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

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Abstract

Using US firm-level data, we document significant differences in pollution abatement activities over the life cycle of firms. Under financial constraints, smaller and younger firms invest more in capital and engage less in pollution abatement; as they accumulate more net worth, their abatement activities accelerate, and their emission intensity reduces. Motivated by this evidence, we develop and quantify a heterogeneous firm model to study the relation between financial frictions, capital investment, and pollution abatement. In the model, smaller and younger firms prefer capital investment over pollution abatement because the returns from the former are higher than those from the latter. More importantly, we show financial frictions make environmental regulation sub-optimal at any level: they reduce aggregate welfare gain by 40%. Finally, we show that green loan policies, even without monitoring, are considerably effective in reducing emission intensity.

JEL Codes: E1, E2, E3, E6, G1, G3, K3, Q5;

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1 Introduction

Economic activities often result in excessive corporate pollution, causing damage to human health, properties, and nature. However, the 2005 Survey of Pollution Abatement Costs and Expenditures suggests that pollution abatement activities increased disproportionally slower than physical capital investment over time.[1] Further analyses by the U.S. Census Bureau and Environmental Protection Agency (EPA) 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 such a 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 effects of financial frictions on corporate policies regarding capital investment and pollution abatement along the life cycle of firms.

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 key difference is that abatement expenditures lack collateralizability compared to capital investment. When the firm is small and constrained, resources are particularly costly, and spending them on capital generates two returns: increased output and relaxed future financial constraints through collateralizability. On the contrary, spending them on abatement only helps to reduce environmental regulation penalties. Therefore, despite stringent environmental regulation and enforcement, the firm may still favor capital investment over abatement activities until it grows itself 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 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 under the existence of financial frictions.

Our first step starts with combining several datasets. We first collect data from the Environ-

[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

mental Protection Agency's Pollution Prevention (P2) database for pollution abatement measures 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 scale a firm's total emissions by its sales revenue to calculate its emission intensity. 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 and property, plant, and equipment), the firm age measure from Compustat, and the financial constraint index (Whited and Wu, 2006; Hadlock and Pierce, 2010).

We find the following intriguing patterns related to financial frictions in the data. Larger, older, and less financially constrained firms disproportionately invest more in pollution abatement 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 scales. Our regression analysis confirms this pattern. Our evidence suggests that firms prioritize expansion through physical capital investment when they are more financially constrained and then accelerate their pollution abatement to comply with regulation when their financial constraints ease. These findings underscore financial constraints' significant impact 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 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 by increasing output and relaxing 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 make the aggregate environment 13% dirtier 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, we show financial frictions make regulatory penalties sub-optimal at any level. 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. It directly increases abatement activities and indirectly speeds 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 related literature here.

I. Corporate Environmental Policies with Financing Constraints. Our paper relates to the large work of 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 that financial frictions hinder corporate abatement activities.

Our quantitative model is closely related to two 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. In both papers, firms choose between two types of capital to determine their emission intensity. In contrast, we directly model abatement as an independent and continuous corporate policy, highlight the continuous trade-off between capital and abatement along the life cycle of firms, and validate the trade-off with microdata.

II. Government Environmental Policies. Our paper also 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). The focus of this literature is 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 heterogeneous firms facing financial constraints during their life cycle. We also show that the efficiency loss of taxes due to financial frictions is substantial.

Our paper also highlights the conditional effectiveness of environmental policies and regulations. It is well documented that governments' environmental initiatives do not always 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. More importantly, we illustrate the advantages of the comprehensive TRI database in analyzing corporate pollution control and outcomes.

Our paper also adds new insight into green loan policies. While literature (Sun et al., 2019; Fan et al., 2021; Dursun-de Neef et al., 2023) finds that the supply of green loans is useful in reducing 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. Our model suggests that despite the existence of financial greenwashing, green loan policies could still effectively reduce the emission intensity of financially constrained firms.

III. 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.[2] In contrast, our analysis examines the firms' optimization behavior under financial constraints and litigation concerns in a general equilibrium setting. Our model highlights that due to the existence of financial frictions, firms may rationally choose not to engage

[2]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 under-perform 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) show that state ownership enhances firms' environmental engagement.

in pollution abatement activities, leading to higher pollution emissions and potentially higher future litigation risks. Our study micro-founds the marginal investors' green preferences as 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 associated aggregate effects. In Section 7, we show the policy implications of regulations and green loans. Finally, we conclude our paper in Section 8.

2 Stylized Facts in the Data

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

2.1 Datasets and Summary

We discuss our main data sources and present summary statistics in this subsection. 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 facilities in manufacturing, starting from 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.[3]

[3]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

Pollution Prevention (P2): In addition to TRI data, we 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 prevention, inventory control, and good operating practices.

Enforcement and Compliance History Online (ECHO): We extract data on environmental litigation from the Enforcement and Compliance History Online database, which records administrative and judicial enforcement actions taken by the EPA. 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.

Final Sample and Summary Statistics: 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. 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 et al. (2022) and Hsu et al. (2022), ensuring accurate matching across databases. Additionally, macroeconomic data is sourced from the Federal Reserve Economic Data (FRED).

We explore the impact of financial constraints on firms' pollution abatement efforts through detailed panel regressions and analysis of new source reduction activities recorded in the P2 database. Key variables of interest from Compustat, including net worth (N), total assets (AT), capital (K), and the number of employees (EMP), serve as proxies for financial constraints and

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.

are used to assess how these constraints.[4] Pollution abatement is quantified by the number of activities per chemical: a1 and a2 denote a firm's unique number of pollution abatement activities at the facility-chemical and facility levels, respectively. Each firm's emissions include production wastes (E1), total releases (E2), onsite releases (E3), and land disposal (E4). The emission intensity is defined as emissions scaled by sales (ES1 to ES4).

[Place Table 1 about here]

Table 1 Panel A reports pooled summary statistics. Specifically, Panel A reports the pooled mean, median, standard deviation (Std), 5^{th} percentile (P5), 25^{th} percentile (P25), 75^{th} percentile (P75), and 95^{th} percentile (P95) of the variables of interest, as well as the valid number of observations for each variable. We have a total of $20,518$ firm-year observations with non-missing pollution abatement. The averages of a1 and a2 are 5.70 and 2.53, respectively, indicating that firms engage in approximately 5.70 and 2.53 pollution prevention activities. The averages of emission intensity based on production wastes (ES1), total releases (ES2), onsite releases (ES3), and land disposal (ES4) stand at $6,084.66$, $1,736.02$, $1,440.71$, and $1,257.55$, respectively. The emission intensity ES1 suggests that every million dollars in sales revenue is associated with $6,084.66$ pounds of production waste. A similar rationale applies to other measures. Panel B presents a correlation matrix for all variables considered in Panel A. Notably, pollution abatement, such as a1, generally shows low correlation with other variables, except for its correlations with the size measures: net worth (N), total assets (AT), capital (K), and employment (EMP), which are 0.19, 0.16, 0.17, and 0.09, respectively.

2.2 The Pecking Order of Abatement and Investment

We explore the heterogeneity of firm growth by examining how firms' pollution abatement activities and capital investment through four metrics to proxy for a firm's size: net worth (N), total assets (AT), capital (K), and the number of employees (EMP). We also consider age and financially constrained indicators in the Internet Appendix II.

Our analysis employs two methods. The first method categorizes firms based on their net worth, total assets, capital, and employment, then calculates time-series averages for the characteristics of each sorted group. On top of that, we further sort on net worth and firm-level

[4] Net worth is defined as the sum of sales revenue (SALE) and plant, property, and equipment (PPET) minus net debt issuance (e.g., Eisfeldt and Muir (2016)). 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.

productivity and report the characteristics of each sorted group. The second method involves panel regressions assessing the impact of net worth, total assets, capital, and the number of employees on pollution abatement and physical capital investment, adjusting for firm-specific and temporal variations to highlight within-firm and across-time differences.

2.2.1 Constructing Firm Groups and the Pecking Order

Constructing Firm Groups In Table 2, we construct quintile 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, and report each group's post-formation average firm characteristics. To do so, we form groups at the end of each year t. We first sort all sample firms into five groups 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, total assets, capital, or the number of employees in year t. In contrast, the high (low) quintile group includes firms with the highest (lowest) financial constraint in year t. After forming the five sorted groups (low to high), we calculate the time-series average of cross-sectional means of firm characteristics across quintile groups.

[Place Table 2 about here]

The Pecking Order in the Dimension of Size Panel A, sorted by net worth, documents that firms with higher net worth are more active in pollution abatement measures (i.e., a1 and a2) and have higher total emissions (i.e., E1, E2, E3, and E4). Yet, they show lower emission intensity (i.e., ES1, ES2, ES3, and ES4) than their smaller counterparts. Panel B, which categorizes firms by total assets, reflects a similar pattern: firms with greater total assets allocate more to pollution abatement and report higher total emissions but with reduced emission intensity. Panel C, focusing on capital, indicates that firms holding more capital not only have higher total emissions but also engage more in pollution abatement activities and achieve lower emission intensity than those holding less capital, hinting at a tendency towards more environmentally friendly practices over time. Finally, Panel D, sorted by the number of employees, demonstrates that firms with more employees tend to engage more in pollution abatement and reduce emission intensity.

Furthermore, our analysis also indicates that smaller firms display higher investment rates (I/K), 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 employee. These patterns, while needing further examination by regression analyses, suggest a nuanced relationship between firm characteristics and their environmental and financial practices.

2.2.2 Visualizing the Pecking Order in Two Dimensions

We explore the pecking order of abatement and investment further by looking at both the dimensions of net worth and productivity. Therefore, we double-sort firms based on both dimensions and generate results in Table 3. For simplicity, we only show the first measure of all four variables of interest (net worth). Productivity is defined as Solow residual from industry-specific Cobb-Douglas production functions. We use two ways to estimate the Solow residual. Details in the estimation refer to Section I.6 of the Internet Appendix. We visualize Table 3 Panel A in Figure 1 to provide a nuanced understanding of how abatement activities, investment rates, total raw emissions, and emission intensity vary across different levels of net worth and productivity.

[Place Table 3 and Figure 1 about here]

In the upper-left panel, abatement activities (a1) are plotted against firms' net worth, differentiated by productivity levels. Pollution abatement activities show a monotone increase in net worth for low-productivity firms, but the growth accelerates significantly for high-productivity firms as net worth increases. This suggests that decisions on abatement activities are not solely determined by size but are also enhanced by productivity heterogeneity. Notably, the disparity in abatement between high and low-productivity firms widens with increasing net worth, highlighting that productivity may generate additional effects on firms' pollution abatement activities.

In the upper-right panel, we focus on the investment rates (I/K), where an inverse relationship between investment rate and net worth is observed, particularly in firms with high productivity. This pattern could indicate that as firms grow larger, they encounter diminishing marginal investment returns. It's notable that investment scales down with net worth, suggesting that productivity drives cross-sectional variation in firms' investment decisions.

In the lower-left panel, total raw emissions (E1) increase with firms' net worth for both productivity groups, although the difference between low and high productivity is small. This trend implies that as firms grow in net worth, their scale of operations increases, generally associated with higher raw emissions. However, more pollution abatement activities can offset this effect, potentially leading to a similar pattern in raw emissions across productivity levels.

Finally, in the lower-right panel, we show that emission intensity (ES1) decreases with net worth. This is consistent with the increasing trend of abatement activities, leading to lower emissions per unit of output. Interestingly, high-productivity firms exhibit lower emission intensity than low-productivity firms at the same net worth, suggesting that productivity is another driving force behind variations in cleanness across firms.

These figures jointly illustrate the interplay between a firm's net worth, productivity, investment, and environmental performance measures. Our model in the following sections will explain such patterns with financial frictions and firm heterogeneity in net worth and productivity.

2.2.3 Validations with Panel Regressions

We further validate the above pecking order of abatement 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 4 that presents the estimation results from the following regression:

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

where $o_{j,t}$ represents outcomes such as pollution abatement, emission intensity, and investment levels of firm j in year t; α_j and α_t denote firm- and year-fixed effects; $s_{j,t}$ denotes size-related metrics (net worth, total assets, capital, and employee count); and $\varepsilon_{j,t}$ captures residuals. The estimated coefficient $\hat{b}$ indicates how outcomes fluctuate with these metrics, 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.

