 0.14 | 0.13 | 0.12 | 0.12 | 0.13 | 0.14 | 0.14 |
| Lev | 0.28 | 0.25 | 0.22 | 0.24 | 0.29 | 0.28 | 0.26 | 0.25 | 0.21 | 0.26 |
| Num | 145 | 130 | 149 | 131 | 113 | 121 | 113 | 110 | 111 | 111 |
| | **Panel C: Incorporation** | | | | | **Panel D: Founding** | | | | |
| Abate | 1.51 | 2.35 | 1.20 | 1.21 | 2.22 | 2.36 | 1.86 | 3.18 | 5.38 | 7.60 |
| Log Emission | 13.51 | 14.33 | 12.56 | 13.78 | 13.03 | 13.74 | 14.02 | 13.61 | 14.84 | 15.00 |
| Log Emission/Sales | 7.82 | 6.69 | 5.76 | 6.34 | 6.32 | 8.37 | 6.80 | 6.73 | 7.38 | 7.15 |
| Log AT | 7.91 | 8.28 | 8.11 | 7.71 | 8.26 | 8.27 | 8.38 | 8.72 | 9.53 | 10.23 |
| Log K | 6.95 | 7.19 | 6.57 | 6.58 | 6.91 | 7.28 | 7.04 | 7.69 | 8.42 | 9.09 |
| Log N | 7.35 | 7.98 | 8.70 | 8.20 | 8.92 | 8.56 | 8.63 | 9.51 | 9.66 | 10.43 |
| Log EMP | 1.97 | 2.15 | 2.13 | 2.23 | 2.49 | 2.39 | 2.34 | 3.23 | 3.34 | 3.70 |
| I/K | 0.23 | 0.22 | 0.21 | 0.18 | 0.17 | 0.21 | 0.21 | 0.18 | 0.16 | 0.16 |
| B/M | 0.68 | 0.61 | 0.65 | 0.77 | 0.66 | 0.68 | 0.66 | 0.65 | 0.62 | 0.54 |
| ROA | 0.09 | 0.13 | 0.12 | 0.13 | 0.13 | 0.12 | 0.14 | 0.13 | 0.13 | 0.14 |
| Lev | 0.25 | 0.23 | 0.24 | 0.25 | 0.30 | 0.24 | 0.22 | 0.22 | 0.27 | 0.29 |
| Num | 49 | 45 | 43 | 45 | 44 | 108 | 105 | 106 | 104 | 102 |

## Table IA.5: Double Sort on Age and Productivity

This table reports the time-series average of cross-sectional means of firm characteristics, categorized into five groups based on firm age, measured using Compustat in Panel A, Worldscope in Panel B, incorporation year in Panel C, and founding year in Panel D, and two groups based on firm-level productivity. The estimation for firm-level productivity is discussed in Section II.1 of the Internet Appendix. We report firm characteristics, including pollution abatement (Abate), raw emissions (Emission), emission intensity (Emission/Sales), and investment rate (I/K), for these double sorts. Detailed descriptions of firm characteristics are provided in Table 1. The sample period covers from 1991 to 2020.