[Place Table 4 about here]

In Panel A, net worth as a measure of $s_{j,t}$ reveals significant insights: Columns 1 to 2 show that one standard deviation increase in net worth boosts pollution abatement by about 21 percentage, underscoring the positive impact of firm size on environmental initiatives. Furthermore, columns 3 to 6 show that a higher net worth corresponds to a marked reduction in emission intensity across various metrics. For instance, one standard deviation increase in total assets leads to a 93 percent decrease in emission intensity related to production (ES1). Finally, increasing net worth implies a lower investment rate in column 7, consistent with a decreasing return to scale in a firm's growth. The return on capital is lower for financially unconstrained firms. Overall, all these effects are highly statistically significant.

Other panels further corroborate these findings across all other size proxies. Panels B, C, and D utilize total assets, capital, and the number of employees as proxies, respectively. The observed pecking order patterns remain consistent across various measures of size, highlighting the robustness of our findings and illustrating the interplay between financial frictions, environmental policies, and investment behaviors. Our empirical evidence highlights that as firms' size increases, they invest more in pollution abatement. At the same time, their investment in expansion decreases, suggesting that they prioritize scaling up operations before committing to pollution abatement investments as they grow.

2.2.4 Pecking Order on Age and Financial Indicators

We show additional pecking order facts on 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 age measures, as expected. We also show the results for financially constrained indicators using Whited and Wu (2006) and Hadlock and Pierce (2010). Such a pecking order between abatement activities and capital investment holds across all different measures. All the results are available in the Internet Appendix II.

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 expenditures made in the prior period, and γ as the transmission elasticity from abatement to emission reduction.

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 π_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 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 expenditures 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 expenditures, 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 bad reputations 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 τ_{jt} follows a log-normal distribution with the actual realized average penalty μ_τ and volatility σ_τ.

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 τ_{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:

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

subject to

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

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

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

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

where r_t is the real interest rate, z_{jt+1} follows an AR(1) productivity process, τ_{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 τ_{jt+1}.

Representative Households We assume a unit measure continuum of identical households who 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 β is the time discount rate and ζ is a constant that captures the disutility of pollution emission (Hsu et al., 2022). 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 Π_t from all the firms and Γ_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 Abatement and Capital Investment There are four key differences between the profit-generating capital investment choice k' and the pollution-reducing abatement investment choice a' in our model:

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

(2) *Regulation:* The return of pollution abatement is subject to additional regulation shock τ_{jt+1}.

(3) *Irreversibility:* Capital investment is reversible, but pollution abatement is not.

Characterizing Decision Rules To characterize the firm's decision rules, we first note that the marginal cost of spending resources on either capital or pollution 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 investments 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. Based on the discussion above, we could derive the following Proposition 1. This proposition extends a similar result from Ottonello and Winberry (2024) on the trade-off between investment and innovation when firms are financially constrained.

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

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

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

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

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 is similar to Khan and Thomas (2013) and Ottonello and Winberry (2024). 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 investments 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 investment and abatement. 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, the marginal benefit is only the discounted expected marginal reduction in regulatory penalty. The first-order condition may not equal abatement investment due to the non-negative abatement $a' \geq 0$.

We have two observations in general. The first to notice is that even without considering the financial wedges, firm size already matters for abatement investment. 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. Second, when firms are financially constrained ($\lambda_t(z,n) > 0$), abatement investment 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 investments must be financed from internal resources or new borrowing, constrained firms would prefer capital investment more.

4.2 Visualization 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 show 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.

[Place Figures 2 and 3 about here]

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 regions is by 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 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, the firm 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 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 investment 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 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, we find that although high-productivity firms emit more as they grow, their engagements in abatement activities also grow faster than 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 and investment that we documented in Section 2.2. We provide visualization plots of the data in Figure 1. 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 and abatement 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 2.2. Therefore, we argue that financial frictions are the key model ingredient when considering corporate abatement activities. Moreover, the model implication that, as they grow, high-productivity firms' abatement investment grows faster and their emission intensity drops faster than low-productivity ones is consistent with Figure 1 and Table 3.

5 Further Validation with Microdata

This section provides empirical analyses to support our model implications. First, we provide additional causal evidence on the pollution abatement induced by financial frictions. Second, we examine the association between firm-level emissions and potential environmental penalties.

5.1 Role of Financial Frictions

This subsection provides causal evidence on the impact of financial frictions on pollution abatement. Consider two firms with identical levels of pollution abatement, investment, net worth, and productivity. A primary challenge in our empirical analysis is identifying exogenous variations in financial frictions to ascertain their causal effect on pollution abatement, controlling for other determinants. We address this by exploiting the exogenous variation provided by enacting anti-recharacterization laws, which, as documented by Chu (2020), alleviate firms' financial constraints by enhancing secured lenders' ability to repossess assets in bankruptcy.[5] 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 the reclassification of their claims. These laws, enacted in states like Texas, Louisiana, Alabama, and Delaware between 1997 and 2002, bolster lenders' confidence by legally safeguarding the terms of debt agreements, thus reducing lending risks. By securing creditor rights, these statutes facilitate greater access to credit for businesses, evidenced by an increase in debt financing, as firms under these laws can secure larger loans and more favorable terms due to decreased lender risk. Institutional details refer to Section I.7 of the Internet Appendix.

Given that anti-recharacterization laws are reasonably unrelated to firms' pollution abatement, we can design an identification test by examining the pollution 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. To verify the law's impact, we estimate the following ordinary least squares regressions:

$$\text{Log}(1 + a_{j,s,t}) = \alpha_j + \alpha_t + b \times \text{Log } N_{j,s,t} \times Law_{s,t} + c \times \text{Controls}_{j,s,t} + \varepsilon_{j,s,t}, \tag{11}$$

where $\text{Log}(1 + a_{j,s,t})$ represents the logarithm of firm j's pollution abatement ($a1$ and $a2$) plus 1, and $Law_{s,t}$ 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 interact the logarithm of firm j's net worth with $Law_{s,t}$ to focus on financially constrained firms with relatively lower net worth. The interaction term allows us to examine whether firms that are more financially constrained (i.e., smaller $\text{Log } N_{j,s,t}$) and sensitive to external financing display a more pronounced effect from the passage of the laws than their counterparts. Our theory predicts that the enactment of these laws improves such firms' borrowing capabilities, thereby easing their financial constraints and

[5] 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.

enabling an increase in pollution abatement (i.e., b to be negative).

Controls$_{j,s,t}$ include firm-level fundamentals such as book-to-market ratio, investment rate, and ROA. We also include firm- and year-fixed effects, α_j and α_t, respectively. 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.

Table 5 reports difference-in-differences estimates of Equation (11) for firms' pollution abatement responses to the passage of anti-recharacterization laws. Columns 1 and 3 present results showing that the negative coefficient on the interaction term indicates that the enactment of anti-recharacterization laws is associated with an increase in pollution abatement among low net worth firms (i.e., a1 in Column 1 and a2 in Column 3), compared to their counterparts in non-enacted states. This association remains robust in Columns 2 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 (Log $N_{j,s,t}$), is the primary driver of the endogenous choice of pollution abatement

[Place Table 5 about here]

Another possibility that may undermine the identification strategy is that the results are driven by preexisting differences between treated firms incorporated in Texas, Louisiana, and Alabama, 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 pollution abatement. Specifically, we construct six variables related to the timing of the anti-recharacterization laws. The independent variables of interest are Law_{-2}, which takes the value of 1 two years before the law's passage; Law_{-1}, one year before; Law_0, the year of passage; Law_1, one year after; Law_2, two years after; and Law_3, three years after. We replace Law 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 Law_{-2} and Law_{-1}. However, the results presented in Table 6 show that the coefficients on Law_{-2} and Law_{-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 Law_1, Law_2, and Law_3 are substantially negative and statistically significant.

[Place Table 6 about here]

Taken together, our tests based on anti-recharacterization laws pinpoint the financial friction mechanism and support a causal interpretation of our baseline results.

5.2 Role of Environmental Litigation

We then examine whether firms with higher emissions face greater litigation penalties and are more likely to face litigation for pollution. To this end, we collect all federal- and state-level cases against pollution to validate the connection with litigation penalties and obtain a more accurate estimate of the probability of litigation associated with environmental issues.[6] We analyze the relationship between firm-level emissions and litigation penalties using the following OLS regression:

$$\text{Log } Penalty_{j,t} = \alpha_j + \alpha_t + b \times \text{Log}(1 + E_{j,t}) + \varepsilon_{j,t}, \tag{12}$$

where the dependent variable represents the logarithm of firm j's litigation penalty, defined as the sum of closed environmental litigation penalties that firm j was involved in during year t. Emissions are calculated by summing the pounds of production-related emissions (E1), total releases (E2), onsite releases (E3), and land disposals (E4) across all plants owned by a firm within a year, as well as both firm- and year-fixed effects in the regression.

[Place Table 7 about here]

In Table 7, we find that emissions significantly relate to the penalties from environmental-related lawsuits across most specifications. When comparing Specifications 1 to 4 with 5 to 8, we notice a drop in significance when firm-fixed effects are controlled, suggesting that many cases are correlated and targeted by EPA policies within a given year. The correlation further decreases as we control for year-fixed effects, indicating the influence of judicial decisions based on precedents, which suggests autocorrelation in the data. However, in Specifications 9 to 12, the positive correlation between higher emissions and greater litigation penalties persists, validating the significant link between emissions and litigation penalties. According to Shapiro and Walker (2018), these results provide a basis for the micro-foundations of emission costs in our quantitative model detailed in Section 3.

[6] More details about these data sources are provided in Section I.3 of the Internet Appendix.

6 Quantitative Assessments

As the primary mechanism of this paper has been highlighted, we now proceed to apply the full 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.

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 8 presents the parameters directly taken from the literature. The model operates at an annual frequency, and the time discount rate β is set to 0.96 to match the average real risk-free rate of 4% per year. The capital share α is set to 0.65 to match a decreasing return to scale of two-thirds. The annual depreciation rate of capital δ_k is set to 0.10 to match the U.S.'s average nonresidential fixed investment rate.

[Place Table 8 about here]

Fitted Parameters The second part of Table 8 presents the parameters we calibrated to match the firm-level moments reported in Table 9. While all parameters are jointly determined, we outline the rough relationships between the parameters and moments. The first set of parameters pertains to output and finance. We set the productivity persistence parameter, ρ_z, to 0.90 and the productivity volatility parameter, σ_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, π_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, θ_k, to 0.40, leading to an equilibrium average firm-level leverage of 34%

[Place Table 9 about here]

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.[7]

Disutility of Pollution While the disutility of pollution parameter ζ 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 ζ. The value of ζ will impact the optimal degree of pollution penalty and the optimal level of abatement. We choose ζ 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 ζ.

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, aggregating across firms, this fact should imply that there will be fewer abatement activities in the aggregate. 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 $a'^*(z)$.

Environmental Distributions in Equilibrium We first check how the environmental activities are distributed across firms. Financial frictions depress abatement primarily in small, financially constrained firms with relatively high returns to capital and low returns to abatement.

[Place Figure 4 about here]

We illustrate this mechanism in Figure 4. 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 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 abate less. Therefore, the distribu-

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

tions 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).

[Place Table 10 about here]

Table 10 shows the aggregate effects of financial frictions. We have two major 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. However, this is not our focus. We focus on how financial frictions affect the economy's abatement activities and emission intensity. This brings us to the second observation: 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 not only hurt economic growth but also 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 Increasing Regulatory Penalties

We first use our calibrated model to assess the aggregate effects of increasing the magnitude of environmental regulation penalties under financial frictions. Since financial frictions hinder firms' incentive to abate, the effects of regulation penalties depend 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 significantly improves the environment (increased abatement, reduced emission intensity, and reduced emission) but significantly reduces economic performance measured in capital, output, and consumption.

[Place Figure 5 about here]

Figure 5 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 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 decreases all measures, and 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 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 output decreases. Then, as the regulatory penalty increases substantially, firms start to participate in abatement activities, and emission intensity starts to decrease. Different from the perspective of the economy, the gap between the baseline and frictionless models is substantial, especially when penalties are large. For a realized $\mu_t au = 0.01$, 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.

[Place Figure 6 about here]

We first show interesting results in Figure 6 how welfare changes with penalties in our baseline economy (left plot) compared to alternative economies in which households are less concerned 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 minus 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.

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 small. In this region, increasing pollution penalties only reduces emissions through reduced production scale. Consequently, the economy generates welfare loss because households suffer from reduced consumption but gain only slowly in emission reduction (see Figure 7 for the decomposition).