| | **L** | **2** | **3** | **4** | **H** | **L** | **2** | **3** | **4** | **H** |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Panel A: Compustat** | | | | | **Panel B: World Scope** | | | | |
| | | | | | **Abate** | | | | | |
| **L** | 1.48 | 1.83 | 2.08 | 1.51 | 2.87 | 1.79 | 2.36 | 2.03 | 1.95 | 2.45 |
| **H** | 2.30 | 2.60 | 3.65 | 7.83 | 8.28 | 3.35 | 2.89 | 4.30 | 6.84 | 10.00 |
| | | | | | **Log Emission** | | | | | |
| **L** | 13.18 | 13.45 | 14.49 | 13.08 | 15.06 | 14.56 | 14.04 | 13.77 | 12.86 | 14.13 |
| **H** | 14.17 | 14.73 | 14.03 | 14.89 | 14.92 | 14.87 | 14.67 | 14.23 | 14.83 | 14.24 |
| | | | | | **Log Emission/Sales** | | | | | |
| **L** | 6.74 | 6.63 | 8.88 | 6.44 | 8.09 | 7.80 | 6.71 | 6.50 | 6.65 | 6.18 |
| **H** | 6.38 | 6.57 | 5.36 | 6.05 | 5.41 | 6.73 | 6.41 | 5.48 | 5.74 | 5.30 |
| | | | | | **I/K** | | | | | |
| **L** | 0.19 | 0.18 | 0.18 | 0.17 | 0.15 | 0.18 | 0.18 | 0.18 | 0.18 | 0.16 |
| **H** | 0.21 | 0.20 | 0.19 | 0.18 | 0.16 | 0.21 | 0.21 | 0.20 | 0.18 | 0.17 |
| | **Panel C: Incorporation** | | | | | **Panel D: Founding** | | | | |
| | | | | | **Abate** | | | | | |
| **L** | 1.32 | 3.84 | 1.20 | 0.98 | 1.57 | 2.51 | 1.93 | 1.55 | 1.98 | 2.75 |
| **H** | 1.82 | 0.97 | 1.23 | 1.78 | 2.71 | 2.17 | 3.09 | 5.76 | 7.44 | 10.21 |
| | | | | | **Log Emission** | | | | | |
| **L** | 12.89 | 14.19 | 13.35 | 13.17 | 13.1 | 12.75 | 14.51 | 12.77 | 13.98 | 15.33 |
| **H** | 14.41 | 14.04 | 12.19 | 14.15 | 13.07 | 13.69 | 14.35 | 13.55 | 15.09 | 14.73 |
| | | | | | **Log Emission/Sales** | | | | | |
| **L** | 6.82 | 7.15 | 6.26 | 6.29 | 6.54 | 6.79 | 9.06 | 6.22 | 7.26 | 8.36 |
| **H** | 6.64 | 5.36 | 4.79 | 6.36 | 5.67 | 5.99 | 5.50 | 5.38 | 5.99 | 5.67 |
| | | | | | **I/K** | | | | | |
| **L** | 0.2 | 0.19 | 0.21 | 0.17 | 0.16 | 0.19 | 0.19 | 0.17 | 0.15 | 0.14 |
| **H** | 0.26 | 0.25 | 0.22 | 0.20 | 0.17 | 0.22 | 0.21 | 0.18 | 0.17 | 0.16 |

## Table IA.6: The Peking Order by Age

This table reports univariate regressions of firms' pollution abatement, emission intensity, and investment on age according to Compustat in Panel A, World Scope in Panel B, incorporation year in Panel C, and founding year in Panel D, as well as firm and year fixed effects. All independent variables are normalized to zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. *t*-statistics based on standard errors clustered at the firm level are reported with ***, **, and * indicating significance at the 1, 5, and 10% levels. The sample period is from 1991 to 2020.

| | (1) Log (1+Abate) | (2) Log (1+Emission) | (3) Log (1+Emission/Sales) | (4) I/K |
|---|---|---|---|---|
| **Panel A: Compustat** | | | | |
| Log(1+Age) | 0.20*** | 0.02 | -0.21*** | -0.02*** |
| [t] | [6.43] | [0.21] | [-2.96] | [-5.87] |
| Observations | 20,055 | 20,055 | 20,039 | 19,938 |
| R-squared | 0.69 | 0.82 | 0.83 | 0.50 |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster SE | Yes | Yes | Yes | Yes |
| **Panel B: World Scope** | | | | |
| Log(1+Age) | 0.11** | 0.22 | 0.01 | -0.02*** |
| [t] | [2.27] | [1.55] | [0.07] | [-4.13] |
| Observations | 16,985 | 16,985 | 16,980 | 16,907 |
| R-squared | 0.68 | 0.82 | 0.83 | 0.49 |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster SE | Yes | Yes | Yes | Yes |
| **Panel C: Incorporation Year** | | | | |
| Log(1+Age) | 0.24** | 0.70 | 0.01 | -0.09*** |
| [t] | [2.57] | [1.26] | [0.01] | [-6.00] |
| Observations | 6,765 | 6,765 | 6,755 | 6,727 |
| R-squared | 0.59 | 0.80 | 0.82 | 0.54 |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster SE | Yes | Yes | Yes | Yes |
| **Panel D: Founding Year** | | | | |
| Log(1+Age) | 0.38*** | 0.01 | -0.32** | -0.03*** |
| [t] | [5.39] | [0.03] | [-2.07] | [-3.92] |
| Observations | 15,743 | 15,743 | 15,740 | 15,643 |
| R-squared | 0.70 | 0.81 | 0.82 | 0.48 |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster SE | Yes | Yes | Yes | Yes |

## Table IA.7: Firm Characteristics Sorted by Financial Constraints

This table reports the time-series average of the cross-sectional means of firm characteristics for five groups sorted by sorted by SA index in Panel A and WW index in Panel B. Abate represents a firm's total pollution abatement activities, aggregated across all its facilities to the firm level. We measure raw emissions (Emission) as the total pollutant releases (measured in pounds) across all of a firm's plants in a given year. Emission intensity (Emission/Sales) is then calculated by normalizing raw emissions by the firm's sales revenue, expressed in millions of dollars. Net worth, total assets, and capital are adjusted for inflation using the Consumer Price Index (CPI) and reported in 2009 million USD. I/K is capital expenditures (item CAPX) divided by property, plant, and equipment (PPENT). B/M is the ratio of book equity to market capitalization. Return on assets (ROA) is operating income after depreciation (item OIADP) scaled by total assets. Book leverage (Lev) is the summation of current liabilities (item DLC) and long-term debt (item DLTT) scaled by total assets. Firm characteristics are described in Table 1. The sample period is 1991 to 2020.

| | **L** | **2** | **3** | **4** | **H** | **L** | **2** | **3** | **4** | **H** |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Panel A: SA** | | | | | **Panel B: WW** | | | | |
| Abate | 8.23 | 3.87 | 1.77 | 2.51 | 1.15 | 8.05 | 4.70 | 2.67 | 1.63 | 0.97 |
| Log Emission | 15.18 | 14.03 | 14.62 | 13.71 | 13.19 | 15.52 | 14.37 | 13.59 | 13.43 | 12.52 |
| Log Emission/Sales | 5.93 | 7.62 | 7.14 | 7.33 | 8.06 | 6.28 | 6.32 | 7.06 | 7.91 | 7.97 |
| Log AT | 10.38 | 8.29 | 8.22 | 7.95 | 7.38 | 10.58 | 8.52 | 7.57 | 6.81 | 5.58 |
| Log K | 9.26 | 7.15 | 7.16 | 6.74 | 6.23 | 9.48 | 7.42 | 6.31 | 5.48 | 4.27 |
| Log N | 10.49 | 8.76 | 8.44 | 8.05 | 7.51 | 10.71 | 8.70 | 7.81 | 7.02 | 5.84 |
| Log EMP | 4.02 | 2.72 | 2.26 | 2.13 | 1.24 | 4.21 | 2.79 | 2.06 | 1.38 | 0.25 |
| I/K | 0.16 | 0.18 | 0.19 | 0.18 | 0.20 | 0.16 | 0.17 | 0.18 | 0.19 | 0.20 |
| B/M | 0.55 | 0.60 | 0.65 | 0.70 | 0.76 | 0.55 | 0.57 | 0.63 | 0.69 | 0.83 |
| ROA | 0.14 | 0.14 | 0.14 | 0.13 | 0.10 | 0.14 | 0.14 | 0.14 | 0.13 | 0.09 |
| Lev | 0.30 | 0.25 | 0.23 | 0.26 | 0.25 | 0.29 | 0.28 | 0.26 | 0.23 | 0.21 |
| Num | 141 | 127 | 134 | 134 | 133 | 130 | 130 | 130 | 130 | 129 |