[Place Figure 7 about here]

Second, not surprisingly, welfare changes depend on the disutility of pollution parameter ζ. We calculate two alternative welfare, assuming a relatively lower disutility $\zeta = 0.10$ *(Less-Concerned)* economy and a relatively higher disutility $\zeta = 0.17$ *(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 optimal regulatory penalty is about 1.5%, which leads to 10% consumption loss and 17% environmental gain (see Figure 7 for the decomposition).

Third, we discuss the role of financial frictions. Under all preferences, welfare changes in the frictionless economy are higher than welfare changes in the baseline economy. More importantly, in the frictionless economy, the optimal penalty is larger because firms are more responsive to increases in regulatory penalties. If we check the decomposition in Figure 7, 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 friction 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; the only reason that they engage in abatement activities is 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 ζ and, therefore, the general environmental penalties μ_τ. In other words, the marginal investors' green preferences is captured by the households' disutility of pollution 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" that firms may use green loans partially or completely for non-abatement activities, such as capital investment, due to imperfect monitoring technology. We show here that green finance could still be a good policy along with moderate pollution penalties even without monitoring.

Implantation 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 θ_a.[8] 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 through firms' pollution abatement costs in a without-green-loan counterfactual world. 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 (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 on 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.

[8] 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 with the ability to get a green loan or bond based on such abatement expenditures.

[Place Figure 8 about here]

Figure 8 shows the 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 percentage 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.

The lower panels show the density distribution of abatement activities and emission intensity from our model-simulated firm sample, respectively. 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. Both the abatement distribution and the emission intensity distribution in the baseline model are dual-peaked, with a second peak with 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 to reduce the inefficient peak in emission intensity distribution.

Allocation and Aggregate Effects of Green Loans We finally show how the newly supplied green loans are allocated and their aggregate implications in Table 11.

[Place Table 11 about here]

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 most of the 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. Third, the green loans lead to economic growth. 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 0.1% reduction of 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 financial frictions play along 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 green loan policies, even without monitoring, are still considerably effective in reducing emission intensity through increasing abatement investment and enhancing firm growth.

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Figure 1. The Pecking Order by Net Worth and Productivity

These figures visualize the pecking order in two dimensions in Table 3 Panel A. It depicts firm characteristics sorted by net worth (N) and productivity (z), including firms' abatement activities (a1) in the upper left panel, investment rate (I/K) in the upper right panel, raw emissions (E1) in the lower left panel, and emission intensity (ES1) 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.

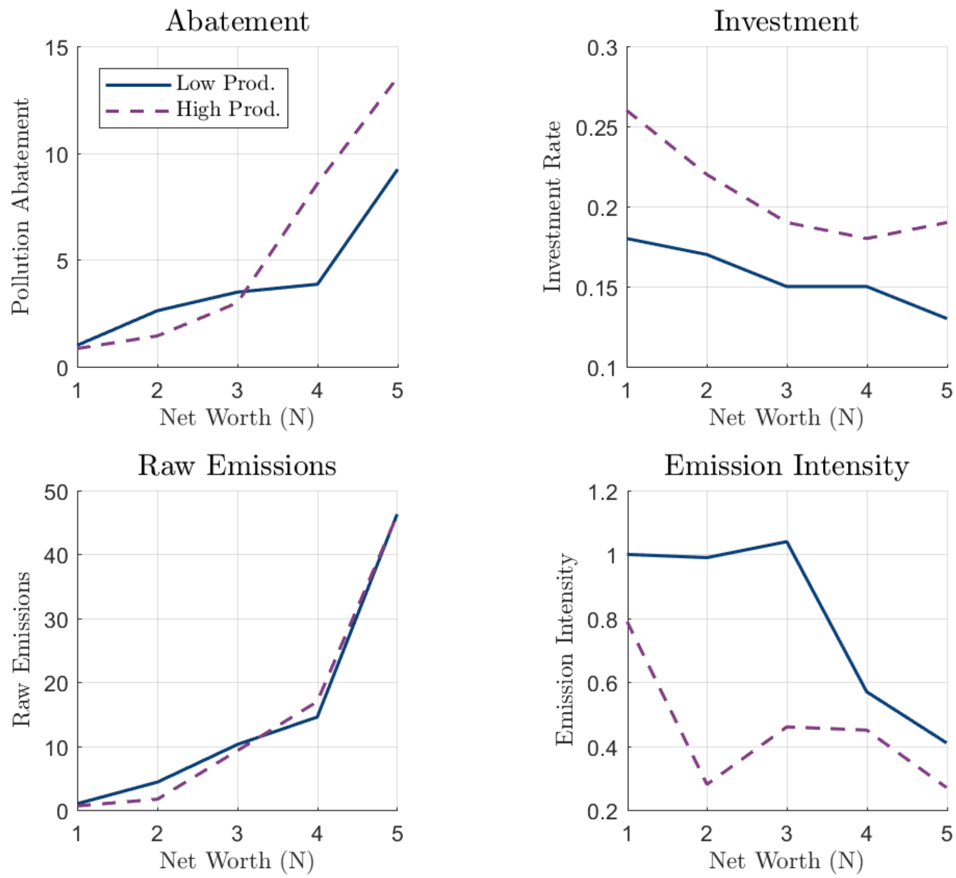

Figure 2. Abatement Activities and Capital Investment Over Size

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.

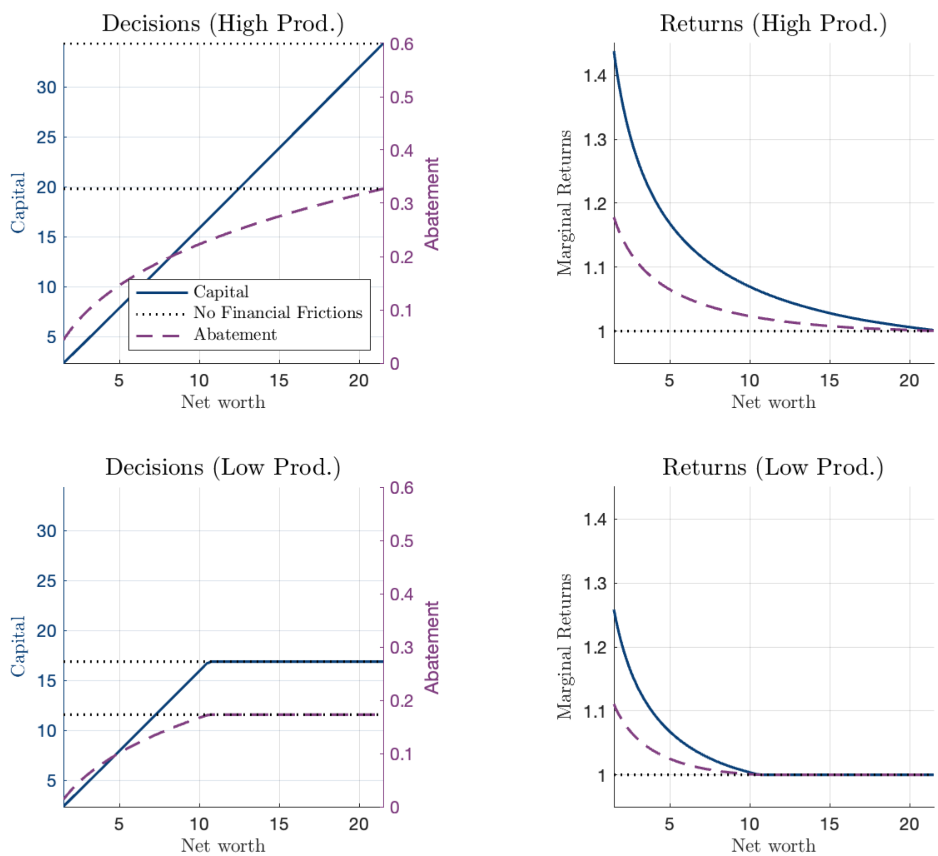

Figure 3. Total Emission and Emission Intensity Over Size

These figures plot firms' realized total emission 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.

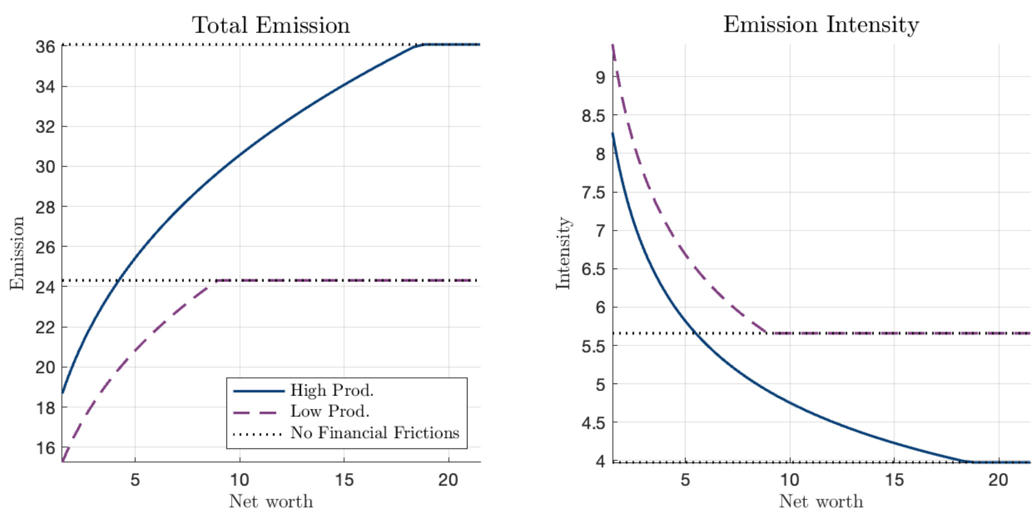

Figure 4. Environmental Distribution in Stationary Equilibrium

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 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 abate less. Therefore, the distributions are dual-peaked with lower abatement and higher emission intensity.

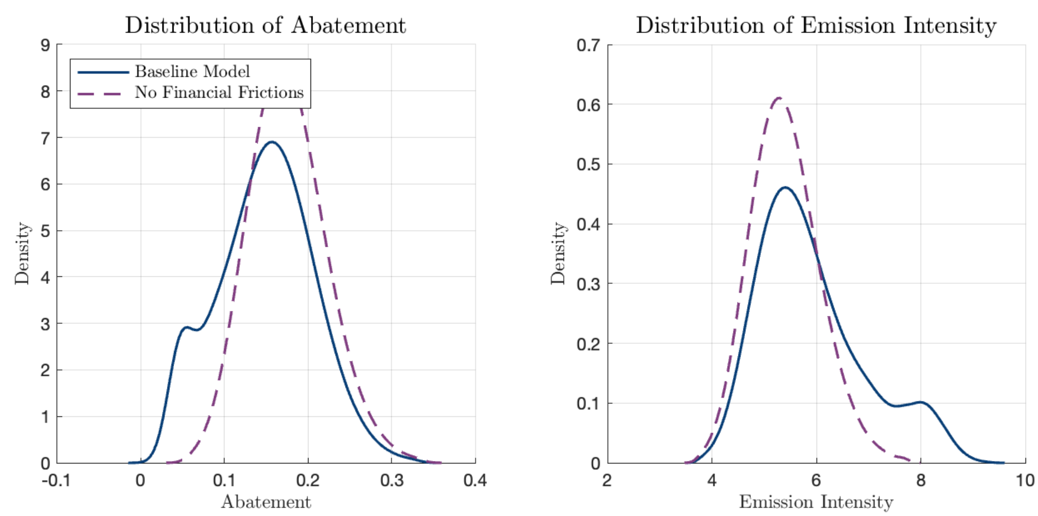

Figure 5. The Effects of Increasing Regulatory Penalty

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 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.

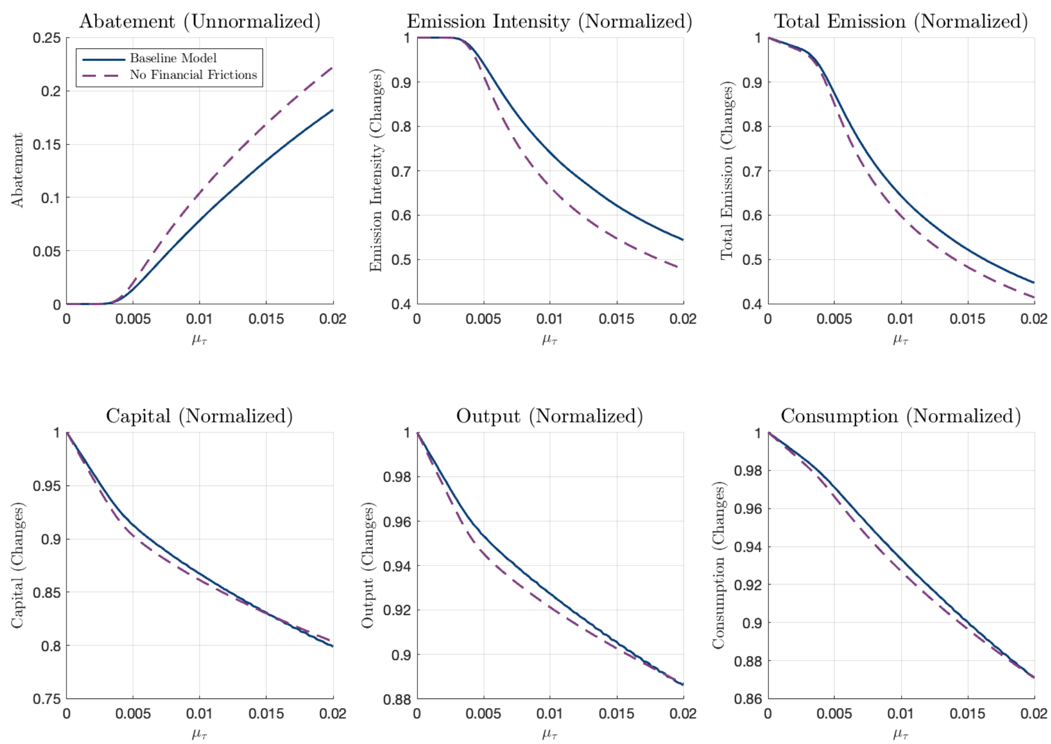

Figure 6. Welfare Implications Under Financial Frictions

These plots show how welfare changes with increased regulatory penalties in our model-simulated firm samples. We simulate in total 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 minus 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.

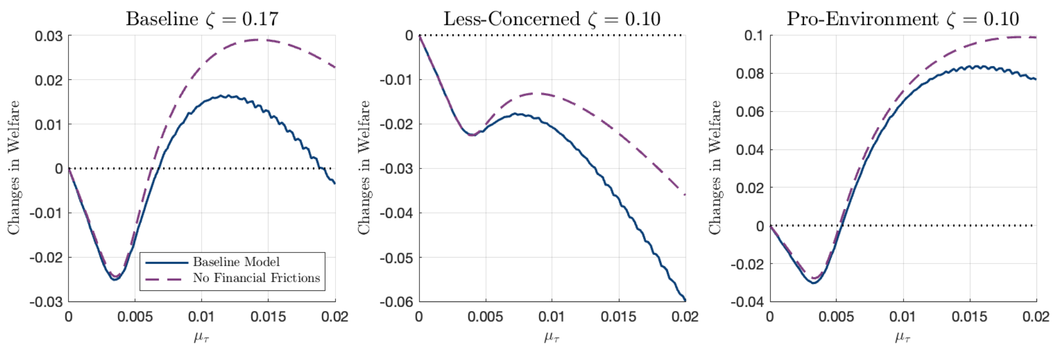

Figure 7. Welfare Implications Decomposition

These plots show how welfare changes with increased regulatory penalties in our model-simulated firm sample for the baseline economy. We simulate in total 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 minus one. Therefore, we could directly observe the changes in the baseline economy relative to the frictionless economy without comparing the absolute values.

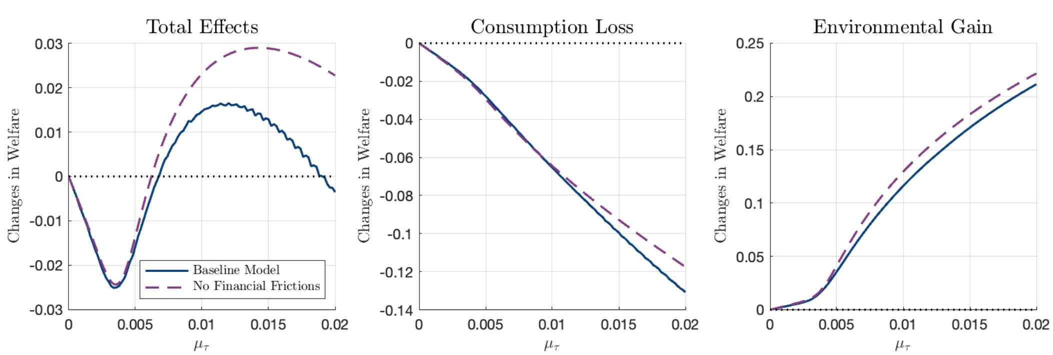

Figure 8. Green Loan Effects on Decision Rules and Distributions

Subplot 1 shows the abatement policies of firms (high productivity) under green loans compared to the baseline model and the frictionless model. 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 emission intensity distribution.

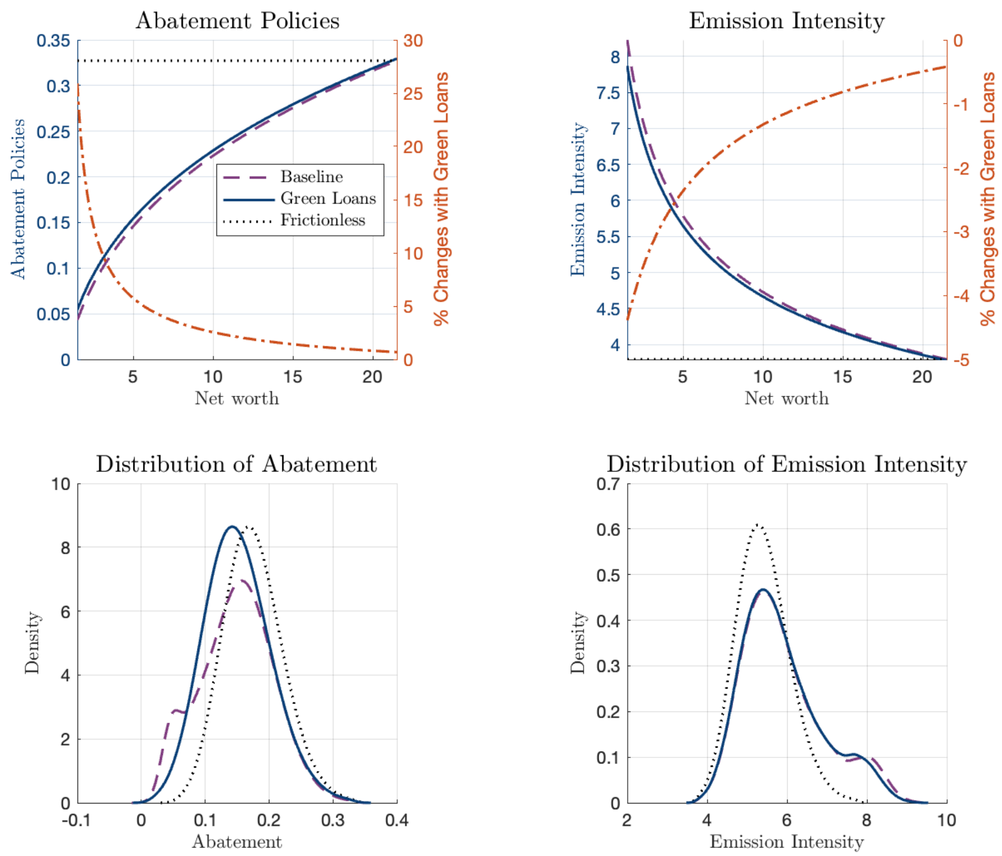

Table 1: Summary Statistics and Correlations

This table presents summary statistics in Panel A and a correlation matrix in Panel B for the firm-year sample. We define pollution abatement as the sum of new source reduction projects undertaken by a firm's facilities at either the facility-chemical or facility level within a specific year. More specifically, a1 and a2 denote a firm's unique number of pollution abatement activities at the facility-chemical and facility levels, respectively. To calculate emission intensity, we first calculate the raw emissions by summing production-related emissions, total releases, onsite releases, and land disposals (measured in pounds) across all of a firm's plants for a specific year. We then report raw emissions represented by E1 (production-related emissions), E2 (total releases), E3 (onsite releases), and E4 (land disposals). This total raw emission is then normalized by the firm's sales revenue, expressed in millions of dollars, which yields the emission intensity. 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.

	a1	a2	E1	E2	E3	E4	ES1	ES2	ES3	ES4	N	AT	K	EMP	B/M	ROA	I/K	Lev
Panel A: Summary Statistics																		
Mean	5.70	2.53	10,578,269.20	1,764,524.00	1469254	944386.5	6,084.66	1,736.02	1,440.71	1257.55	13,232.92	8,803.51	2,871.07	18.60	0.65	0.18	0.13	0.26
Std	21.51	6.23	42,903,151.80	10,707,621.00	10,167,460.00	9,231,497.00	69,600.29	30,059.55	25,702.59	26,240.23	39,512.55	33,566.03	10,407.94	68.51	0.66	0.12	0.09	0.16
P5	0	0	48.90	0.00	0.00	0.00	0.03	0.00	0.00	0.00	83.64	57.62	12.21	0.30	0.14	0.05	0.01	0.00
P25	0	0	33,165.00	2526.9.	691.00	0.00	32.34	2.14	0.57	0.00	615.53	349.70	83.75	1.57	0.32	0.11	0.09	0.14
Median	0	0	291,795.66	40,311.00	22,475.00	1,535.55	252.99	32.56	17.58	0.90	2,645.71	1,327.27	331.67	4.90	0.52	0.16	0.13	0.25
P75	4	2	253,6163.00	365,699.00	229,982.70	57,294.60	1,543.23	226.59	151.8	25.98	10,136.93	5,269.51	1,478.71	14.40	0.81	0.22	0.17	0.37
P95	25	12	48,856,898.00	7,284,471.00	5,937,795.00	2,376,500.00	1,6311.6	2,439.21	1,914.48	814.22	53,436.94	36,865.67	12,970.55	73.53	1.55	0.40	0.26	0.54
Observations	20,518	20,518	20,518	20,518	20,518	20,518	20,039	20,039	20,039	20,039	1,0387	20,055	20,055	20,438	20,448	20,401	20,495	20,473
Panel B: Correlation Matrix																		
a1	1	0.77	0.30	0.18	0.16	0.13	0.04	0.01	0.00	0.03	0.19	0.16	0.17	0.09	-0.06	-0.02	0.07	0.03
a2		1	0.32	0.14	0.13	0.08	0.01	-0.01	-0.01	0.00	0.17	0.20	0.12	0.16	-0.08	-0.01	0.08	0.04
E1			1	0.46	0.41	0.36	0.09	0.02	0.02	0.05	0.25	0.19	0.28	0.06	-0.01	-0.10	0.01	0.06
E2				1	0.94	0.73	0.04	0.08	0.07	0.19	0.19	0.15	0.27	0.03	0.03	-0.10	-0.03	0.11
E3					1	0.52	0.04	0.07	0.07	0.18	0.19	0.15	0.28	0.03	0.04	-0.10	-0.04	0.11
E4						1	0.07	0.14	0.12	0.40	0.09	0.10	0.16	0.01	0.02	-0.08	-0.01	0.08
ES1							1	0.77	0.77	0.12	-0.02	-0.01	-0.01	-0.01	-0.01	0.05	-0.15	-0.01
ES2								1	1	0.33	-0.01	-0.01	-0.01	-0.01	-0.01	0.02	-0.14	0.00
ES3								1	1	0.32	-0.01	-0.01	-0.01	-0.01	-0.01	0.02	-0.14	0.00
ES4										1	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	-0.01	0.01
N											1	0.77	0.89	0.68	-0.05	-0.06	0.01	0.08
AT												1	0.73	0.45	-0.04	-0.04	-0.04	0.14
K													1	0.43	0.00	-0.11	-0.03	0.10
EMP														1	-0.08	0.00	0.03	0.08
B/M															1	-0.17	-0.31	0.06
I/K																1	0.19	-0.26
ROA																	1	-0.14
Lev																		1

Table 2: Firm Characteristics

This table reports the time-series average of the cross-sectional means of firm characteristics for five groups sorted by net worth in Panel A, total assets in Panel B, capital in Panel C, and employee in Panel D. Pollution abatement is measured as the sum of new source reduction projects undertaken by facilities of a firm at either the facility-chemical or facility level within a specific year. Raw emissions are derived by aggregating the pounds of production-related emissions (E1), total releases (E2), onsite releases (E3), and land disposals (E4) from all plants owned by a firm within a year. Emission intensity 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, with the components of the raw emissions represented by ES1 (production-related emissions), ES2 (total releases), ES3 (onsite releases), and ES4 (land disposals). 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. Group characteristics are described in Table 1. The sample period is 1991 to 2020.