## Table IA.8: Double Sort on Financial Constraints and Productivity

This table reports the time-series average of cross-sectional means of firm characteristics, categorized into five groups based on financial constraints, measured using SA index in Panel A and WW index in Panel B, and two groups based on firm-level productivity. The estimation for firm-level productivity is discussed in Section II.1 of the Internet Appendix. We report firm characteristics, including pollution abatement (Abate), raw emissions (Emission), emission intensity (Emission/Sales), and investment rate (I/K), for these double sorts. Detailed descriptions of firm characteristics are provided in Table 1. The sample period covers from 1991 to 2020.

| | **L** | **2** | **3** | **4** | **H** | **L** | **2** | **3** | **4** | **H** |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | **Panel A: SA** | | | | | **Panel B: WW** | | |
| | | | | | **Abate** | | | | | |
| **L** | 2.98 | 1.70 | 1.77 | 2.35 | 0.85 | 3.18 | 2.64 | 1.89 | 1.22 | 0.81 |
| **H** | 9.73 | 6.40 | 3.60 | 2.52 | 1.99 | 10.08 | 7.05 | 4.56 | 2.73 | 1.41 |
| | | | | | **Log Emission** | | | | | |
| **L** | 14.97 | 14.11 | 14.13 | 13.48 | 12.54 | 15.24 | 13.91 | 13.69 | 13.52 | 11.21 |
| **H** | 15.21 | 13.88 | 14.17 | 14.69 | 13.85 | 15.53 | 15.14 | 13.77 | 13.08 | 12.15 |
| | | | | | **Log Emission/Sales** | | | | | |
| **L** | 7.07 | 8.13 | 7.13 | 8.61 | 7.08 | 6.56 | 7.50 | 7.96 | 8.75 | 6.86 |
| **H** | 5.78 | 5.45 | 5.78 | 6.64 | 6.22 | 5.77 | 6.76 | 5.81 | 5.93 | 5.51 |
| | | | | | **I/K** | | | | | |
| **L** | 0.14 | 0.17 | 0.18 | 0.18 | 0.20 | 0.14 | 0.17 | 0.18 | 0.19 | 0.19 |
| **H** | 0.17 | 0.18 | 0.19 | 0.19 | 0.21 | 0.17 | 0.17 | 0.18 | 0.19 | 0.24 |

## Table IA.9: The Peking Order by Financial Constraints

This table reports univariate regressions of firms' pollution abatement, emission intensity, and investment on SA index in Panel A and WW index in Panel B, as well as firm and year fixed effects. All independent variables are normalized to zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. *t*-statistics based on standard errors clustered at the firm level are reported with ***, **, and * indicating significance at the 1, 5, and 10% levels. The sample period is from 1991 to 2020.

| | (1) Log (1+Abate) | (2) Log (1+Emission) | (3) Log (1+Emission/Sales) | (4) I/K |
|---|---|---|---|---|
| | | **Panel A: SA** | | |
| SA | -0.37*** | -0.28 | 0.49*** | 0.02*** |
| [t] | [-8.03] | [-1.64] | [4.49] | [4.32] |
| Observations | 20,021 | 20,021 | 20,005 | 19,904 |
| R-squared | 0.69 | 0.82 | 0.83 | 0.49 |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster SE | Yes | Yes | Yes | Yes |
| | | **Panel B: WW** | | |
| WW | -0.12*** | -0.68*** | 0.43*** | 0.00 |
| [t] | [-3.31] | [-4.38] | [4.55] | [0.29] |
| Observations | 19,444 | 19,444 | 19,443 | 19,339 |
| R-squared | 0.69 | 0.82 | 0.83 | 0.49 |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster SE | Yes | Yes | Yes | Yes |