	Panel A: Net Worth					**Panel B: Total Assets**				
	L	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
a1	1.21	2.69	4.08	8.50	15.16	1.50	2.37	4.34	7.04	11.70
a2	0.78	1.35	2.21	3.36	6.50	0.79	1.16	2.02	2.72	5.23
Log E1	13.39	14.64	15.88	16.31	17.39	13.90	14.8	15.87	16.42	17.19
Log E2	12.21	12.58	13.38	14.25	15.55	12.85	13.22	13.62	14.36	15.51
Log E3	11.99	12.24	13.18	13.97	15.43	12.57	12.99	13.32	14.07	15.38
Log E4	12.04	11.96	12.66	13.45	14.48	12.74	12.98	13.14	13.88	14.71
Log ES1	9.36	8.06	8.25	7.81	7.42	9.49	8.63	8.42	8.13	7.66
Log ES2	7.85	6.14	5.95	5.95	5.90	8.46	7.40	6.68	6.28	6.26
Log ES3	7.79	5.85	5.81	5.72	5.79	8.25	7.25	6.48	6.10	6.14
Log ES4	6.74	5.50	5.32	5.20	4.95	8.15	7.27	6.37	5.85	5.67
Log AT	5.42	6.90	7.96	9.03	10.93	5.19	6.51	7.45	8.50	10.58
Log K	3.91	5.53	6.64	7.93	9.83	3.87	5.23	6.18	7.34	9.48
Log N	5.54	7.02	8.05	9.10	10.95	5.61	6.74	7.59	8.51	10.35
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	0.6	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	0.3	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**				
	L	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
a1	1.25	2.40	4.40	8.02	10.86	1.52	2.56	3.60	4.80	13.88
a2	0.78	1.20	1.99	3.23	4.73	0.75	1.12	1.54	2.29	5.99
Log E1	13.32	14.51	15.24	16.44	17.33	15.03	15.72	15.87	16.26	17.05
Log E2	12.29	12.99	13.13	14.12	15.67	13.76	13.56	13.6	14.74	15.17
Log E3	11.96	12.68	12.81	13.89	15.52	13.56	13.31	13.33	14.54	15.03
Log E4	12.12	12.82	12.62	13.57	14.97	13.66	13.00	12.99	14.21	14.31
Log ES1	9.32	8.68	8.24	8.46	8.09	9.69	8.46	8.15	7.97	7.35
Log ES2	8.23	7.56	6.64	6.92	6.69	8.71	6.82	5.91	6.43	5.53
Log ES3	7.99	7.39	6.45	6.79	6.56	8.52	6.63	5.65	6.28	5.38
Log ES4	7.82	7.47	6.35	6.67	6.24	8.47	6.51	5.28	5.96	4.76
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	-0.38	0.87	1.71	2.51	4.33
I/K	0.21	0.19	0.18	0.17	0.15	0.20	0.18	0.17	0.17	0.18
B/M	0.76	0.67	0.62	0.60	0.62	0.79	0.73	0.64	0.59	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	0.29	0.28
Num	134	134	134	134	133	132	132	132	132	131

Table 3: 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. Two estimations for firm-level productivity (i.e., z1 and z2) are discussed in Section I.6 of the Internet Appendix. We report firm characteristics, including pollution abatement (a1), investment rate (I/K), raw emissions (E1), and emission intensity (ES1) for these double sorts. Detailed descriptions of group 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: Productivity z1					**Panel B: Productivity z2**				
					a1					
L	1.30	3.40	4.54	5.02	12.01	1.27	3.12	4.71	5.02	7.75
H	1.11	1.87	3.89	11.16	17.62	0.75	1.88	3.80	10.14	17.27
					I/K					
L	0.18	0.17	0.15	0.15	0.13	0.20	0.18	0.16	0.14	0.13
H	0.26	0.22	0.19	0.18	0.19	0.29	0.22	0.19	0.17	0.18
					Log E1					
L	13.56	15.03	15.88	16.23	17.39	13.49	14.94	15.79	15.90	17.19
H	13.10	14.08	15.78	16.39	17.38	12.84	13.99	15.85	16.49	17.43
					Log ES1					
L	8.56	8.55	8.60	8.01	7.67	8.58	8.44	8.47	7.71	7.81
H	8.33	7.27	7.80	7.77	7.24	7.82	7.11	8.01	7.96	7.30

Table 4: The Peking Order by Various Measures

This table reports univariate regressions of firms' pollution abatement, emission intensity, and investment on the net worth (N) in Panel A, total assets (AT) in Panel B, capital (K) in Panel C, and employee 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+a1)	(2) Log (1+a2)	(3) Log (1+ES1)	(4) Log (1+ES2)	(5) Log (1+ES3)	(6) Log (1+ES4)	(7) I/K
Panel A: Net Worth							
Log N	0.22***	0.21***	-0.93***	-0.86***	-0.75***	-0.46***	-0.02***
[t]	[2.83]	[3.38]	[-5.30]	[-4.85]	[-4.09]	[-3.18]	[-2.71]
Observations	10,380	10,380	10,376	10,376	10,376	10,376	10,317
R-squared	0.74	0.74	0.86	0.86	0.87	0.84	0.56
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
Panel B: Total Assets							
Log AT	0.13***	0.12***	-0.75***	-0.66***	-0.57***	-0.38***	-0.02***
[t]	[2.61]	[3.13]	[-6.42]	[-5.64]	[-4.78]	[-3.88]	[-2.97]
Observations	20,055	20,055	20,039	20,039	20,039	20,039	19,938
R-squared	0.69	0.70	0.84	0.83	0.85	0.81	0.49
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
Panel C: Capital							
Log K	0.14***	0.13***	-0.63***	-0.57***	-0.48***	-0.29***	-0.04***
[t]	[2.69]	[3.43]	[-5.39]	[-5.25]	[-4.37]	[-2.92]	[-6.53]
Observations	20,052	20,052	20,039	20,039	20,039	20,039	19,938
R-squared	0.69	0.70	0.84	0.83	0.84	0.81	0.50
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
Panel D: Employee							
Log EMP	0.19***	0.16***	-0.61***	-0.54***	-0.48***	-0.26***	-0.02***
[t]	[4.08]	[4.64]	[-6.10]	[-5.17]	[-4.46]	[-2.86]	[-4.05]
Observations	20,438	20,438	19,963	19,963	19,963	19,963	20,323
R-squared	0.69	0.70	0.84	0.83	0.84	0.81	0.49
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

Table 5: Pollution Abatement and The Effect of Anti-recharacterization Laws

This table reports changes in firms' pollution abatement following the adoption of anti-recharacterization laws. The independent variable, *Law*, 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. The dependent variables are the firm's pollution abatement, $a1$ in Columns 1 and 2, and $a2$ in Columns 3 and 4. Independent variables include net worth and controls such as book-to-market ratio, investment rate, and ROA, with detailed definitions provided in Table 1. All regressions incorporate firm and year fixed effects. t-statistics, based on standard errors clustered at the firm level, are denoted with , , and * for significance at the 1%, 5%, and 10% levels, respectively. The sample period from 1994 to 2004 encompasses the duration of the adoption of anti-recharacterization laws.

	(1)	**(2)**	**(3)**	**(4)**
Law	0.05	0.06	0.04	0.04
[t]	[0.76]	[0.85]	[0.64]	[0.70]
Log N	0.01	-0.01	0.02	0.01
[t]	[0.07]	[-0.08]	[0.19]	[0.07]
Log N x Law	-0.10**	-0.10**	-0.09**	-0.09**
[t]	[-2.21]	[-2.20]	[-2.40]	[-2.44]
Observations	3,048	2,999	3,048	2,999
R-squared	0.87	0.87	0.86	0.86
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes

Table 6: The Dynmiac Effect of Anti-recharacterization Laws

This table explores changes in firms' pollution abatement following the adoption of anti-recharacterization laws. The independent variables of interest include time-specific dummies: Law_{-2}, Law_{-1}, Law_0, Law_1, Law_2, and Law_3. These dummies indicate the status of the law two years before adoption (Law_{-2}), one year before (Law_{-1}), the year of adoption (Law_0), one year after (Law_1), two years after (Law_2), and three years after (Law_3) the law's implementation. The dependent variables are the firm's pollution abatement measures, a1 in Columns 1 and 2, and a2 in Columns 3 and 4. 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.

	(1)	**(2)**	**(3)**	**(4)**
Log N × Law_{-2}	-0.03	-0.02	-0.03	-0.03
[t]	[-0.81]	[-0.69]	[-1.08]	[-0.89]
Log N × Law_{-1}	-0.02	-0.02	-0.03	-0.03
[t]	[-0.36]	[-0.43]	[-0.74]	[-0.77]
Log N × Law_0	-0.07	-0.08	-0.07*	-0.07*
[t]	[-1.57]	[-1.63]	[-1.67]	[-1.70]
Log N × Law_1	-0.14**	-0.14**	-0.11**	-0.11**
[t]	[-2.47]	[-2.44]	[-2.52]	[-2.47]
Log N × Law_2	-0.13**	-0.13**	-0.12***	-0.12***
[t]	[-2.44]	[-2.46]	[-2.66]	[-2.67]
Log N × Law_3	-0.13*	-0.12	-0.15***	-0.14**
[t]	[-1.86]	[-1.60]	[-2.80]	[-2.55]
Observations	2,360	2,306	2,360	2,306
R-squared	0.89	0.89	0.89	0.89
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes

Table 7: Litigation Penalties and Emissions

This table reports the impact of firms' emissions on their litigation penalties. We collect a firm's litigation penalties from its lawsuits relevant to environmental issues from the Integrated Compliance Information System. We regress the logarithm of firm j's litigation penalty in year t on the logarithm of firm j's emissions plus 1 in year t, as well as firm and year fixed effects. Emissions are calculated by summing the pounds of production-related emissions (E1), total releases (E2), onsite releases (E3), and land disposals (E4) across all plants owned by a firm within a year. 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 based on coverage of the Enforcement and Compliance History Online (ECHO) system.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log (1+E1)	0.86***				0.25				0.23			
[t]	[10.17]				[0.69]				[0.58]			
Log (1+E2)		0.94***				0.83**				0.69*		
[t]		[11.14]				[2.20]				[1.78]		
Log (1+E3)			0.91***				0.85**				0.78*	
[t]			[10.74]				[2.08]				[1.74]	
Log (1+E4)				0.81***				0.57*				0.55*
[t]				[9.56]				[1.83]				[1.78]
Observations	1,522	1,522	1,522	1,522	1,522	1,522	1,522	1,522	1,522	1,522	1,522	1,522
R-squared	0.09	0.11	0.10	0.09	0.43	0.43	0.43	0.43	0.45	0.46	0.46	0.46
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Calibrated Parameter Values and Sources

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 9.

Symbols	Descriptions	Values	Sources
Fixed Parameters			
β	Discount factor	0.96	Annual Frequency
α	Capital share	0.55	DRS of Two-thirds
δ_k	Capital depreciation rate	0.10	BEA Data
ζ	Dis-utility of pollution emission	0.17	Uncalibrated
Fitted Parameters			
ρ_z	Productivity persistence (fixed)	0.90	Targeted Moments
σ_z	Productivity volatility	0.05	Targeted Moments
π_d	Exogenous exit risk	0.09	Targeted Moments
n_0	Net worth of entry	2.50	Targeted Moments
θ_k	Collateral constraint	0.40	Targeted Moments
$\bar{e}$	Highest emission intensity	10.0	Targeted Moments
γ	Elasticity of abatement into intensity	5.0	Targeted Moments
μ^τ	Mean of pollution penalty	0.01	Targeted Moments
σ^τ	Volatility of pollution penalty	0.01	Targeted Moments

Table 9: Targeted Moments: Model and Data

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 fit the emission intensity distribution simultaneously, 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 distribution of pollution penalty, which is 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 8.

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

Table 10: The Aggregate Effects of Financial Frictions

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.

Outcomes	Output	Capital	Consump.	Abatement	Emission	Emission 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%

Table 11: The Allocation and Aggregate Effects of Green Loan Policies ($\theta_a = 1$)

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%.

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	Emission 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%

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

Min Fang, Po-Hsuan Hsu, and Chi-Yang Tsou

May 31, 2024

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I Data Appendix

I.1 The 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 releasing 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.[1] 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.[2]

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

[1]The changes and updates of the list of these pollutants are provided on the EPA website. See /www.epa.gov/sites/production/files/2020-01/documents/tri_chemical_list_changes_01_21_2020.pdf.

[2]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.

is worth noting that the TRI program has included approximately 98% of facility-level emission data in 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 outlined by the EPA, these categories enable a detailed analysis of emissions, 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. Onsite 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.

[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.5 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),[3] 8.2 (energy recovery on-site), 8.3 (energy recovery off-site),

[3] 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).

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).[4]

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: 52808LM-NMCHIGHW) 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

[4] Details available in the TRI database. See https://www.epa.gov/sites/production/files/2019-08/documents/basic_data_files_documentation_aug_2019_v2.pdf.

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.

[Place Table IA.1 about here]

The list of various abatement activities is available in Table IA.1. In our empirical analysis, we count the frequency of these process-related abatement and operating-related activities as plants' abatement intensity.

I.3 Data Collection of Civil Cases against Pollution

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.

I.4 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 upper case 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.5 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.[5] 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.[6]

I.6 Firm-level Productivity Estimation Details

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:

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

[5] See Corporate Research Project: http://www.corp-research.org/dowchemical.

[6] Dow's settlement: https://www.michigan.gov/ag/0,4534,7-359-92297_47203-511944--,00.html.

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:

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

in which ϕ_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:

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

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:

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

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

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

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:

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

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 (I.4) to estimate $\widehat{z}_{i,j,t}$. Given this estimation of firms' productivity, we obtain the alternative estimation of firms' productivity.

I.7 Institutional Details on Anti-Recharacterization Laws

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 collaterals 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.

II Empirical Appendix

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

II.1 The Pecking Order on Age Measures

Table IA.2 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. Pollution abatement is measured as the sum of new source reduction projects undertaken by facilities of a firm at either the facility-chemical or facility level within a specific year. Raw emissions are derived by aggregating the pounds of production-related emissions (E1), total releases (E2), onsite releases (E3), and land disposals (E4) from all plants owned by a firm within a year. Emission intensity 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, with the components of the raw emissions represented by ES1 (production-related emissions), ES2 (total releases), ES3 (onsite releases), and ES4 (land disposals). 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. Group characteristics are described in Table 1. The sample period is 1991 to 2020.

[Place Table IA.2 about here]

Table IA.3 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. Two estimations for firm-level productivity (i.e., z1 and z2) are discussed in Section I.6 of the Internet Appendix. We report firm age according to Compustat in Panel A, World Scope in Panel B, incorporation year in Panel C, and founding year in Panel D for these double sorts. The sample period covers from 1991 to 2020.

[Place Table IA.3 about here]

Table IA.4 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.

[Place Table IA.4 about here]

II.2 The Pecking Order on Financial Constrained Indicators

Table IA.5 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. Pollution abatement is measured as the sum of new source reduction projects undertaken by facilities of a firm at either the facility-chemical or facility level within a specific year. Raw emissions are derived by aggregating the pounds of production-related emissions (E1), total releases (E2), onsite releases (E3), and land disposals (E4) from all plants owned by a firm within a year. Emission intensity 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, with the components of the raw emissions represented by ES1 (production-related emissions), ES2 (total releases), ES3 (onsite releases), and ES4 (land disposals). 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. Group characteristics are described in Table 1. The sample period is 1991 to 2020.

[Place Table IA.5 about here]

Table IA.6 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. Two estimations for firm-level productivity (i.e., z1 and z2) are discussed in Section I.6 of the Internet Appendix. We report the SA index in Panel A and the WW index in Panel B for these double sorts. The sample period covers from 1991 to 2020.

[Place Table IA.6 about here]

Table IA.7 reports univariate regressions of firms' pollution abatement, 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.7 about here]

II.3 Adjustment for Emission Reductions

In this subsection, we consider an alternative (albeit related) measure of pollution abatement activities adjusted for emission reductions to test the robustness of our measure of pollution abatement activities. In the main paper, our measure of pollution abatement activities is considered by summing the total number of pollution abatement activities for a firm's facility located in a state in a given year when we treat different pollution abatement activities to generate an identical effect on emission reductions. In this subsection, we attempt to differentiate pollution abatement activity categories by estimating their capacities for emission reductions.

In particular, for each pollution abatement activity category (i.e., W Code in the P2 database), we track the lump sum of reductions in chemical emissions from 1992 to 2017. A greater reduction in emissions suggests that such a pollution abatement investment is more effective in reducing chemical emissions. However, the corresponding emissions reduction cannot be directly used to construct our adjusted abatement investment because of concerns about outliers in reduction or counter-intuitive non-negative reductions (i.e., no effect on or an increase in emissions.) To address this issue, for all abatement activities, we sort all categories with non-negative reduction of emissions into five groups and then assign an adjusted score ranging from 6 to the highest quintile to 2 to the lowest quintile, with a score of 1 indicating all remaining categories with missing or negative reductions.[7] Such adjusted scoring ensures that our weighting is less affected by outliers. Finally, we calculate a facility's adjusted pollution abatement activities as the weighted sum by multiplying the number of each pollution abatement activity by the corresponding adjusted score in a given year.

In the following subsection, we examine the joint link between emission-reduction-adjusted pollution abatement activities and financial constraints. We show that financially constrained firms are less likely to invest in pollution abatement.

[7] All pollution abatement activities are supposed to decrease the amount of released chemical pollutants. However, we may observe negative reductions due to measurement errors and data limitations.

II.4 Emission Reduction and Pollution Abatement Activities

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 incorporating the joint link between facility-level abatement activity and emission reduction. The Pollution Prevention database includes information on how much facilities have 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 facility level each year. In Panel A of Table IA.8, we present a negative correlation coefficient between the reduction in toxic emissions (Reduction) and the abatement investment (x), which is significant at the 1% level.

[Place Table IA.8 about here]

We then examine the relation between facility-level emission reduction and abatement activity more formally by estimating OLS regressions,

$$\Delta E_{p,i,s,t+1} = bx_{p,i,s,t} + c_1\, \Gamma_{i,t} + c_2\, X_{s,t} + \psi_p + \pi_t + \varepsilon_{p,i,s,t}, \tag{II.1}$$

for which we control a list of firm-level control variables, including size, book-to-market ratio, investment rate, and profitability, and state-level control variables for local fundamentals, including income per capita and population, as well as facility and year fixed effects. Standard errors are clustered at the facility level in Specifications 1 and 2 and the state level in Specifications 3 and 4. As presented in Panel B of Table IA.8, all specifications indicate that estimated coefficients on pollution abatement investment are statistically significantly negative at the 1% level, suggesting that pollution abatement investment 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

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

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:

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

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 $b_t^{\prime *}(z)$ would then be for any z', $d_{t+1}(z') \geq 0$ holds, which is

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

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

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

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 $b_t^{\prime *}(z)$ after solving the optimal policies $k_t^{\prime *}(z)$ and $a_t^{\prime *}(z)$.

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

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

where $n' = z'\left(k_t^{\prime *}(z)\right)^{\alpha} + (1-\delta)k_t^{\prime *}(z) - \frac{\tau'\bar{e}z'\left(k_t^{\prime *}(z)\right)^{\alpha}}{1+a_t^{\prime *}(z)} - b_t^{\prime *}(z)$ 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

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

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

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,

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

We can now define

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

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 $k'^*_{(*)}(z)$.

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

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

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

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

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).

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

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 $a'_{\widetilde{(\text{it+1})}(z,n)}$, then $a'_{(\text{it+1})}(z,n) = max\{0, a'_{\widetilde{(\text{it+1})}(z,n)}\}$.

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

Step 6: Update the financial wedge $\lambda_{(\mathrm{it})}(z,n)$ 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 $k'_{(\mathrm{it})}(z,n)$, $b'_{(\mathrm{it})}(z,n)$, $a'_{(\mathrm{it})}(z,n)$, $\lambda_{(\mathrm{it})}(z,n)$, and $\mu_{(\mathrm{it})}(z,n)$.

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:

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

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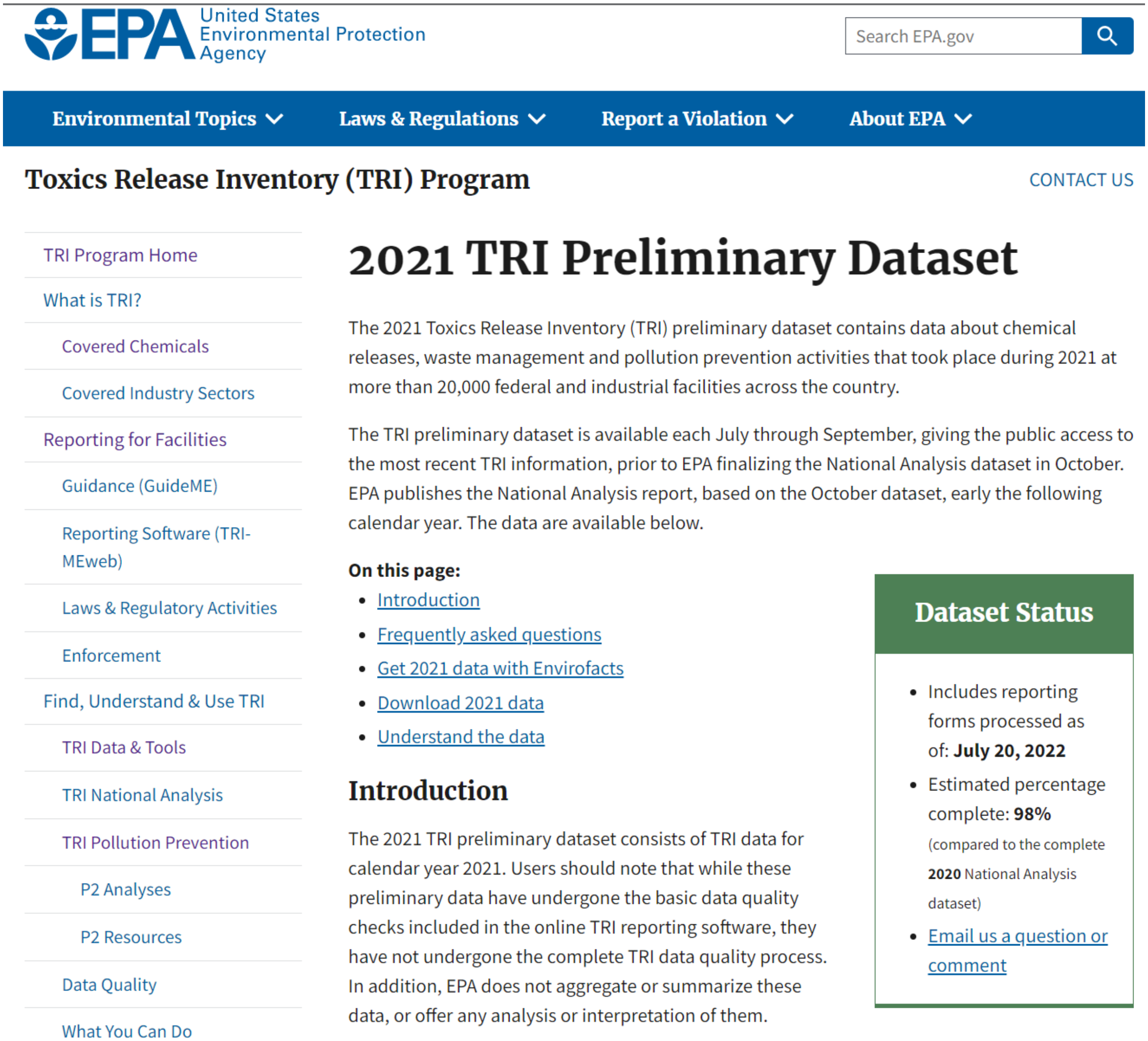
Figure IA.1. The Annual Updates of the TRI Program



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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
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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