**Table IA.10**: **The Peking Order by Various Measures - Capital Intensive Abatement**

| | (1) Log N | (2) Log AT | (3) Log K | (4) Log EMP | (5) Age Comp | (6) SA | (7) WW |
|---|---|---|---|---|---|---|---|
| | | | | Abatement - Log (1+Abate) | | | |
| Size | 0.14** | 0.07* | 0.10** | 0.11*** | 0.27*** | -0.32*** | -0.07** |
| [t] | [2.25] | [1.71] | [2.35] | [3.06] | [3.59] | [-7.35] | [-2.18] |
| Observations | 10,379 | 20,052 | 20,049 | 20,435 | 18,235 | 20,018 | 19,441 |
| R-squared | 0.65 | 0.51 | 0.51 | 0.51 | 0.47 | 0.52 | 0.51 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster SE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: This table reports univariate regressions of firms' capital intensive pollution abatement in Panel A and abatement intensity in Panel B on the size, including logarithm of the net worth (N), total assets (AT), capital (K), employee (EMP), age, or financial constraint, including the SA and WW indexes, as well as firm and year fixed effects. All independent variables are normalized to zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. $t$-statistics based on standard errors clustered at the firm level are reported with ***, **, and * indicating significance at the 1, 5, and 10% levels. The sample period is from 1991 to 2020.

**Table IA.11**: **The Peking Order by Various Measures - Imputed Abatement Expenditures**

| | (1) Log N | (2) Log AT | (3) Log K | (4) Log EMP | (5) Log Age | (6) SA | (7) WW |
|---|---|---|---|---|---|---|---|
| | **Abatement Cost - Log (1+Abate Cost)** | | | | | | |
| Size | 0.51*** | 0.38*** | 0.32*** | 0.40*** | 0.51*** | -0.31*** | -0.52*** |
| [t] | [6.82] | [9.22] | [7.44] | [8.85] | [3.71] | [-9.16] | [-10.12] |
| Observations | 10,380 | 20,049 | 20,047 | 19,971 | 20,049 | 19,443 | 20,015 |
| R-squared | 0.80 | 0.77 | 0.77 | 0.77 | 0.76 | 0.77 | 0.78 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster SE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: This table reports univariate regressions of firms' pollution abatement cost in Panel A and abatement cost intensity in Panel B on the size, including logarithm of the net worth (N), total assets (AT), capital (K), employee (EMP), age, or financial constraint, including the SA and WW indexes, as well as firm and year fixed effects. All independent variables are normalized to zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. *t*-statistics based on standard errors clustered at the firm level are reported with ***, **, and * indicating significance at the 1, 5, and 10% levels. The sample period is from 1991 to 2020.

## Table IA.12: Emission Reduction and Abatement Investment

This table shows the joint link between emission reduction and operating or capital-intensive abatement activities. We report panel regressions of emission reduction on abatement investment, together with other firm characteristics. All variables are normalized to a zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. *t*-statistics based on standard errors that are clustered at the firm level are reported in parentheses. ***, **, * indicate significance at the 1, 5, and 10% levels in Panel A, and all regressions in Panel B are conducted at the annual frequency. The sample period is from 1991 to 2020.

| | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| | **Operating** | | **Capital-Intensive** | |
| Log (1+Abate) | -0.03*** | -0.04*** | -0.02*** | -0.03*** |
| [t] | [-4.11] | [-4.12] | [-3.85] | [-3.27] |
| Log N | | -0.05 | | -0.05 |
| [t] | | [-1.46] | | [-1.52] |
| B/M | | 0.00 | | 0.00 |
| [t] | | [0.56] | | [0.51] |
| I/K | | -0.02** | | -0.01* |
| [t] | | [-1.98] | | [-1.89] |
| ROA | | 0.02** | | 0.02* |
| [t] | | [2.01] | | [1.91] |
| Observations | 9,211 | 4,927 | 9,208 | 4,926 |
| R-squared | 0.18 | 0.23 | 0.18 | 0.23 |
| Facility FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Cluster SE | Yes | Yes | Yes | Yes |