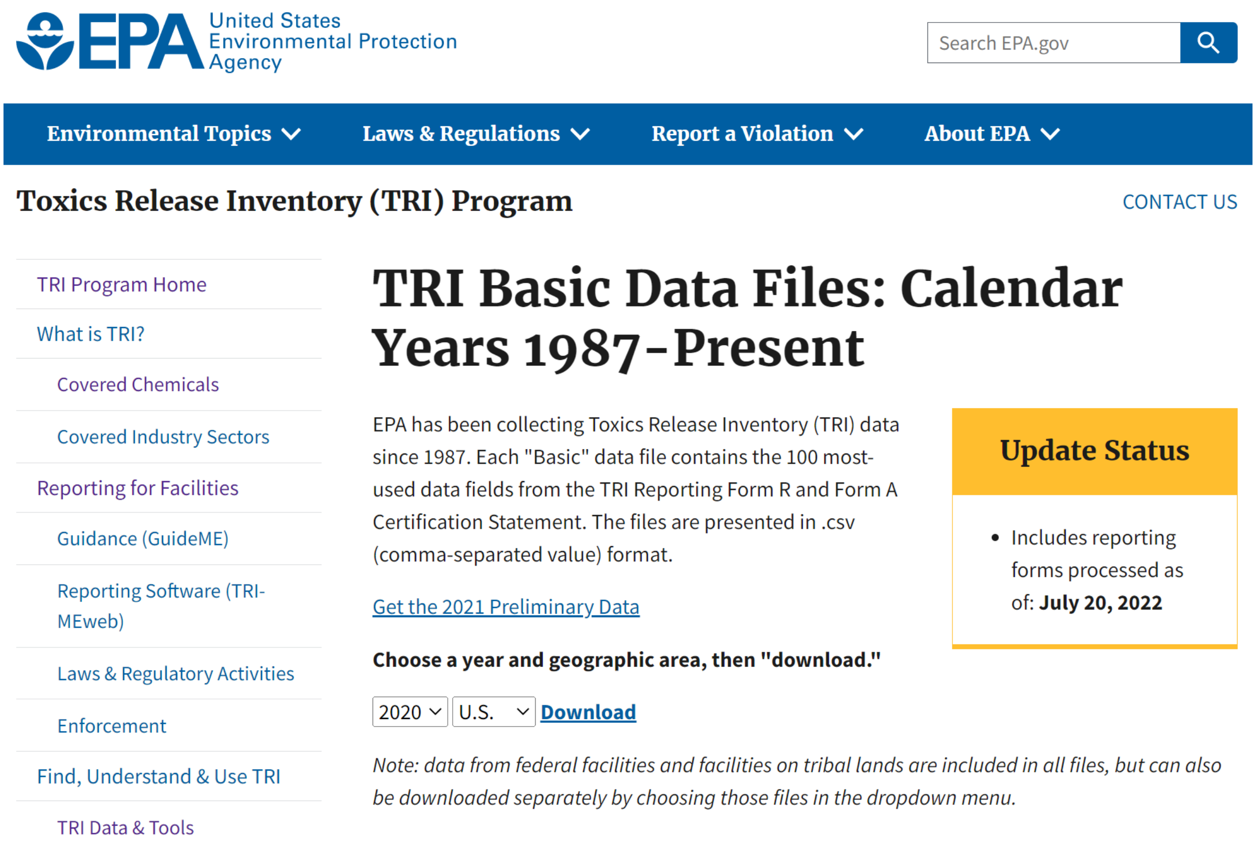
The 2021 TRI preliminary dataset consists of TRI data for calendar year 2021. Users should note that while these preliminary data have undergone the basic data quality checks included in the online TRI reporting software, they have not undergone the complete TRI data quality process. In addition, EPA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



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TRI Basic Data Files: Calendar Years 1987-Present

EPA has been collecting Toxics Release Inventory (TRI) data since 1987. Each "Basic" data file contains the 100 most-used data fields from the TRI Reporting Form R and Form A Certification Statement. The files are presented in .csv (comma-separated value) format.

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

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Note: data from federal facilities and facilities on tribal lands are included in all files, but can also be downloaded separately by choosing those files in the dropdown menu.

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

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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.

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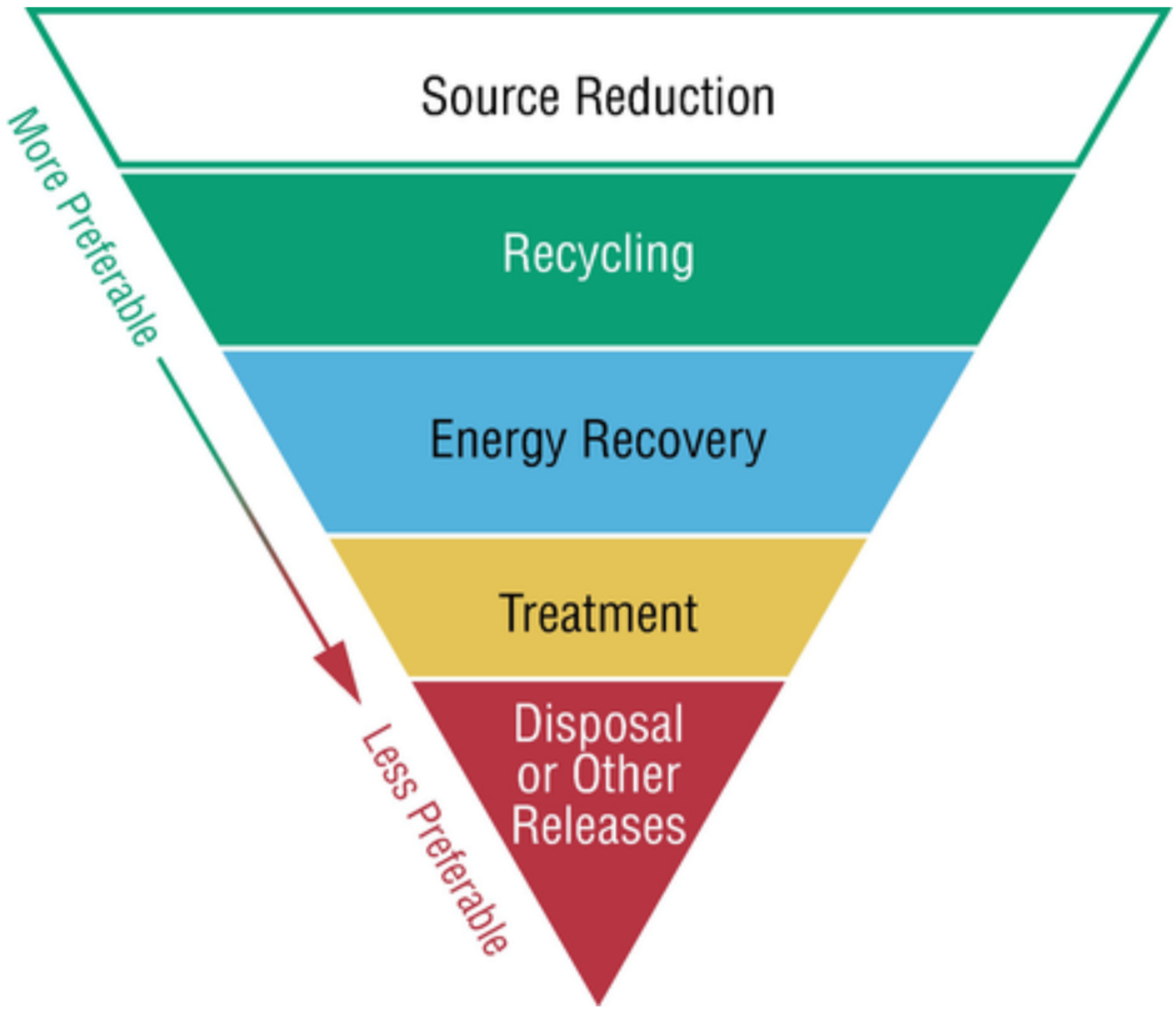
File Types and Contents

- 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

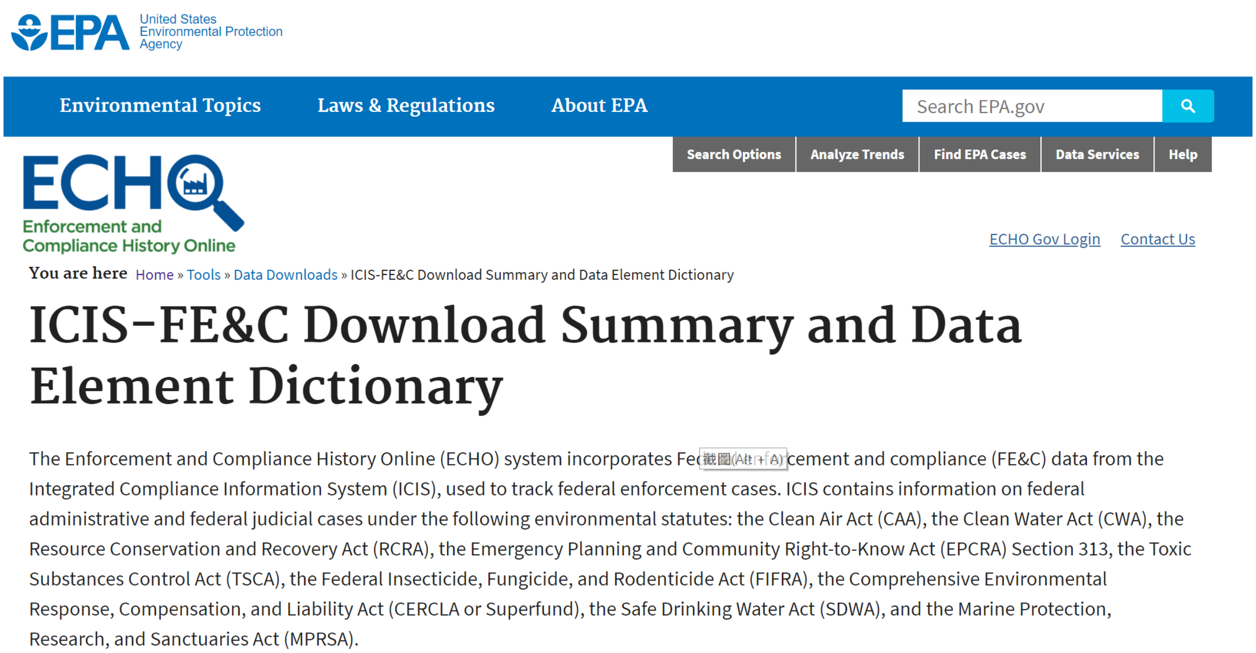


Figure IA.7. Civil cases and settlements.
Source: https://echo.epa.gov/tools/data-downloads/icis-fec-download-summary

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	Abatement Activities
W13	Improved maintenance scheduling, record keeping, or procedures
W14	Changed production schedule to minimize equipment and feedstock changeovers
W15	Introduced an in-line product quality monitoring or other process analysis system
W19	Other changes in operating practices
W21	instituted procedures to ensure that materials do not stay in inventory beyond
W22	Began to test outdated material - continue to use if still effective
W23	Eliminated shelf-life requirements for stable materials
W24	Instituted better labeling procedures
W25	Instituted clearinghouse to exchange materials that would otherwise be discarded
W29	Other changes in inventory control
W31	Improved storage or stacking procedures
W32	Improved procedures for loading, unloading, and transfer operations
W33	Installed overflow alarms or automatic shutoff valves
W35	Installed vapor recovery systems
W36	Implemented inspection or monitoring program of potential spill or leak sources
W39	Other spill or leak prevention
W41	Increased purity or raw materials
W42	Substituted raw materials
W43	Substituted a feedstock or reagent chemical with a different chemical
W49	Other raw material modifications
W50	Optimized reaction conditions or otherwise increased efficiency of synthesis
W51	Instituted recirculation within a process
W52	Modified equipment, layout, or piping
W53	Use of a different process catalyst
W54	Instituted better controls on operating bulk containers to minimize discarding
W55	Changed from small volume containers to bulk containers to minimize discarding
W56	Reduced or eliminated use of an organic solvent
W57	Used biotechnology in manufacturing process
W58	Other process modifications
W59	Modified stripping/cleaning equipment
W60	Changed to mechanical stripping/cleaning devices (from solvents or others)
W61	Changed to aqueous cleaners (from solvents or other materials)
W63	Modified containment procedures for cleaning units
W64	Improved draining procedures
W65	Redesigned parts racks to reduce drag-out
W66	Modified or installed rinse systems
W67	Improved rinse equipment design
W68	Improved rinse equipment operation
W71	Other cleaning and degreasing modifications
W72	Modified spray systems or equipment
W73	Substituted coating materials used
W74	Improved application techniques
W75	Changed from spray to other systems
W78	Other surface preparation and finishing modifications
W81	Changed product specifications
W82	Modified design or composition of product
W83	Modified packaging
W84	Developed a new chemical product to replace the previous chemical product
W89	Other product modifications

Table IA.2: 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. Pollution abatement is measured as the sum of new source reduction projects undertaken by facilities of a firm at either the facility-chemical or facility level within a specific year. Raw emissions are derived by aggregating the pounds of production-related emissions (E1), total releases (E2), onsite releases (E3), and land disposals (E4) from all plants owned by a firm within a year. Emission intensity 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, with the components of the raw emissions represented by ES1 (production-related emissions), ES2 (total releases), ES3 (onsite releases), and ES4 (land disposals). 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. Group characteristics are described in Table 1. The sample period is 1991 to 2020.

	Panel A: Compustat					**Panel B: World Scope**				
	L	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
a1	2.78	3.23	3.74	6.75	10.88	3.74	3.75	3.33	6.52	11.03
a2	1.36	1.46	1.94	2.37	5.01	1.85	1.76	1.82	3.05	3.90
Log E1	16.28	15.71	15.67	15.93	17.00	16.46	16.09	16.03	16.13	16.17
Log E2	13.76	14.16	14.26	14.4	15.08	14.65	14.48	13.95	14.24	14.37
Log E3	13.48	13.97	14.12	14.13	14.96	14.46	14.35	13.82	13.88	14.23
Log E4	12.92	13.85	13.90	13.90	14.09	14.16	14.1	13.17	13.43	13.23
Log ES1	9.17	8.5	8.83	8.37	7.67	9.13	8.63	8.16	8.00	7.45
Log ES2	7.28	6.73	8.07	7.59	6.11	7.75	6.72	6.22	6.05	5.72
Log ES3	7.08	6.51	7.81	7.54	5.94	7.62	6.55	5.88	5.41	5.48
Log ES4	5.85	6.23	8.01	7.49	5.52	7.09	6.37	5.42	5.51	4.97
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	7.95	8.03	8.74	8.75	10.07	9.06	9.04	9.29	9.45	10.10
Log EMP	1.96	2.26	2.86	2.76	3.95	2.45	2.66	2.75	3.17	3.43
Age	5.46	14.93	27.35	39.7	54.56	6.95	17.02	27.86	51.85	91.88
I/K	0.20	0.19	0.18	0.17	0.16	0.18	0.19	0.19	0.18	0.16
B/M	0.69	0.71	0.66	0.61	0.56	0.69	0.63	0.63	0.65	0.55
ROA	0.11	0.12	0.14	0.14	0.13	0.12	0.12	0.13	0.14	0.14
Lev	0.29	0.25	0.22	0.25	0.29	0.28	0.26	0.25	0.22	0.26
Num	144	129	148	129	112	120	112	110	110	111
	Panel C: Incorporation					**Panel D: Founding**				
	L	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
a1	2.29	3.20	1.75	1.73	3.25	3.39	2.78	4.72	7.34	12.03
a2	0.98	1.30	1.22	1.05	1.66	1.50	1.31	2.32	3.52	4.49
Log E1	15.27	16.37	14.89	16.05	15.95	15.48	15.55	15.36	16.54	16.91
Log E2	13.49	14.32	12.66	13.8	13.05	13.75	14.03	13.61	14.85	14.99
Log E3	12.43	14.22	12.43	13.68	12.45	13.25	13.70	13.33	14.70	14.85
Log E4	13.32	14.09	12.43	12.14	12.45	13.47	13.86	12.97	14.23	14.03
Log ES1	9.62	8.89	7.73	8.13	8.53	9.49	8.38	8.01	8.07	8.16
Log ES2	7.82	6.69	5.76	6.34	6.32	8.37	6.80	6.73	7.38	7.15
Log ES3	7.66	6.43	5.56	6.07	5.33	8.08	6.58	6.60	7.33	7.11
Log ES4	6.32	6.36	4.99	5.12	5.91	8.11	6.49	6.43	7.26	6.95
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	1.98	2.19	2.16	2.26	2.50	2.41	2.37	3.22	3.34	3.71
Age	14.96	23.41	32.63	53.94	103.32	18.05	36.90	65.7	94.8	137.99
I/K	0.22	0.21	0.21	0.18	0.17	0.19	0.20	0.17	0.16	0.16
B/M	0.68	0.60	0.64	0.76	0.66	0.68	0.66	0.65	0.62	0.53
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	0.23	0.27	0.29
Num	48	44	43	44	44	107	103	104	103	101

Table IA.3: Double Sort on Net Worth and Productivity - Age

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. Two estimations for firm-level productivity (i.e., z1 and z2) are discussed in Section I.6 of the Internet Appendix. We report firm age according to Compustat in Panel A, World Scope in Panel B, incorporation year in Panel C, and founding year in Panel D for these double sorts. The sample period covers from 1991 to 2020.

	L	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
	Panel A: Productivity z1					**Panel B: Productivity z2**				
	Panel A: Compustat									
L	21.19	24.40	28.11	37.65	47.19	20.91	23.93	28.37	37.77	45.04
H	18.51	20.79	26.69	34.33	46.41	16.52	20.67	26.63	34.83	47.21
	Panel B: World Scope									
L	33.45	34.28	44.11	41.74	42.35	34.94	33.93	43.52	39.89	36.77
H	34.31	33.13	41.50	56.17	55.37	27.67	33.71	42.07	55.29	53.70
	Panel C: Incorporation Year									
L	33.61	39.20	50.29	64.20	57.16	33.04	41.67	48.17	51.28	45.14
H	28.44	40.87	58.51	59.96	52.12	26.90	38.77	59.55	63.37	58.65
	Panel D: Founding Year									
L	49.41	59.49	69.28	81.12	102.12	49.68	58.56	65.90	78.14	100.02
H	43.94	54.07	79.18	90.09	106.66	36.84	54.23	81.85	90.67	105.56

Table IA.4: 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+a1)	(2) Log (1+a2)	(3) Log (1+ES1)	(4) Log (1+ES2)	(5) Log (1+ES3)	(6) Log (1+ES4)	(7) I/K
Panel A: Compustat							
Log(1+Age Comp)	0.21***	0.18***	-0.22***	-0.20***	-0.19***	-0.03	-0.02***
[t]	[6.10]	[6.74]	[-3.11]	[-2.96]	[-2.78]	[-0.50]	[-5.91]
Observations	20,518	20,518	20,039	20,039	20,039	20,039	20,401
R-squared	0.69	0.7	0.84	0.83	0.84	0.81	0.49
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
Panel B: World Scope							
Log(1+Age WS)	0.11**	0.11***	0.02	0.01	0.05	-0.05	-0.02***
[t]	[2.29]	[3.02]	[0.18]	[0.07]	[0.64]	[-0.61]	[-4.18]
Observations	17,441	17,441	16,980	16,980	16,980	16,980	17,363
R-squared	0.68	0.69	0.84	0.83	0.85	0.81	0.49
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
Panel C: Incorporation Year							
Log(1+Age Incorp)	0.25**	0.19**	-0.19	0	-0.11	0.2	-0.09***
[t]	[2.32]	[2.30]	[-0.59]	[0.01]	[-0.35]	[0.47]	[-6.06]
Observations	6,918	6,918	6,755	6,755	6,755	6,755	6,880
R-squared	0.6	0.59	0.84	0.82	0.84	0.76	0.54
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
Panel D: Founding Year							
Log(1+Age Found)	0.39***	0.32***	-0.33**	-0.32**	-0.32**	-0.03	-0.03***
[t]	[4.98]	[5.46]	[-2.07]	[-2.07]	[-2.19]	[-0.18]	[-4.00]
Observations	16,056	16,056	15,740	15,740	15,740	15,740	15,956
R-squared	0.7	0.71	0.83	0.82	0.83	0.81	0.48
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

Table IA.5: 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 SA index in Panel A and WW index in Panel B. Pollution abatement is measured as the sum of new source reduction projects undertaken by facilities of a firm at either the facility-chemical or facility level within a specific year. Raw emissions are derived by aggregating the pounds of production-related emissions (E1), total releases (E2), onsite releases (E3), and land disposals (E4) from all plants owned by a firm within a year. Emission intensity 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, with the components of the raw emissions represented by ES1 (production-related emissions), ES2 (total releases), ES3 (onsite releases), and ES4 (land disposals). 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. Group characteristics are described in Table 1. The sample period is 1991 to 2020.

	Panel A: SA					**Panel B: WW**				
	L	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
a1	12.55	5.83	2.76	3.72	1.81	12.17	7.27	4.10	2.42	1.47
a2	5.06	2.79	1.37	1.64	0.98	5.46	2.80	1.81	1.20	0.87
Log E1	16.98	15.58	15.95	15.89	15.79	17.24	16.44	15.45	15.18	13.77
Log E2	15.18	14.03	14.62	13.71	13.19	15.52	14.37	13.59	13.43	12.52
Log E3	15.02	13.81	14.50	13.30	12.96	15.38	14.11	13.40	13.16	12.11
Log E4	14.19	13.66	14.36	13.15	12.41	14.73	13.88	13.16	13.23	12.31
Log ES1	7.57	8.34	8.28	8.77	9.43	7.75	8.23	8.35	8.86	9.20
Log ES2	5.93	7.62	7.14	7.33	8.06	6.28	6.32	7.06	7.91	7.97
Log ES3	5.78	7.57	7.01	6.95	7.83	6.15	6.16	6.95	7.72	7.70
Log ES4	5.16	7.54	6.97	7.16	7.52	5.70	5.88	6.87	7.84	7.63
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	10.10	8.47	8.30	7.89	7.47	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
Age	49.72	38.13	24.55	13.65	7.17	43.74	30.78	24.22	20.32	17.77
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	0.6	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.6: Double Sort on Net Worth and Productivity - Financial Constraints

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. Two estimations for firm-level productivity (i.e., z1 and z2) are discussed in Section I.6 of the Internet Appendix. We report the SA index in Panel A and the WW index in Panel B for these double sorts. The sample period covers from 1991 to 2020.

	L	**2**	**3**	**4**	**H**	**L**	**2**	**3**	**4**	**H**
	Panel A: Productivity z1					**Panel B: Productivity z2**				
	Panel A: SA									
L	-3.27	-3.81	-4.06	-4.32	-4.51	-3.26	-3.80	-4.05	-4.32	-4.46
H	-3.28	-3.73	-4.02	-4.27	-4.50	-3.35	-3.74	-4.02	-4.27	-4.51
	Panel B: WW									
L	-0.23	-0.31	-0.37	-0.42	-0.49	-0.23	-0.31	-0.37	-0.42	-0.49
H	-0.25	-0.32	-0.38	-0.43	-0.51	-0.26	-0.33	-0.38	-0.43	-0.51

Table IA.7: The Peking Order by Financial Constraints

This table reports univariate regressions of firms' pollution abatement, 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.

	(1) Log (1+a1)	(2) Log (1+a2)	(3) Log (1+ES1)	(4) Log (1+ES2)	(5) Log (1+ES3)	(6) Log (1+ES4)	(7) I/K
				Panel A: SA			
SA	-0.40***	-0.33***	0.52***	0.49***	0.48***	0.07	0.02***
[t]	[-7.70]	[-8.14]	[4.70]	[4.49]	[4.35]	[0.67]	[4.32]
Observations	20,021	20,021	20,005	20,005	20,005	20,005	19,904
R-squared	0.7	0.71	0.84	0.83	0.85	0.81	0.49
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
				Panel B: WW			
WW	-0.12***	-0.11***	0.45***	0.43***	0.38***	0.23***	0
[t]	[-3.04]	[-3.52]	[4.86]	[4.55]	[3.99]	[2.99]	[0.29]
Observations	19,444	19,444	19,443	19,443	19,443	19,443	19,339
R-squared	0.69	0.7	0.84	0.83	0.85	0.81	0.49
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

Table IA.8: Emission Reduction and Abatement Investment

This table shows the joint link between emission reduction and abatement investment. In Panel A, we present the correlation matrix to document the correlation between emission reduction and abatement investment (a1). In Panel B, 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 facility 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 2017

Panel A: Correlation

	Reduction	a1
Reduction	1	-0.11***
a1		1

Panel B: Regressions

	(1)	**(2)**	**(3)**	**(4)**
a1	-10.62	-10.79	-10.62	-10.79
	(-4.25)	(-4.23)	(-3.17)	(-3.21)
Log ME		-3.12		-3.12
		(-0.81)		(-0.84)
B/M		0.48		0.48
		(0.35)		(0.35)
I/K		-2.51		-2.51
		(-2.15)		(-1.69)
ROA		3.26		3.26
		(2.66)		(2.51)
Income per Capita		4.63		4.63
		(0.95)		(0.79)
Log Population		0.90		0.90
		(0.03)		(0.03)
Observations	31,165	30,536	31,165	30,536
R-squared	0.33	0.33	0.33	0.33
Facility FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes