Does Financial Development Favor Clean Technology Adoption Along Green Transition?

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January 31, 2025

Abstract

This paper employs a general equilibrium model of firm dynamics to investigate how financial development influences firms' adoption of clean technologies through two opposing mechanisms. In partial equilibrium, financial development directly facilitates adoption by easing collateral constraints. In general equilibrium, however, financial development tends to impede green transition by crowding out clean investment in technology adoption by financially unconstrained firms. The higher demand for production inputs (i.e., capital and labor) along with financial development raises their prices, reducing unconstrained firms' profits and slowing their accumulation of internal funds for technology adoption. A numerical exploration of the model indicates that as financial markets become highly developed, the adverse general equilibrium effect outweighs the direct benefits, ultimately hindering green transitions. Furthermore, reducing the upfront costs of clean technologies is shown to alleviate the adverse impacts of financial development on green transition.

Keywords: Financial development, Clean technology adoption, Green transition, Firm dynamics

JEL Codes: E22, G31, O11, Q52, Q53, Q56, Q58

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1 Introduction

Industrial emissions, as byproducts of modern production, are viewed by policymakers and economists as one of the primary obstacles to economic development (Ito and Zhang, 2020). A potential solution to this issue is the green transition, which aims to decouple pollution from modern production through large-scale corporate investment in clean technologies (De Haas et al., 2024). However, the adoption of these clean technologies is progressing slowly, particularly in developing countries. For instance, as estimated by IEA (2024), the annual investments in clean technologies in developing countries currently amount to approximately \$270 billion, which is significantly below the necessary \$1.6 trillion per year to be on track for a 1.5-degree pathway by the 2030s. Is the slow pace of green transition in these regions attributed to underdeveloped financial markets? The adverse effects of such underdeveloped financial markets on economic growth are well-documented, highlighting that firms often face limited access to external credit. This lack of access can hinder their ability to quickly reach optimal production scales, thereby reducing per capita income and total factor productivity [1]. However, the impact of financial frictions on the environment remains relatively under-explored. To date, there is a lack of rigorous evidence regarding how these financial frictions influence corporate decisions related to the adoption of clean technologies.

This paper studies the effect of financial development on green transition. Financial development reduces frictions in financial markets, enabling more firms to access external credit. Unlike the growing body of literature on green finance, this paper concentrates on the relationship between regular finance and environmental sustainability. Green finance emphasizes the role of financial markets in directing investments towards green projects and away from brown industries and firms (for a review, see Giglio et al., 2021). The capital allocation associated with green finance embodies the inherent trade-off between economic growth and environmental protection, as economic growth necessitates the investment of capital into the most productive projects, whereas green investments often yield lower returns in comparison to their brown counterparts. This paper, however, explores the hypothesis that diminishing financial frictions may simultaneously promote economic growth and mitigate industrial pollution through its effects on the green transition.

[1] For more on the effects of financial development on productivity and economic growth, see Hsieh and Klenow (2009); Banerjee and Moll (2010); Buera et al. (2011); Greenwood et al. (2013); Moll (2014); Uras (2014); David and Venkateswaran (2019).

This study investigates two distinct channels through which financial development influences the green transition. In partial equilibrium, financial development facilitates the transition by enabling firms to borrow more against their collateral capital. Clean technologies typically entail significant up-front capital expenditures but benefit from lower operational costs (Pigato et al., 2020) [2]. Young firms tend to struggle to finance these high startup costs without access to external credit, despite the fact that clean technologies are generally more profitable than their traditional counterparts due to their lower operating costs. In general equilibrium, however, financial development tends to impede green transition by crowding out investment in clean technology adoption of large firms that are not financially constrained. Higher demand for production inputs, including capital and labor, raises their prices. For unconstrained firms, production scales are sensitive to variations in input prices. As input prices rise, their production scales tend to decrease, which in turn lowers their profits. As a result, diminished retained profits hinder these firms' ability to adopt clean technologies.

I find that financial development is not always beneficial to green transition. In fact, developing highly-developed financial markets could slow down the green transition as the adverse *general equilibrium* effects outweigh the *direct* benefits in partial equilibrium. Furthermore, the adverse impacts of financial development in general equilibrium are weakened when the upfront costs of clean technology are lower. The policy implication of my findings suggests a nuanced approach for different economies. Developing countries could benefit from financial development both in terms of productivity and environmental quality. Conversely, developed countries may need to concentrate more on reducing the upfront cost of clean technology, either through innovation or government intervention, as further financial liberalization does not support green goals.

I consider a general equilibrium model with heterogeneous firms to explore how financial development affects the adoption of clean technology and clean production. The model is based on the framework developed by Midrigan and Xu (2014). I make three assumptions. First, each period, a constant fraction of new entrepreneurs enter the market, all starting with dirty technology due to its lower startup costs [3]. As these entrepreneurs accumulate sufficient internal net worth, they can choose to adopt clean technology by covering

[2]Utility-scale solar PV and wind projects in the power sector are a good example: compared to thermal power plants with continued expenditure on burning fossil fuels, they require significant initial spending but are then very cheap to run (IEA, 2024).

[3]The assumption is to avoid the self-financing channel that undoes the role of external financial and also limits the importance of financial development. With this assumption, there are always small entrepreneurs who own far less net worth compared to the start-up cost of clean technology.

the upfront cost. This assumption is essential for simulating the green transition. Second, the primary difference between dirty and clean technologies is that dirty technology generates pollution, which is subject to government taxation. This implies that producing with clean technology is cheaper than producing with dirty technology, so that entrepreneurs are always willing to use the former once they pay the upfront cost. Third, financial frictions take the form of simple collateral constraints on the amount of debt and financial development is modeled to be the relaxation of these constraints. This leads to the observation that, in general equilibrium, not all entrepreneurs adopt clean technology, as their capacity to finance the necessary upfront investment is restricted.

In this model, financial frictions prevent young and small entrepreneurs from adopting clean technology due to their limited net worth, which is primarily accumulated by retained profits. These entrepreneurs are typically significantly financially constrained. This aligns with my key empirical finding: firms without financial constraints are more likely to adopt clean technology. By exploring the Toxic Release Inventory (TRI) establishment-level microdata from the U.S. Environmental Protection Agency (EPA) from 1991 to 2022, I discovered that financially constrained firms tend to invest less in both clean technology and end-of-pipe solutions. As a result, these firms exhibit higher emission intensity. I categorize firms' abatement activities into two main types: technology adoption and end-of-pipe solutions. To mitigate pollution, firms can either adopt clean technology, which reduces emissions during the production process, or implement end-of-pipe solutions, which address emissions after production through methods such as filters and scrubbers (Frondel et al., 2007; Hammar and Löfgren, 2010; Turken et al., 2020).

As described above, my model highlights two opposing forces of financial development on the green transition: the positive *direct* effect in partial equilibrium and the negative *general equilibrium* effect. The *direct* effect arises from easier access to external financing, which enables more entrepreneurs to adopt clean technology. However, in the general equilibrium, the reallocation of production inputs resulting from rising input prices reduces profits for unconstrained entrepreneurs. This decline in profits weakens their ability to adopt clean technology, ultimately hindering the green transition.

A numerical exploration indicates that the *direct* effect diminishes as financial markets become more advanced, while the *general equilibrium* effect strengthens. Consequently, the relationship between financial development and the share of clean production follows an inverse U-shape. This pattern is observed in both open and closed economies. The *di-*

rect effect diminishes due to the presence of a minimal net worth requirement for all entrepreneurs. In my model, entrepreneurs have access to only one financial instrument: a one-period risk-free bond. This uncontingent debt mandates a minimum net worth that ensures entrepreneurs can repay their debt at any time. While financial development allows entrepreneurs to borrow more, which reduces the internal funds required to cover the upfront costs of clean technology, this reduction is constrained by the minimal net worth requirement, limiting the *direct* effect. However, the *general equilibrium* effect becomes increasingly pronounced as more dirty entrepreneurs become relatively unconstrained. In an open economy, the increase in wages accompanying financial development reduces the production scale for more entrepreneurs. In a closed economy, the *general equilibrium* effect is further amplified as both wages and interest rates rise during financial development. As a result, the profits of unconstrained firms decrease even more, making it increasingly difficult for them to adopt clean technology.

Moreover, my results also suggest that lowering the startup costs for clean technologies can alleviate the detrimental effects of financial development on the green transition. By lowering these costs, clean technologies become more accessible, thereby ensuring that only the youngest and poorest entrepreneurs use dirty technologies. It is observed that all dirty entrepreneurs are significantly constrained, making their production scales and profits only marginally influenced by the increases in wages and interest rates. This highly weakens the adverse *general equilibrium* effects.

This paper contributes to three strands of literature. First, it extends the empirical research on the relationship between corporate financial constraints and environmental performance. While existing studies focus on firm heterogeneity and compare corporate emissions between constrained and unconstrained firms (Antunes et al., 2008; Xu and Kim, 2022; Bartram et al., 2022; Martinsson et al., 2024; De Haas et al., 2024), I account for the general equilibrium effects of relaxing credit constraints and find that, although relaxing constraints tends to reduce pollution at the firm level, wage and interest rate increases during financial development can offset these gains. This is especially true in well-developed financial markets.

Second, this paper builds on macroeconomic literature that examines the impact of financial development on technology adoption, but extends these studies to the environmental context. Cole et al. (2016) provide a review of this strand of literature and summarize common properties of technology differences in these studies: better technologies have higher expected levels of productivity and involve a higher fixed cost in terms of adoption. This paper novelly extends the application of this setting into the environmental context where clean technology has higher expected profits (due to its lower variable costs) but also incurs larger upfront costs.

Third, this paper is complementary to the effects of financial markets on the environment. For example, De Haas and Popov (2022) show that an expanding stock market can facilitate the transition to low-carbon growth by enhancing the energy efficiency of carbon-intensive sectors. Specifically, Aghion et al. (2024) claims that financial frictions hinder innovation-driven green transitions due to the path dependence inherent in innovation. Andersen (2016) argue that reducing credit constraints encourages firms to adopt more productive technologies, which subsequently lowers their emission intensity, as more productive firms invest more in end-of-pipe emission abatement. My contribution to this body of work is to propose another mechanism through which financial markets can influence the green transition: by influencing the adoption of clean technology.

The remainder of this paper is organized as follows. Section 2 provides preliminary empirical evidence on the relationship between firms' financial constraints and their environmental performances. Section 3 outlines the theoretical model. Section 4 presents the main quantitative results, and Section 5 concludes.

2 Data and Motivating Evidence

In this section, I analyze the relationship between corporate environmental performance and financial constraints using facility-level microdata from the Toxic Release Inventory (TRI) provided by the EPA. TRI data includes information on two types of corporate abatement activities: end-of-pipe solutions and the adoption of clean technologies. The difference between these two is that clean technologies impact the production process itself, while end-of-pipe solutions do not; instead, their purpose is to emissions after they have generated (Hammar and Löfgren, 2010; Turken et al., 2020). Firm-specific *net emissions*, which refer to the amount of pollutants released into the environment, are calculated as follows: they are equal to *gross emissions* – the total pollutants generated during production– minus minus the pollutants abated through *end-of-pipe* solutions:

$$\textit{net emissions} = \textit{gross emissions} - \textit{end-of-pipe abatement}$$

In this way, a firm's *net emissions* depend on its investments in both clean technologies and *end-of-pipe* abatement activities. The former help to reduce the firm's *gross emissions*, while the latter increases the total amount of pollutants that are abated.

In this section, I will examine the effects of firms' financial constraints on their investments in clean technologies and end-of-pipe solutions. These investments play a crucial role in determining the firms' net emissions. I will begin by describing the data sources, followed by the three key empirical findings regarding firms' net emission intensity, end-of-pipe abatement efforts, and clean technology adoption. These insights will inform the modeling assumptions in the subsequent sections.

2.1 Data Source

To study firm-level emissions from U.S. public manufacturing companies, I use plant-level pollutant data from the TRI database, maintained by the EPA. The TRI database contains annual records of chemical production, processing, and release, dating back to 1986, for plants that report under EPA regulations. Facilities in TRI-reportable industries with more than ten employees and that exceed certain chemical usage thresholds are required to submit reports. In 2022, 88% of TRI-reporting plants were in the manufacturing sector. Although the data are self-reported, the EPA monitors quality through error correction and detailed reviews, with non-compliance potentially leading to legal penalties (Xu and Kim, 2022). Studies such as Akey and Appel (2021) confirm that TRI data are of high quality, with little systemic over- or under-reporting.

TRI data provides detailed information on companies' emission activities, including source reduction, recycling, energy recovery, treatment, and releases. For source reduction activities, facilities are required to report whether they engage in such activities and, if they do, to specify the categories of activities at the chemical level. For other activities, facilities must report the specific amounts of chemicals involved. This information allows us to analyze corporate *net emissions*, *end-of-pipe abatement*, and *gross emissions* which depend on firms' activities of *clean technology adoption*.

Source reduction aims to eliminate the generation of hazardous substances by modifying production processes. The EPA classifies source reduction into five categories: process and equipment modifications, operating practices, inventory management, and material/product modifications. Of these categories, process and equipment modifications—such as enhancements to industrial processes and equipment—are the most common and serve as indicators of *clean technology adoption* in this study .

There are three types of end-of-pipe solutions: recycling (converting discarded materials into raw materials), energy recovery (generating energy from waste combustion), and treatment (modifying hazardous materials). I define corporate *end-of-pipe abatement* as the total quantity of pollutants abated through recycling, energy recovery, and treatment. Data on firms' *net emissions* and *gross emissions* come from two variables in the TRI database: **Total Toxic Releases** (the sum of toxic chemicals released into the environment) and **Production Waste** (the sum of toxic chemicals generated during production). Plant-level data are aggregated at the parent company level to generate firm-level observations.

The TRI database includes 794 chemicals that meet criteria such as (1) being carcinogenic or causing chronic health effects, (2) posing acute health risks, or (3) causing significant environmental harm. I use the total quantities of all TRI chemicals as the measure of plants' emissions and abatement, treating all chemicals equally to ensure comprehensive coverage (Xu and Kim, 2022).

To supplement TRI data, I extract firm-level financial information, including *sales* and *total assets*, from the Compustat database. I measure financial constraints using the book value of total assets. Gertler and Gilchrist (1994) argue that small firms are more likely to face financing constraints because they are typically younger and less well known, and thus more vulnerable to capital market imperfections arising from information asymmetries and collateral constraints.

I link TRI data to Compustat using parent company names, following the approach of Hsu et al. (2023). My sample includes plants that either report *Production Waste* or indicate source reduction activities [4]. Additionally, firms must have positive *total assets* and *sales*, and my focus is on manufacturing firms with SIC codes between 2000 and 3999. The final sample spans from 1991 to 2022, ensuring broad coverage and data quality (Hsu et al., 2023), and includes an unbalanced panel of 8,504 plants from 1,338 U.S. public firms, totaling 99,559 plant-year observations. Figure A.1 shows the number of firms and facilities in the sample by year.

[4]As described in the "TRI Basic Data Files Documentation", zeros in the data represent not only numeric number "zero" but also missing data. According to the TRI plant reporting criteria, plants included in the TRI data must be classified into the following two groups: (1) they have positive *Production Waste"* and thus they manufacture of process TRI-listed chemicals. (2) they have zero *Production Waste"* but they report to conduct a source reduction activity which reduce their generation of waste to zero. Therefore, I exclude firms that cannot be classified into these two groups from the sample since they have missing emission data.

2.2 Summary Statistics

Table 1 presents the summary statistics for key variables, including the mean, median, standard deviation (SD), 25th percentile (P25), 75th percentile (P75), and the number of valid observations for each variable. The firm's *net emission intensity* (or *gross emission intensity*) in year t is calculated by scaling each firm's net (or gross) emissions of its sales (in millions of dollars). The *end-of-pipe abatement ratio* measures the proportion of each firm's end-of-pipe abatement among its gross emissions. Another key outcome variable is the plant-specific *adoption frequency*, which captures the number of chemicals for which plant i adopts clean technology in year t.

Table 1: Summary Statistics

	N	Mean	Median	SD	P25	P75
Net Emission Intensity	16,895	4,948	31	307,070	2	208
End-of-Pipe Abatement Ratio	16,888	0.69	0.88	0.36	0.45	0.98
Gross Emission Intensity	16,895	30669	306	1,900,229	41	1,740
Assets	16,895	6,554	900	23,888	242	3,613
Adoption Frequency (Plant)	99,559	0.16	0.00	0.92	0	0

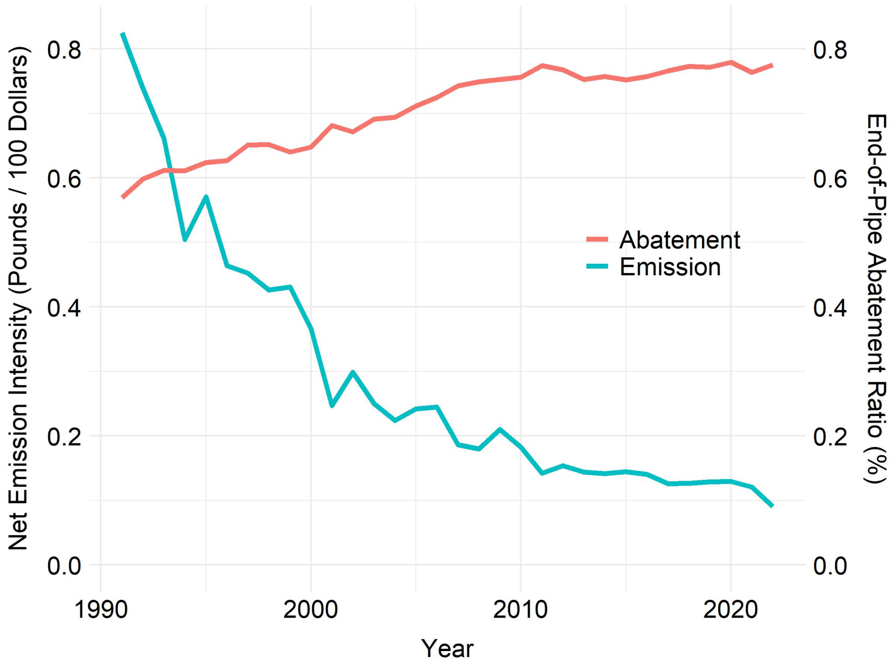


Figure 1: Average Net Emission Intensity and End-of-Pipe Abatement Ratio, 1991-2022
Note: This figure displays the time series of average net emission intensity and end-of-pipe abatement ratio for all companies in the sample, spanning the period from 1991 to 2022. To mitigate the influence of outliers, I exclude the top 1% of firms with the highest net emission intensity during this period from the net emission intensity time series.

Figure 1 illustrates the time series of average net emission intensity and end-of-pipe abatement ratio for firms in the sample by year. The data shows a downward trend in net emission intensity over time, accompanied by a steady increase in the end-of-pipe abatement ratio.

2.3 Motivating Evidence

Evidence 1: On average, firms with tighter financial constraints have higher net emission intensity — As a measure of financial constraints, firms' total assets are negatively correlated with net emission intensity. Figure 2 shows a clear negative relationship in both 1991 and 2021.

To get more empirical regularities relating net emission intensity to corporate financial constraint, I run a linear regression as follows:

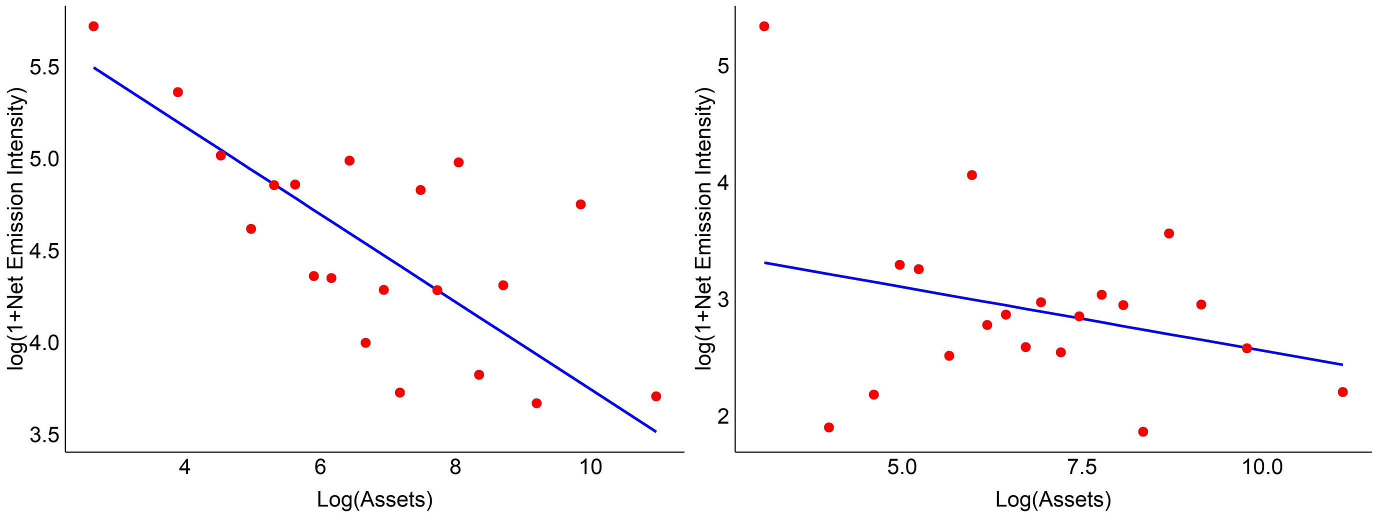
$$\log\left(1 + Emission\ Intensity_{c,t}\right) = \alpha + \beta \log(Assets)_{c,t} + FEs + \epsilon_{c,t} \tag{1}$$

where c denotes a firm and t denotes a year. I impose year-fixed effects to account for unobserved yearly variation, which is the same for all companies. Additionally, I consider industry-year and state-year fixed effects to control for time-varying industry and region-specific differences. It is worth noting that I do not include firm-level fixed effects for two reasons. First, the main variation of firm-specific $\log(assets)$ stems from differences between firms. The adjusted R-square from the regression that decomposes within-firm and cross-firm differences in $\log(assets)$ is approximately 95%, indicating that 95% of the variation in $\log(assets)$ is due to cross-firm differences. The regression is as follows:

$$\log(Assets)_{c,t} = \phi_c + \phi_t + u_{ct} \tag{2}$$

Second, s noted on the EPA website, firm-specific emission intensity is not directly comparable across years because the EPA has updated the list of chemicals subject to TRI reporting multiple times throughout the sample period [5].

[5] The details of these changes are available at https://www.epa.gov/system/files/documents/2024-01/tri-chemical-list-changes-12-27-2023_0.pdf.



(a) 1991 **(b)** 2021

Figure 2: Firm's Release Intensity vs. Total Assets, 1991 and 2021

*Notes:*The figure illustrates the relationship between firm-level net emission intensity (measured in pounds per million dollars) and total assets for the years 1991 (panel a) and 2021 (panel b). To analyze this relationship, I divide the sample into twenty deciles based on firms' total asset values and calculate the corresponding mean net emission intensity and total assets for each decile. A linear line relates the firm-specific net emission intensities to total assets at the same firm. The line is fit to the entire sample, not simply the decile means. Both y and x are presented on a logarithmic scale to enhance comparability across a wide range of values. To avoid zero values, I add one to firm-specific net emission intensities and then take a logarithmic scale.

Columns (1) through (3) of Table 2 present the regression results across different specifications. The coefficient β is consistently and significantly negative, indicating that larger firms, which face fewer financial constraints, tend to have lower net emission intensity. For example, in column (3), a one percent increase in total assets is associated with a 0.28 percent reduction in net emission intensity. Standard errors are clustered at the firm level (Table 2) and at the industry-year level (Table A.1) to address firm-specific autocorrelation and within-industry variation, respectively.

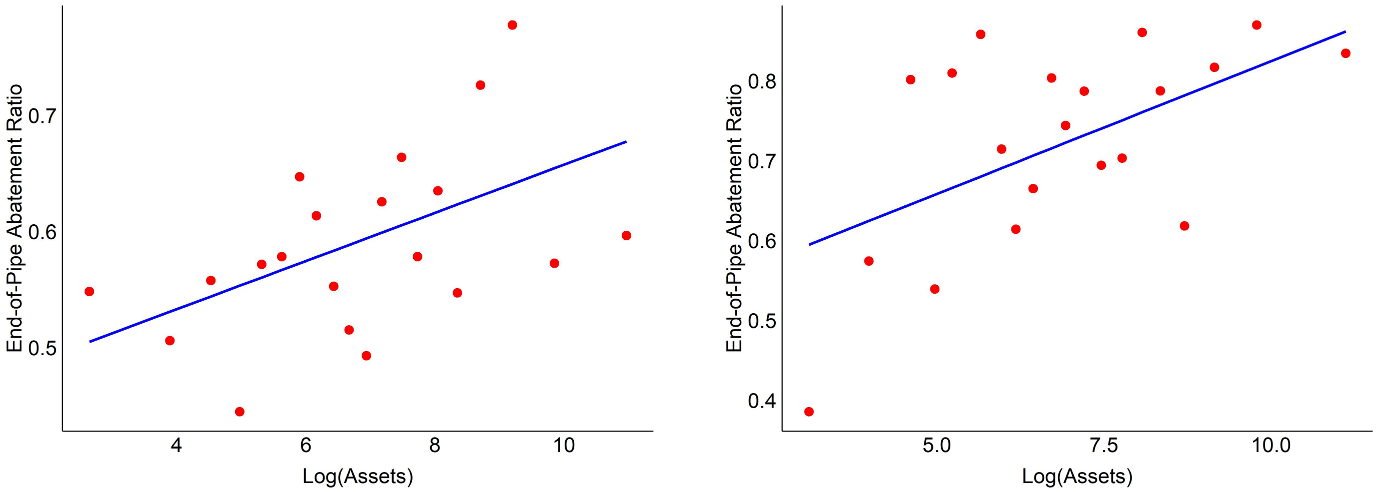
Table 2: Financial Constraints, Emission Intensity and Abatement Ratio

	log (1 + net emission intensity)			end-of-pipe abatement ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
log(assets)	-0.2661***	-0.2753***	-0.2819***	0.0190***	0.0222***	0.0202***
	(0.0365)	(0.0354)	(0.0369)	(0.0049)	(0.0047)	(0.0048)
Observations	16,895	16,895	16,895	16,888	16,888	16,888
Adj. R-square	0.0777	0.1998	0.3083	0.0591	0.1748	0.2944
Year FE	Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes
State-Year FE			Yes			Yes

Notes: This table investigates the correlation between corporate financial constraints and both net emission intensity and end-of-pipe abatement ratio. Columns (1) to (3) present results using the log(1+*net emission intensity*) as the dependent variable, while columns (4) to (6) use the *end-of-pipe abatement ratio* as the dependent variable. The key independent variable across all models is log(*assets*). Industry classifications are based on the 2-digit SIC code, and each firm is weighted by the inverse probability of its inclusion in the dataset. Standard errors are clustered at the firm level and are reported in parentheses. $*p < 0.1$; $**p < 0.05$;$***p < 0.01$.

Evidence 2: Financially constrained firms tend to exert lower end-of-pipe abatement efforts. — One explanation for the higher net emission intensity of financially constrained firms is their reduced investment in end-of-pipe abatement activities. Abatement is often a costly endeavor, particularly for financially constrained firms due to their higher financing costs. Figure 3 illustrates the positive relationship between firm total assets and the end-of-pipe abatement ratio. This positive correlation holds for both 1991 and 2021.

I also conducted a regression similar to equation (1), substituting the dependent variable with the end-of-pipe abatement ratio. The results, presented in columns (4) through (6) of Table 2, show that firms with larger asset bases consistently engage in more end-of-pipe abatement efforts. Specifically, Column (6) indicates that a 1% increase in total assets is associated with a 0.02% increase in the end-of-pipe abatement ratio.



(a) 1991

(b) 2021

Figure 3: Firm's Abatement Ratio vs. Total Assets, 1991 and 2021

Notes: The figure depicts the relationship between the firm-level end-of-pipe abatement ratio (expressed as a percentage) and total assets for the years 1991 (panel a) and 2021 (panel b).The sample is divided into twenty deciles based on total asset values, with the mean end-of-pipe abatement ratio and total assets calculated for each decile. A linear trend line relates the firm-specific end-of-pipe abatement ratio to firms' total assets in the same firm. The line is fit to the entire sample, not simply the decile means. The x-axis is displayed on a logarithmic scale to account for the wide range of asset values.

Evidence 3: Facilities owned by more financially constrained parent companies are less likely to adopt clean technology. Another reason for lower net emission intensity among financially unconstrained firms is their higher adoption rate of clean technology, which reduces their gross emissions.

I begin by using facility-level panel data to explore the relationship between clean technology adoption and the financial constraints of parent companies. The regression model is as follows:

$$\log(1 + Adoption\ Frequency)_{i,c,t} = \alpha + \beta \log(Assets)_{c,t} + \gamma Firm\ Controls_{c,t} + FEs + \varepsilon_{i,c,t} \quad (3)$$

where i denotes the facility, and c denotes the parent company. I control for production volume ($\log(sales)$) at the firm level and weight each facility by the inverse of the number of facilities owned by its parent company to avoid the over-representation of larger firms.

Unlike other regressions in this section that aggregate facility emissions into firm emissions, This approach helps avoid confounding effects related to size since larger firms may possess more facilities and consequently have higher overall technology adoption rates. Instead, I regress the frequency of clean technology adoption at the facility level on the total assets of the parent company, with both variables in logarithmic form. The underlying assumption is that facilities belonging to financially constrained firms are also likely to face experience credit shortages.

Furthermore, I measure facilities' propensities and abilities to adopt clean technologies using the frequency of adoption rather than using a binary variable that simply indicates whether a facility adopted technology. This approach is necessary because, in the sample, clean technology adoption is relatively uncommon, with only about 6.7% of facilities adopting new technologies each year on average. Figure A.3 reports the yearly clean technology adoption rate from 1991 to 2022. To enhance the variation in the dependent variable, I count the number of technology adoption events for each facility per year instead of relying on a simple binary indicator [6].

The results in Table 3, columns (1) to (3), indicate that a relaxation of financial constraints significantly increases the frequency of clean technology adoption. Specifically, a 1% increase in total assets is associated with a 0.02% increase in the frequency of adoption. Across all specifications, the estimated coefficients are positive and significant[7].

Next, to provide more evidence on differences in clean technology adoption between financially constrained and unconstrained firms, I examine the relationship between firm-specific gross emission intensity, which can be reduced through clean technology adoption, and financial constraints. The scatter plot in Figure 4 shows a clear negative correlation between total assets and gross emission intensity. Moreover, regression results in Table 3, column (6), suggest that a 1% increase in total assets corresponds to a 0.38% reduction in gross emission intensity. The point estimates in columns (4) and (5) are of similar magnitude.

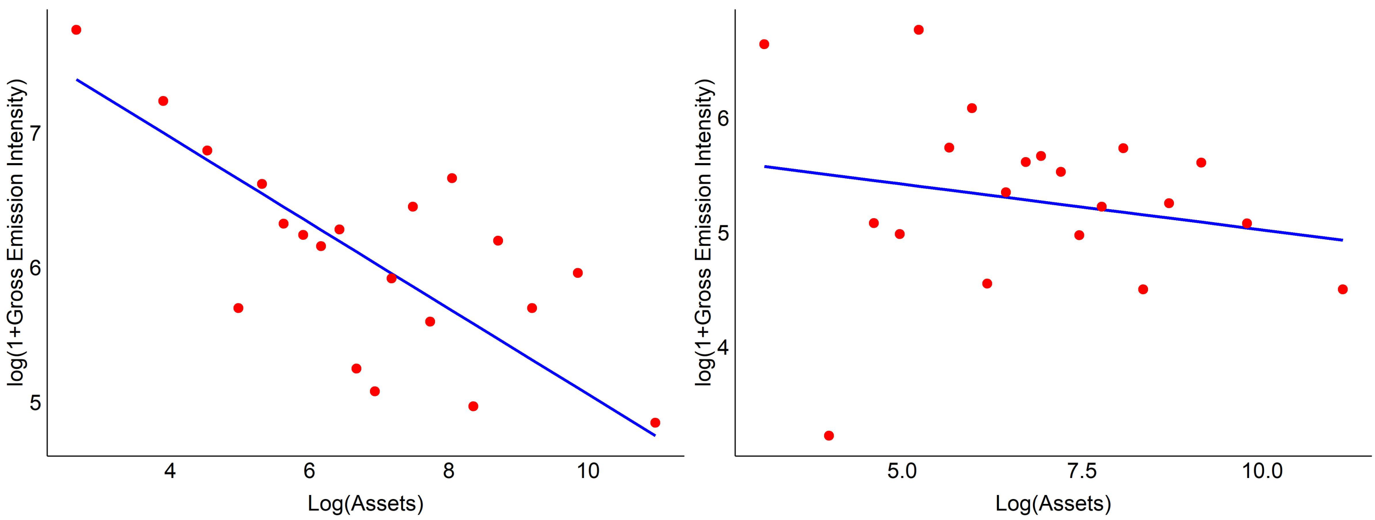
[6] The chemical-level data reported by TRI provides me the opportunity to count the number of chemicals for which each facility adopts clean technology in a year. I use the number as the dependent variable.

[7] Standard errors are clustered at the facility level. Results with standard errors clustered at the industry-year level are reported in Table A.2.

Table 3: Clean Technology Adoption

	log(1+adoption frequency)			log (1 + gross emission intensity)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(asset)	0.0234***	0.0158**	0.0161***	-0.3784***	-0.3740***	-0.3874***
	(0.0062)	(0.0062)	(0.0062)	(0.0381)	(0.0379)	(0.0402)
Observations	99,559	99,559	99,559	16,895	16,895	16,895
Asjusted R2	0.0205	0.0463	0.0835	0.0782	0.2059	0.3147
Year FE	Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes
State-Year FE			Yes			Yes
Control	Yes	Yes	Yes			

Notes: Columns (1) through (3) report the *facility-level* regression of adoption frequency on total assets, with each facility weighted by the inverse number of facilities owned by its parent company within the sample. Standard errors are clustered at the facility level and are reported in parentheses for each regression. Columns (4) through (6) display the regression of *firm-level* gross emission intensity on total assets, where each firm is weighted by the inverse probability of being included in the dataset. Industry classifications are based on 2-digit SIC codes. Standard errors are clustered at the firm level and are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.



(a) 1991 **(b)** 2021

Figure 4: Firm's Waste Production Intensity vs. Total Assets, 1991 and 2021

Notes: The figure plots the relationship between firm-level waste production intensity (pounds per million dollars) and total assets in 1991 (panel (a)) and 2021 (panel (b)). I divide the sample into twenty deciles based on total assets and then compute the mean values of emission intensity and total assets. The line is fit to the entire sample, not simply the decile means. Both y and x are presented on a logarithmic scale to enhance comparability across a wide range of values. To avoid zero values, I use one to firm-specific waste intensities and then take a logarithmic scale.

2.4 Summary: Features for Model Assumptions

The empirical studies above show that smaller firms facing greater financial constraints tend to have higher pollution intensity (*Evidence 1*). This result can be attributed to their lower abatement efforts (*Evidence 2*) and inabilities to adopt clean technology (*Evidence 3*). The latter two empirical patterns inform the assumptions of our model, which I summarize in following two points.

First, to capture the lower adoption rates among smaller firms, I assume that adopting clean technology requires firms to accumulate internal funds. This assumption highlights the critical role of financial development. Firms initially operate in the "dirty" sector, where the low upfront cost of dirty technology makes it more attractive. However, they have the opportunity to transition to clean technology—characterized by zero emissions—by paying an upfront cost. In a well-developed financial market, all firms will adopt clean technology, as it is more profitable by avoiding pollution tax expenditures and firms are able to finance the startup cost fully through the external funds. In contrast, in less-developed financial markets, firm net worth plays a pivotal role as collateral, limiting borrowing capacity. As a result, small firms are unable to adopt clean technology due to insufficient net worth to support them externally financing the startup cost. As a consequence, firms with little net worth upon entry must accumulate it over time to adopt clean technology, becoming larger and less financially constrained in the process.

Second, to account for the negative relationship between financial constraints and end-of-pipe abatement efforts, I assume that firms operate as monopolistic competitors. In my model, firms have decreasing return-to-scale revenue functions, which ensure that they can earn positive profits in each period. Generally, the decreasing returns to scale could be rationalized by assuming either a decreasing return-to-scale Cobb-Douglas production function or the monopolistic nature of the competitive environment (Cooley and Quadrini, 2001). However, the former cannot support my empirical finding. I illustrate it by using the following decreasing return-to-scale Cobb-Douglas production function as an example:

$$y_{it} = k_{it}^{\alpha} l_{it}^{\beta} z_{it}^{\gamma}, \ \alpha + \beta + \gamma < 1$$

where i and t refer to firm and period, respectively. y, k, l, z are output, capital, labor and net emission, respectively. With this production function, all firms have equal net emission intensities, defined as net emission per unit of output :

$$\frac{z_{it}}{y_{it}} = \gamma \tag{4}$$

For firms that have not adopted clean technology, their emission intensities are fully determined by their end-of-pipe abatement. Consequently, equal emission intensities imply equal end-of-pipe abatement efforts, which contradicts my empirical finding that financially constrained firms have lower end-of-pipe abatement effort. In contrast, when I assume monopolistic competition along with a constant return-to-scale Cobb-Douglas production function, financially unconstrained firms demonstrate higher end-of-pipe abatement efforts. This occurs because less constrained firms charge lower prices, thereby reducing the ratio of pollution taxes to output prices, making abatement relatively more attractive.

3 Model

Motivated by the empirical evidence in section 2, I present a dynamic model of firm entry, production, pollution abatement, and technology adoption, building upon the framework developed by Midrigan and Xu (2014). I will first outline the model setup and specify the decision rules governing the agents' behavior. Then, I define the balanced growth path and compare the model's outcomes with those of the macroeconomic neoclassical model from an aggregate perspective.

In the model, as in Antunes et al. (2008), I assume that only a single financial instrument is available: a one-period risk-free bond.

3.1 Model Setup

The economy is populated by a unit measure of workers and a measure N_t of entrepreneurs. All agents are assumed to have utility

$$U = \sum_{t=0}^{\infty} \beta^t \ln(C_t) \tag{5}$$

where C_t is the agent's consumption at period t. Each entrepreneur owns a firm, which produces and sells a variety of intermediate good in a monopolistic competitive market. The unique final food is produced using all intermediate good with an elasticity of substitution

$\sigma \in (1, \infty)$:

$$Y_t = \left(\frac{1}{N}\right)^{\frac{1}{\sigma-1}} \left[\int_0^N Y_{it}^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}} \tag{6}$$

Entrepreneurs — In each period, entrepreneurs allocate their income between consumption and savings. They hire workers in a competitive labor market and invest their accumulated savings into their firms to finance production capital. Thus, their income is derived from their firm's retained profits and asset gains. Entrepreneurs can also borrow using a one-period risk-free bond.

There are two production technologies: dirty technology, which emits pollution and is subject to a constant tax rate, τ, and clean technology, which produces no emissions. In each period, entrepreneurs who use dirty technology can also allocate resources to end-of-pipe abatement to reduce the pollution tax. Clean technology is more profitable because it reduces the resources spent on abatement activities and the pollution tax paid by the firm. Financial frictions in the model take the form of borrowing constraints: the amount an entrepreneur can borrow is limited to a fraction of their total capital plus the upfront investment in clean technology adoption.

Following Shapiro and Walker (2018), I model the dirty technology and emission function as

$$Y_{it}^d = (1 - \xi_{it})F(L_{it}, K_{it}) \tag{7}$$

$$Z_{it} = (1 - \xi_{it})^{\frac{1}{\rho}} F(L_{it}, K_{it}) \tag{8}$$

where ξ_{it} is the share of production inputs (i.e. labor and capital) that are allocated to abatement activities and $\rho \in (0, 1)$ governs the efficiency of abatement efforts. $F(L_{it}, K_{it})$ is potential output: the output that would be produced if there were no pollution abatement. If $\xi_{it} = 0$, there is no abatement, and each unit of output generates one unit of pollution. Increase in the abatement effort (ξ_{it}) will divert input in production to abatement activities: both output and emissions are negatively related to it. By eliminating $(1 - \xi_{it})$, the production function of the dirty technology could be written as a Cobb-Douglas function of pollution and potential output:

$$Y_{it}^d = Z_t^\rho F(L_{it}, K_{it})^{1-\rho} \tag{9}$$

The clean technology does not emit pollution and its production function accordingly is equivalent to the potential output in equations (7) and (8). I assume it to be a Cobb-Douglas function:

$$Y^c_{it} = F(L_{it}, K_{it}) = s_{it} K^{\alpha}_{it} L^{1-\alpha}_{it} \tag{10}$$

where s_{it} represents individual productivity, following a stationary first-order Markov process with the state $S = \left\{ s_i, s_2, \cdots, s_{N_p} \right\}$ and transitional probability denoted by $f_{ij} \equiv Prob(s_{t+1} = s_j | s_t = s_i)$. The stationary distribution of the Markov process is denoted as $G(s)$.

In this way, the production function of the dirty technology is

$$Y^d_{it} = Z^{\rho}_t \left[s_{it} K^{\alpha}_{it} L^{1-\alpha}_{it} \right]^{1-\rho} \tag{11}$$

At the end of each period, vN_t new entrepreneurs enter the economy with certain net worth, $\bar{a}\,\overline{y}_t$, where $\bar{a}$ is a constant and $\overline{y}_t$ represents the average output per firm, defined by

$$\overline{y}_t \equiv \frac{Y_t}{N} = \left[\frac{1}{N} \int_0^N y_{it}^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}}$$

Upon entry, these entrepreneurs use dirty technology. Over time, they have the option to adopt clean technology at the end of period t, incurring an upfront investment in the sunk cost proportional to the average output, denoted by $\kappa \overline{y}_{t+1}$. Following Cooley and Quadrini (2001), I assume that exit is exogenous: each entrepreneur faces a probability v of becoming unproductive and exiting the market each period. Thus, the number of entrepreneurs entering and exiting the market each period remains balanced, keeping the mass of entrepreneurs in the economy constant over time. This assumption of exogenous exit facilitates the balanced growth path discussed in the following section.

Worker — A worker supplies $\gamma^t_L v_{it}$ efficiency of labors each period, where v_{it} follows a stationary first-order Markov process on $V = \{v_1, v_2, \cdots, v_{N_w}\}$ with transition probability denoted by $g_{ij} = Prob(v_{t+1} = v_j | v_t = v_i)$. Workers allocate labor earning into consumption and saving each period, and they are not allowed to borrow.

The Time Line

At the beginning of period t, entrepreneurs observe their productivities, s_{it}. Following Midrigan and Xu (2014), I assume that entrepreneurs decide how much capital to install at period t after observing the stochastic productivity at the same period. This assumption rules out the distortions of capital allocation among firms which are caused by idiosyncratic uncertainties, helping us only focus on distortions caused by financial frictions.

Given the amount of net worth inherited from last period, A_{it}, and productivity level at period t, each entrepreneur chooses the optimal level of capital (K_{it}) and labor (L_{it}) allocated to the production, and efforts (ξ_{it}) devoted to the abatement activities, which are indexed by the pollution level (Z_{it}), to maximize her periodic profits, denoted by $\Pi^j(s_{it}, A_{it})$, $j \in \{d, c\}$.

The profit is different across technologies. For entrepreneurs who use dirty technology, the profit function is given by

$$\Pi^d(s_{it}, A_{it}) = \max_{L_{it}, K_{it}, Z_{it}} p_{it} Y^d_{it} - wL_{it} - (r+\delta)K_{it} - \tau Z_{it} \tag{12}$$

$$\text{s.t.} \quad p_{it} = \left(\frac{Y^d_{it}}{\overline{y}_t}\right)^{-\frac{1}{\sigma}} \tag{13}$$

$$K_{it} - A_{it} \leq \theta K_{it} \tag{14}$$

where $\{w, r\}$ are equilibrium wage and interest rate, δ is capital depreciation rate. Equation (13) is the demand of each intermediate good, coming from the CES aggregate function in equation (6). The borrowing constraint, reflected by equation (14), states that borrowing ($K_{it} - A_{it}$), the gap between capital that the firm uses in production and its equity, cannot exceed a proportion of its capital. $\theta \in [0, 1]$ governs the strength of financial frictions in the economy. $\theta = 1$ represents a perfect financial market without frictions. Equation (14) implicitly restricts the net worth of each entrepreneur (A_{it}) to be positive otherwise her own firm goes bankrupt.

Although entrepreneurs using clean technology aim for similar objectives and emit zero pollution ($Z_{it} = 0$) , they face a less restrictive borrowing constraint:

$$K_{it} - A_{it} \leq \theta(K_{it} + \kappa \overline{y}_t) \tag{15}$$

This constraint reflects the assumption that the investment in clean technology adoption is considered a physical asset that can be used as collateral. Consequently, entrepreneurs can finance part of the upfront investment in clean technology through borrowing, which allows their net worth to be negative. In the absence of financial frictions, firms can fully finance both their capital and the upfront investment in clean technology through borrowing.

After production, vN_t entrepreneurs exit the market after repaying their debts. The unintended exit requires that entrepreneurs must be able to repay its debt under the worst-possible scenario:

$$K_{it} - A_{it} \leq K_{it} + \Pi(s_{it}, A_{it}) + rA_{it} \tag{16}$$

The inequality states that debts, at any time, must be smaller than all resources that the entrepreneur gains, i.e. the sum of periodic income and capital stock. The lower bound of entrepreneurs' net worth is therefore implicitly determined by

$$A_{min} = -\frac{\Pi(s_1, A_{min})}{1+r} \tag{17}$$

The remaining entrepreneurs allocate retained profits ($\Pi(s_{it}, A_{it})$) and saving return (rA_{it}) into consumption (C_{it}) and savings ($A_{it+1} - A_{it}$) to maximize her utility characterized by equation (5). Those who use dirty technology also decides whether to adopt clean technology in the next period. The budget constraint at period t of entrepreneurs who do not adopt clean technology at period $t+1$ (whatever technologies that they currently use) is given by

$$C_{it} + A_{it+1} = \Pi^j(s_{it}, A_{it}) + (1+r)A_{it}, \quad j \in \{c, d\} \tag{18}$$

On the other hand, entrepreneurs who use dirty technology at period t but decide to adopt clean technology at period $t+1$ have budget constraint as

$$C_{it} + A_{it+1} + \kappa\overline{y}_{t+1} = \Pi^d(s_{it}, A_{it}) + (1+r)A_{it} \tag{19}$$

At the end of each period, vN_t new entrepreneurs enter the economy, ensuring that the total number of incumbent entrepreneurs remains constant.

3.2 Recursive Formulation and Decision Rule

Since labor efficiency increases at a constant rate, γ_L, the economy grows at the same rate as well. To define a stationary equilibrium, I normalize all variables related to entrepreneurs at period t by the average output, $\overline{y}_t$ due to the property that profits and the optimal choice of capital are homogeneous of degree one in $(A_{it}, \overline{y}_t)$. And similarly all variables at period t related to workers are normalized by γ_L^t. Re-scaled variables are denoted by corresponding lowercase letters. In equilibrium which will be defined in the following section, wage and interest rate are constant, hence I suppress dependence of value functions on wages and interest rates where convenient for notation.

Clean entrepreneurs — The Bellman equation along a balanced growth path of a clean entrepreneur with net worth a and productivity s_i is

$$V^c(a, s_i) = \max_{x \geq a_{min}} \left\{ \ln\left(\pi^c(a, s_i) + (1+r)a - \gamma_L x\right) + \beta(1-v)\sum_{j=1}^{N_p} f_{ij} V^c(x, s_j) \right\} \tag{20}$$

where

$$\pi^c(a, s_i) = \max_{k,l} \left(s_i k^\alpha l^{1-\alpha}\right)^{\frac{\sigma-1}{\sigma}} - wl - (r+\delta)k \tag{21}$$

$$\text{s.t.} \quad k \leq \frac{1}{1-\theta}a + \frac{\theta}{1-\theta}\kappa \tag{22}$$

The RHS of equation (20) specifies the decision faced by a clean entrepreneur. The first term reflects the current utility and the last term is the expected continuation value. a_{min} is determined in equation (17). Equation (22) is the collateral constraint, which implicitly restrict entrepreneurs net worth to be larger than $-\theta\kappa$. Hence, minimal net worth of clean entrepreneurs is $\min\{a_{min}, -\theta\kappa\}$.

Dirty entrepreneurs — The Bellman equation of a dirty entrepreneur is

$$\begin{aligned} V^d(a, s_i) = \max_x \Bigg\{ & \ln\left(\pi^d(a, s_i) + (1+r)a - \gamma_L x\right) \\ & + \beta(1-v) \max\left[\sum_{j=1}^{N_p} f_{ij} V^d\left(x, s_j\right), \sum_{j=1}^{N_p} f_{ij} V^c\left(x-\kappa, s_j\right)\right] \Bigg\} \end{aligned} \tag{23}$$

where

$$\pi^d(a, s_i) = \max_{k,l,z} \left[z^\rho \left(s_i k^\alpha l^{1-\alpha}\right)^{1-\rho}\right]^{\frac{\sigma-1}{\sigma}} - wl - (r+\delta)k - \tau z \tag{24}$$

$$\text{s.t.} \quad k \leq \frac{1}{1-\theta}a \tag{25}$$

The dirty entrepreneurs' continuation value is the envelope over the NPV of the two options on whether they adopt clean technology or not, which is determined by future profits. Firm profits depend on its net worth and productivity. Although clean technology is inherently more profitable for a given level of net worth and productivity, its upfront costs reduce firms' net worth, increasing the cost of capital and thereby diminishing the profitability of clean technology. Consequently, clean technology becomes viable only for entrepreneurs who have accumulated sufficient net worth to ensure that, even after covering the upfront costs of adoption, their credit constraints remain manageable. The condition for clean technology adoption for a certain net worth x is given by

$$\sum_{j=1}^{N_p} f_{ij} V^c\left(x-\kappa, s_j\right) \geq \sum_{j=1}^{N_p} f_{ij} V^d\left(x, s_j\right), \quad x - \kappa \geq \min\{a_{min}, -\theta\kappa\} \tag{26}$$

Finally, solving the profit maximization problem of dirty entrepreneurs in equations (24) and (25) gives the following equation of emission intensity, defined as pollution per unit of production:

$$e(a,s_i) = \left[\frac{\frac{\rho}{\tau}\left(\frac{w}{\alpha}\right)^{\alpha}\left(\frac{r+\mu^d(a,s_i)+\delta}{1-\alpha}\right)^{1-\alpha}}{s_i(1-\rho)}\right]^{1-\rho} \tag{27}$$

where $\mu^d(a,s_i)$ is the multiplier on the collateral constraint (25). It is shown that the emission intensity is decreasing with net worth of entrepreneurs who are financially constrained. Relaxing financial constraint decreases a firm's pollution intensity because it increases abatement efforts. Less financially constrained firms charge lower prices, implying that the ratio of pollution taxes to output prices is higher.

Workers — The Bellman equation of a worker is

$$V^w(a,v_i) = \max\left\{\ln\left(wv_i + (1+r)a - \gamma_L x\right) + \beta\sum_{j=1}^{N_w} g_{ij}V^w(x,s_j)\right\} \tag{28}$$

3.3 Balanced Growth Path

Let's denote the stationary population density of dirty (clean) entrepreneurs by $n^d(a,s_i)$ ($n^c(a,s_i)$), which is interpreted as the fraction of dirty (clean) entrepreneurs who have net worth a and productivity s_i among all entrepreneurs. Two population densities must add up 1:

$$\sum_{i=1}^{N_p}\int_{\overline{A}} dn^d(a,s_i) + \sum_{i=1}^{N_p}\int_{\overline{A}} dn^c(a,s_i) = 1 \tag{29}$$

where $\overline{A}$ is the compact set of all values that entrepreneurs' net worth can take.

The population density of dirty entrepreneurs evolves over time according to

$$n^d(a',s_i) = v\mathbf{I}_{\{a'=\overline{a}\}}G(s_i) + (1-v)\sum_{j=1}^{N_p}\int_{\overline{A}} f_{ji}\mathbf{I}_{\{g^d(a,s_j)=a',\zeta(a,s_j)\neq 1\}}dn^d(a,s_j) \tag{30}$$

where $g^d(a,s_j)$ is the saving decisions of dirty entrepreneurs who will not adopt clean technology, and $\zeta(a,s_j)$ is an index for whether an entrepreneur choose to adopt clean technology. The first part of the equation reflects the number of new entrepreneurs while the second part counts the number of those who will not adopt clean technology in the next period.

Similarly, the evolution of clean entrepreneurs' population density is given by

$$\begin{aligned} n^c(a',s_i) &= (1-v)\sum_{j=1}^{N_p}\int_{\overline{A}} f_{ji}\mathbf{I}_{\{g^{ds}(a,s_j)-\kappa=a',\zeta(a,s_j)=1\}}dn^d(a,s_j) \\ &+ (1-v)\sum_{j=1}^{N_p}\int_{\overline{A}} f_{ji}\mathbf{I}_{\{g^{c}(a,s_j)=a'\}}dn^c(a,s_j) \end{aligned} \tag{31}$$

where $g^{ds}(a,s_j)$ is the amount of net worth hold by an entrepreneur who will adopt clean technology, and $g^c(a,s_j)$ is the saving decision of clean entrepreneurs.

A *balanced growth path* consists of a set of prices (w,r), three policy functions for entrepreneurs, $g^h(a,s_i), h \in \{d,ds,c\}$, and one for workers, $g^w(a,\nu_i)$, a switching index $\zeta(a,s_i)$, two population densities for entrepreneurs, $n_t^h(a,s), h \in \{d,c\}$, and one for workers, $n^w(a,\nu)$, as well as labor, capital, pollution and output by entrepreneurs, $l^h(a,s_i)$, $k^x(a,s_i)$, $z(a,s_i)$, $y^x(a,s_i)$, $h \in \{d,c\}$, such that:

(i) Given (w,r,τ), labor demand, capital demand and pollution solve profit maximization problems (21) and (24).

(ii) Given (w,r,τ), policy functions solve corresponding Bellman equations (20), (23) and (28).

(iii) The evolution of population densities for entrepreneurs follow (30) and (31).

(iv) Labor and capital market clear:

$$Y_t\sum_{h=d,c}\left[\sum_{i=1}^{N_p}\int_{\overline{A}} l^h(a,s_i)dn^h(a,s_i)\right] = \gamma_L^t \tag{32}$$

$$Y_t\sum_{h=d,c}\left[\sum_{i=1}^{N_p}\int_{\overline{A}} k^h(a,s_i)dn^h(a,s_i)\right] = Y_t\sum_{h=d,c}\left[\sum_{i=1}^{N_p}\int_{\overline{A}} g^h(a,s_i)dn^h(a,s_i)\right] + \gamma_L^t A^w \tag{33}$$

where γ_L^t is the total amount of efficiency units of labor and A^w is the integral of saving decisions across workers, given by

$$A^w = \sum_{i=1}^{N_w}\int_{\overline{A}^w} g^w(a,v_i)dn^w(a,v_i)$$

3.4 Aggregate Reduced Form

Even though the model has complex micro-structure, the economy behaves like a neoclassic growth model with total factor productivity (TFP) losses from misallocation caused by financial frictions.

The total amount of output produced by dirty entrepreneurs and clean entrepreneurs is defined by

$$Y_t^h = \left(\frac{1}{N}\right)^{\frac{1}{\sigma-1}} \left[\int_{i \in I_h} \left(y_{it}^h\right)^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}}, \quad h \in \{d, c\}$$

where I_h is the set of $h-$type entrepreneurs. Integrating the profit maximization decision rules across clean and dirty entrepreneurs, respectively, gives the aggregate output of dirty and clean entrepreneurs as Cobb-Douglas specifications with a lower TFP compared to the economy without frictions:

$$Y_t^h = S_t^h Z_t^{\rho(h)} \left(K_t^{h^\alpha} L_t^{h^{1-\alpha}}\right)^{1-\rho(h)}, \quad h\{d, c\} \tag{34}$$

where K_t^h and L_t^h are the total amount of capital and labor used in production by h-type entrepreneurs. $\rho(h) = \rho$ when $h = d$ and $\rho(h) = 0$, otherwise. S_t^h is the TFP across h-type entrepreneurs, of which the explicit expression can be found in the appendix A.2.

In an efficient economy where entrepreneurs do not face collateral constraints, the TFP is equal to its efficient level, denoted by $\overline{S}^h$:

$$\overline{S}^h \equiv \left[\sum_{j=1}^{N_p} \int_{\overline{A}} s_j^{(1-\rho(h))(\sigma-1)} dn^h(a, s_j)\right]^{\frac{1}{\sigma-1}} \tag{35}$$

However, financial frictions lead to a misallocation of capital between firms, preventing financial resources being allocated to those producers who have highest productivity. This effect lowers TFP and lead to inefficiency:

$$S_t^h < \overline{S_t}^h$$

In addition to the analogy of widely-used Cobb-Douglas production function in neoclassic growth model, the economy also has constant shares of labor, capital and pollution tax revenue while capital income share is eroded by financial frictions. The expression of inputs' income shares are also shown in the appendix A.2.

Importantly, the aggregation gives us the following expression of total emissions in equilibrium:

$$Z_t = \frac{\sigma - 1}{\sigma} \frac{\rho}{\tau} \epsilon(r, w) Y_t \tag{36}$$

where $\epsilon \equiv \left(Y_t^d / Y_t\right)^{\frac{\sigma-1}{\sigma}}$ is the share of output produced by dirty entrepreneurs among total output. As discussed in the introduction, financial frictions influence total emissions through its effects on real output and the share of dirty production. With this equation, I am able to evaluate whether the effects of financial development on green transition, measured by $\epsilon(r, w)$, is large enough such that pollution is reduced in the following section.

4 Quantitative Results

4.1 Calibration

To study the quantitative effects of financial frictions on clean technology adoption, model parameters need to be assigned. At this stage, I assign parameter values based on existing literature. Future work will aim to link the theoretical model in Section 3 to real data. Parameters are classified into three categories: standard macroeconomic parameters, firm dynamic parameters, and environmental parameters. Table 4 lists each parameter's value and its corresponding literature source.

Assuming a period length of one year, I set the discount factor to $\beta = 0.98$. I adopt an annual discount rate ($\delta = 0.06$) and capital share ($\alpha = 1/3$) consistent with values from Greenwood et al. (2013)[8]. The annual economic growth rate is set at 4 percent, and the elasticity of substitution between intermediate inputs is set to $\sigma = 3$, as typical estimates in trade and industrial organization literature suggest a range of three to ten (Hsieh and Klenow, 2009).

For the productivity process, I express firms' productivity as $s_t = \exp(e_t)$ and assume that e_t evolves according to an AR(1) process with Gaussian disturbances. I use the same values for the persistence (ρ_s) and volatility (σ_s) of e_t as in Midrigan and Xu (2014). The average probability of firm exit is about 4.5 percent (Cooley and Quadrini, 2001) and I around it to 0.05, $v = 0.05$.

For environmental parameters, the efficiency of abatement effort is set at $\rho = 0.05$. The firms' emissions function (see equation 7), in conjunction with the production function (see equation 8), indicates that pollution intensity is a function of abatement investments:

$$\frac{Z_{it}}{Y_{it}^d} = (1 - \xi_{it})^{\frac{1-\rho}{\rho}} \tag{37}$$

Shapiro and Walker (2018) estimate ρ based on data related to firms' pollution intensity and abatement costs, finding values that range from 0.0005 to 0.0557 across industries, with a mean of 0.011. We select a slightly higher value to focus on a highly polluting industry where the need for clean technology adoption is particularly strong.

[8]These values are calibrated to the United States.

For the remaining two environmental parameters, the values are selected based on heuristic assumptions without direct support from literature, with plans to calibrate them using data in future work. I set the environmental tax rate at $\tau = 0.02$. The upfront cost of clean technology, relative to a firm's average one-period output ($\overline{y}$), denoted by κ, is a critical parameter as it significantly impacts firms' decisions regarding technology adoption. In the benchmark scenario, κ is set to one, making the cost equivalent to the average of firms' one year's output. For additional analysis, I also explore a lower value of $\kappa = 0.1$ assess its impact.

Table 4: Parameters Value – Benchmark Economy

Parameter	Description	Value	Source
Standard Parameters:			
β	Discount factor	0.98	Standard
σ	Elasticity of substitution between intermediate goods	3.00	Hsieh and Klenow (2009)
α	Capital share	0.33	Greenwood et al. (2013)
δ	Capital depreciation rate	0.06	Greenwood et al. (2013)
γ_L	Growth rate of the economy	1.04	Standard
Firm Dynamic Parameters:			
ρ_s	Persistence in the AR(1) process of firm productivity	0.10	Midrigan and Xu (2014)
σ_s	Variance in the AR(1) process of firm productivity	0.50	Midrigan and Xu (2014)
v	Rate of producers' entry and exit	0.05	Cooley and Quadrini (2001)
$\bar{a}$	Initial assets of producers upon entry	0^+	
Environmental Parameters:			
ρ	Efficiency of abatement effort	0.05	Shapiro and Walker (2018)
τ	Environmental tax rate	0.20	
κ	Upfront cost of adoption clean technology	1.00	

4.2 Quantitative Results

Effects of Financial Frictions: Open Economy

Table 5 presents the effects of financial development, modeled by increasing θ from 0 to 1, in an open economy with a constant 4% interest rate. Panel A focuses on the scenario where the upfront cost of adopting clean technology is high.

While real output steadily rises with θ, the impact on industrial pollution is nonlinear

—-initially increasing, then decreasing, with a turning point around $\theta = 0.5$. This quadratic relationship is driven by its effect on the relative size of dirty production. For θ values between 0 and 0.5, financial development reduces the fraction of dirty output from 43% to 25%. In contrast, when θ exceeds 0.5, further relaxing collateral constraints reverses this trend, raising dirty output from 24% at $\theta = 0.5$ to 48% at $\theta = 1$.

Table 5: The Effects of Financial Development: Open Economy

	$\theta = 0$	$\theta = 0.2$	$\theta = 0.4$	$\theta = 0.5$	$\theta = 0.6$	$\theta = 0.8$	$\theta = 1$
Panel A: With Upfront Cost of Clean Technology ($\kappa = 1$)							
Wage	0.441	0.481	0.531	0.564	0.603	0.702	0.852
Fraction output dirty (%)	43.07	34.55	26.33	24.52	24.62	28.87	48.08
Fraction constrained (%)	86.03	81.19	74.39	69.20	61.28	38.52	0.00
Output	1.015	1.101	1.211	1.284	1.374	1.603	1.965
Pollution	0.0728	0.0634	0.0531	0.0525	0.0564	0.0771	0.1574
Panel B: With Low Upfront Cost of Clean Technology ($\kappa = 0.1$)							
Wage	0.481	0.516	0.561	0.589	0.621	0.710	0.946
Fraction output dirty (%)	6.05	5.11	4.17	3.69	3.25	2.72	5.69
Fraction constrained (%)	84.98	80.10	73.36	69.02	63.28	47.32	0.00
Output	1.085	1.164	1.264	1.328	1.400	1.600	2.135
Pollution	0.0109	0.0099	0.0088	0.0082	0.0076	0.0072	0.020

Notes: This table reports the effects of financial development in an open economy where the interest rate is fixed at 4 percent. The output and pollution are re-scaled by labor supply, hence the output can be explained as the overall labor productivity. The fraction of dirty output corresponds to the variable ϵ in equation (36). Fraction constrained is the share of entrepreneurs with binding credit constraint.

There are two opposite effects of financial development on clean technology adoption and,consequently, on dirty production. On the one hand, fixing the level of wages, relaxing collateral constraints allows an entrepreneur to borrow more, given their level of net worth. This directly reduces the net worth required to adopt clean technology, thereby encouraging its adoption and scaling up clean production. This refers to as the *direct* effect, which promotes a green transition. On the other hand, more efficient capital allocation raises wages in the general equilibrium. Higher wages reduce profits, particularly for less constrained firms, as their profits are more sensitive to labor costs. As wages increase, firms' ability to accumulate the net worth necessary for adopting clean technology diminishes, thereby slowing the transition to cleaner production. Consequently, this *general equilibrium* effect of financial development hinders the adoption of clean technology. Figure 5 shows the *direct* effect of financial development on clean technology adoption, showing that the net worth threshold declines sharply as θ increases when θ is not larger than 0.5. Figure 6 illustrates the *general equilibrium* effect: as θ increases, the profits of most dirty firms decline (panel (a)), and the share of small dirty entrepreneurs grows (panel (b)). In Figure 6, I select the values of θ as $\{0, 0.6, 0.8, 0.9\}$ such that the collateral constraints faced by firms are relaxed in a double scale, since the tightness of these constrains are governed by the formula $\frac{1}{1-\theta}$.

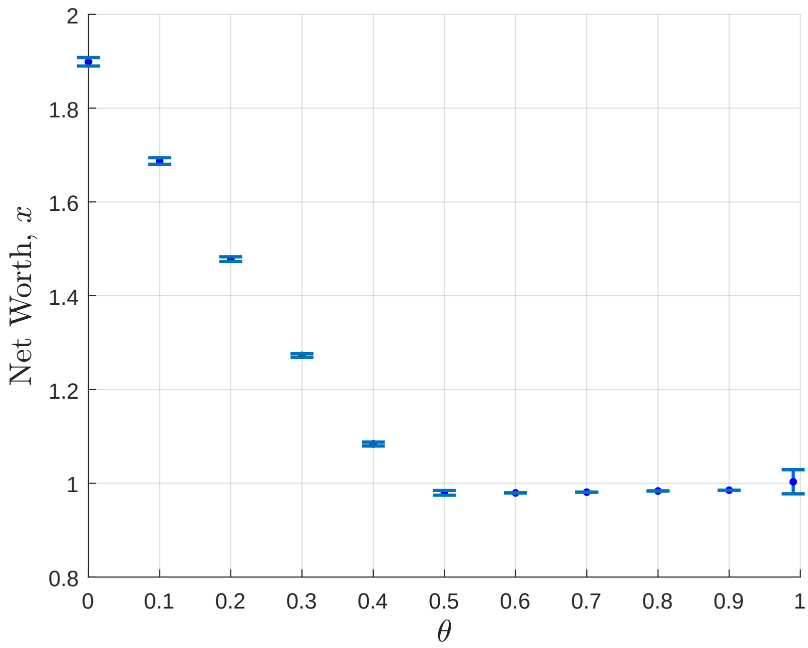
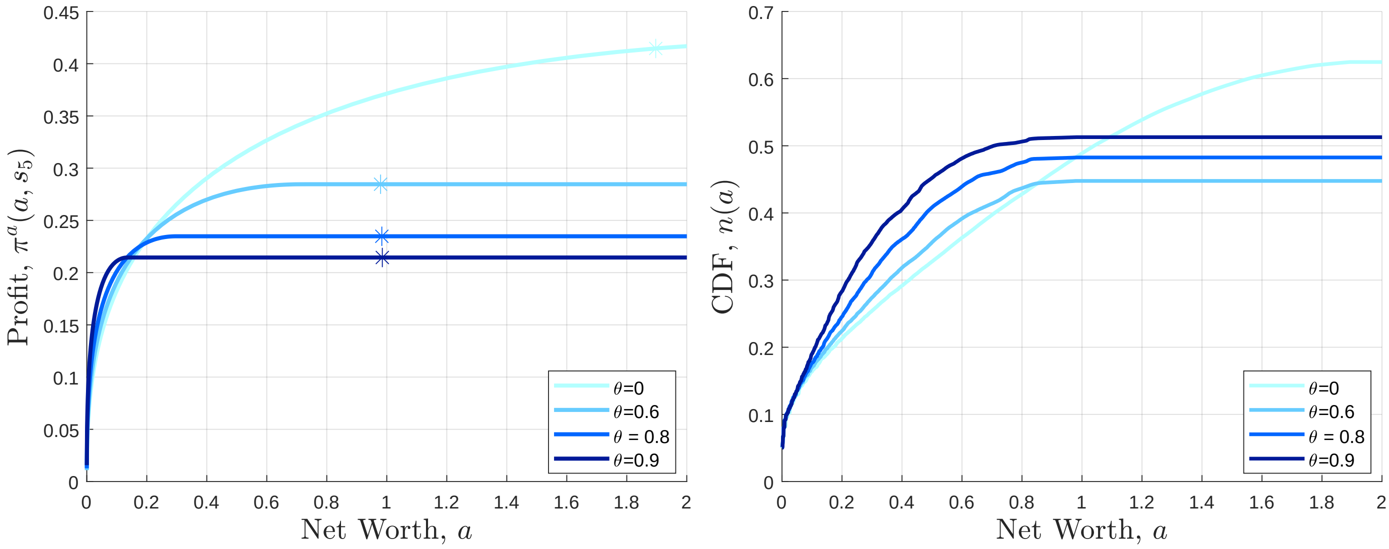


Figure 5: Net Worth Threshold of Clean Technology

Notes: This figure plots the net worth threshold of clean technology adoption. Dirty entrepreneurs whose net worth exceeds this threshold will opt for clean technology. For a given θ, the threshold decreases as productivity increases. The figure shows the upper bound (corresponding to the lowest productivity) and the lower bound (corresponding to the highest productivity) of the threshold for each θ, along with the mean threshold value.

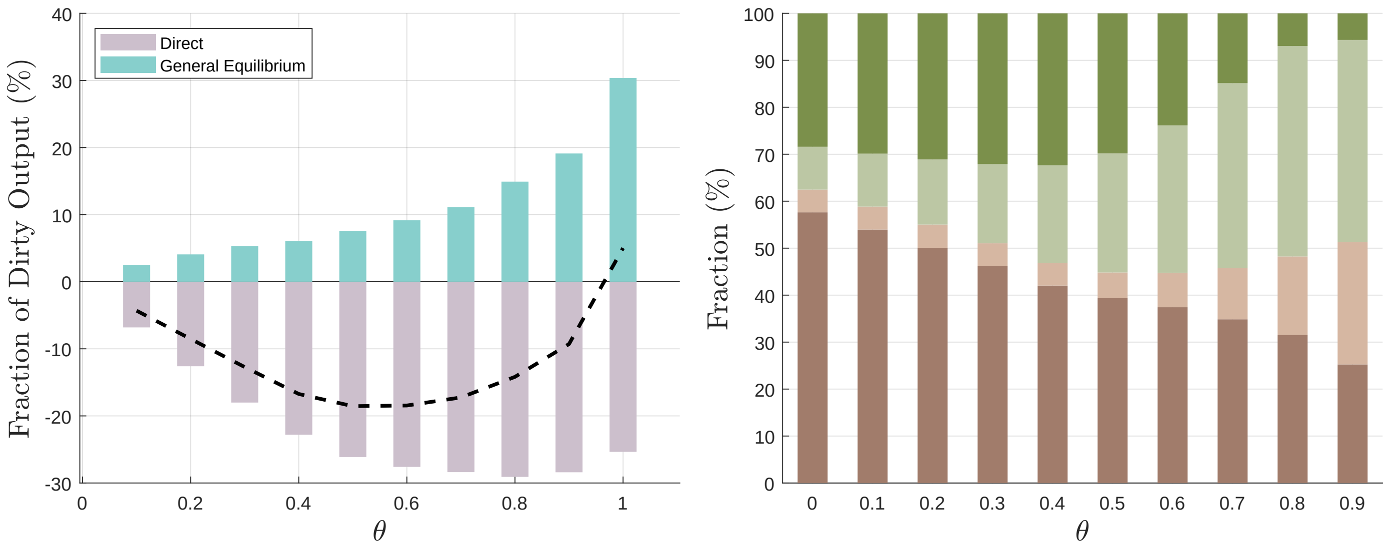
The overall impact of financial development on dirty production is driven by the balance between two opposing forces – the negative *direct* effect and positive *general equilibrium* effect, as illustrated in Figure 7a. The *direct* effect is limited in a highly developed financial market since the technology adoption decisions in these markets are distorted by the minimal assets requirements (see equation (17)) due to the mere financial instrument of firms – the risk-free bond, rather than their financial constraints. All eligible entrepreneurs—those whose net worth meets the minimum required—can cover the start-up costs. As a result, further relaxation of credit constraints has a small additional impact. In contrast, the *general equilibrium* effect is enlarging with financial development. As the share of financially constrained dirty entrepreneurs decreases, as shown by the growing proportion of light brown bars in Figure 7b, rising wages lead to more entrepreneurs who earn less profits. The increase in wages plays a larger role in slowing the accumulation of net worth, making it hard for more firms to adopt clean technology. Once θ becomes sufficiently large, the *general equilibrium* effect ultimately outweighs the *direct* effect, and financial development starts to favor dirty production.



(a) Profits **(b)** CDF

Figure 6: Profits and Cumulative Distribution Function (CDF) of Dirty Entrepreneurs

Notes: This figure plots the profits and cumulative distribution function (CDF) of dirty entrepreneurs as a function of their net worth. In panel (a), productivity is fixed at the medium level (s_5), and the asterisk marks the net worth threshold for clean technology adoption.



(a) Effects Decomposition **(b)** Shares of Entrepreneurs

Figure 7: Effects Decomposition and Fractions of Four Types of Entrepreneurs

Notes: Panel (a) in this figure shows the cumulative magnitude of the *direct* and *general equilibrium* effects on the share of dirty output, with the baseline set at $\theta = 0$. The cumulative *direct* effect is equal to the change in the share of dirty output as θ increases from 0 to various levels, while keeping wages fixed at the $\theta = 0$ level. The *general equilibrium* effect is the difference between the total effect and the direct effect. The dashed line indicates the total effect of financial development. Panel (b) reports the composition of entrepreneurs in the economy. The dark green (green) bar represents the constrained dirty (clean) entrepreneurs while the light bars represent the unconstrained ones.

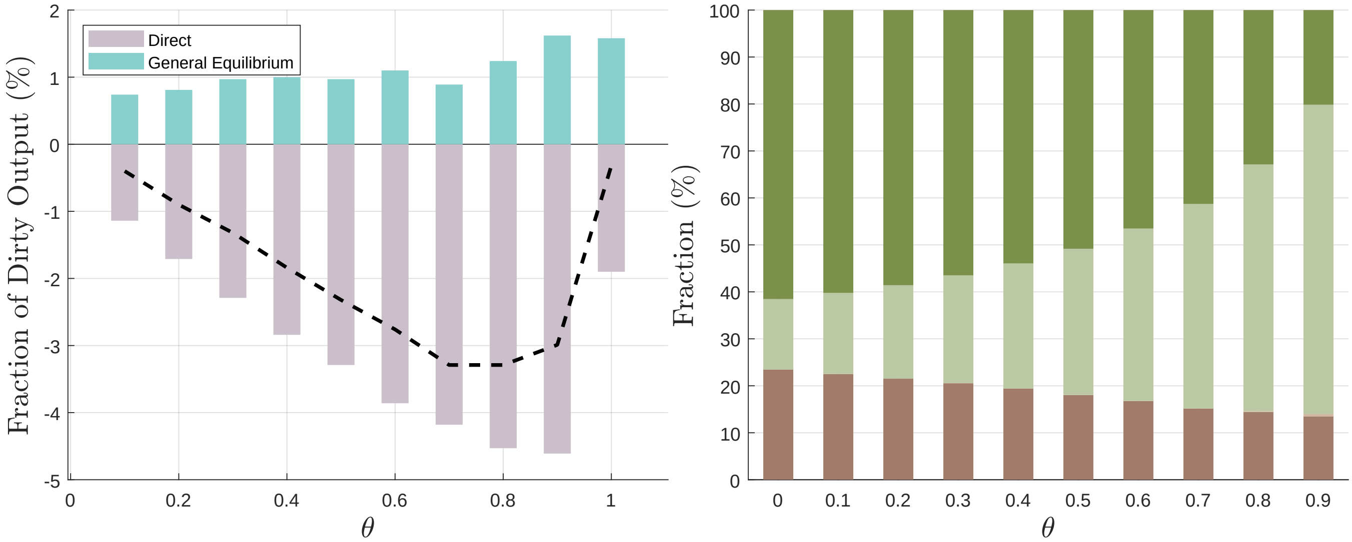
It is noteworthy that the *direct* effect on the fraction of dirty output in Figure 7a turns positive when θ exceeds approximately 0.8, as indicated by the declining cumulative direct effect. This suggests that, even though wages no longer increase with θ in general equilibrium, financial development ultimately begins to favor dirty production in the final stages of market development. This occurs because the dirty sector retains a higher proportion of financially constrained entrepreneurs compared to the clean sector. In a simple scenario where the number of dirty and clean firms is fixed, financial development tends to benefit the sector with a higher proportion of constrained firms. While allowing firms to switch between sectors through the adoption of clean technology mitigates the advantage of dirty production in the early stage of financial development, this extensive margin effect diminishes over time. Consequently, the relative benefit to the dirty sector prevails, even in the presence of technological transition.

Role of the Upfront Cost (κ)

Table 5 panel (b) presents the effects of financial development when the upfront cost of clean technology is low ($\kappa = 0.1$). In this case, pollution levels are significantly lower compared to the high-cost scenario, as the reduced upfront cost enables a larger number of entrepreneurs to adopt clean technology, leading to a smaller share of dirty entrepreneurs and a reduction in dirty output.

The quadratic relationship between financial development and pollution, as well as the share of dirty production, remains; however, the turning point shifts to a much higher level – $\theta = 0.9$. This is mainly due to the relatively muted *general equilibrium* effect, allowing the *direct* effect consistently to dominate. As Figure 8a shows, the cumulative general equilibrium effect changes little with θ, particularly when compared to the much larger cumulative direct effect. This suggests that the rise in wages in general equilibrium has little impact on accelerating the accumulation of net worth by dirty entrepreneurs for the adoption of clean technology.

In this case, clean technology is quite affordable. Only a few share of firms who are very small are forced to use dirty technology. As a result, those dirty entrepreneurs face quite tight financial constraints (as illustrated in Figure 8b). Wage increases in equilibrium have small effects on their profits since these profits are highly determined by their collateral constraints. Consequently, the *general equilibrium* effect almost vanishes when the upfront cost of clean technology is relatively low. Figure 9 compares the profits of dirty entrepreneurs between fixed and flexible wages, showing that rising wages in general equilibrium do not overturn the positive relationship between financial development and dirty entrepreneurs' earnings.

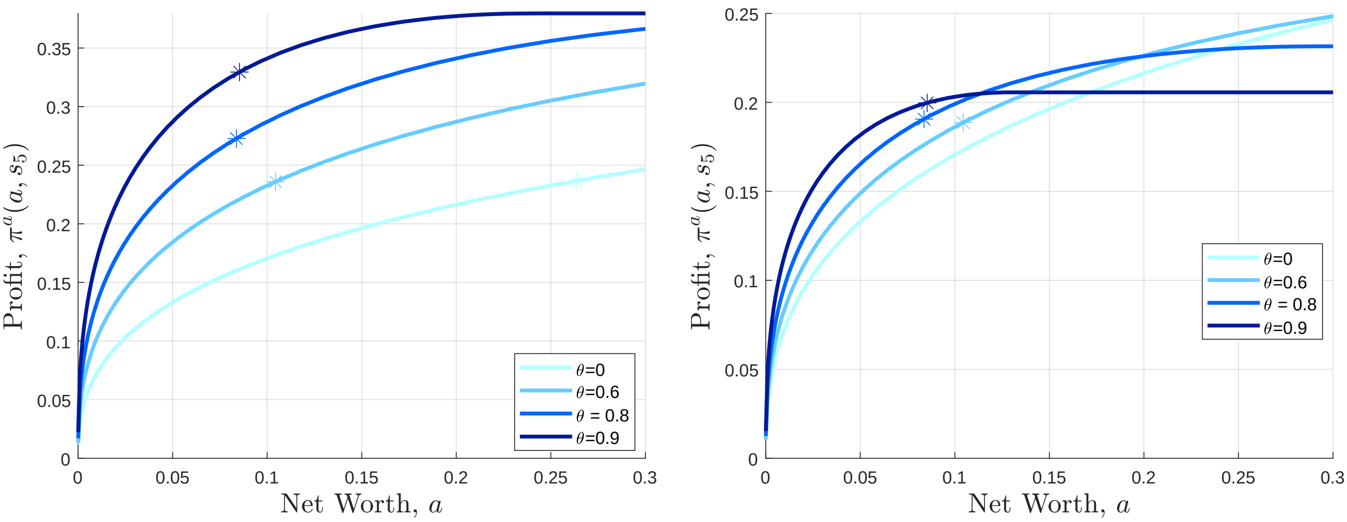


(a) Effects Decomposition

(b) Shares of Entrepreneurs

Figure 8: Effects Decomposition and Fractions of Four Types Entrepreneurs ($\kappa = 0.1$)

Notes: This figure is the counterpart of Figure 7, reflecting the scenario where the upfront cost of clean technology is low ($\kappa = 0.1$). Panel (b) presents two key differences: first, all dirty entrepreneurs are financially constrained; second, the share of dirty entrepreneurs decreases as θ increases, regardless of its level. The latter occurs due to the near disappearance of the *general equilibrium* effect.



(a) Fixed Wage

(b) Wage in General Equilibrium

Figure 9: Profits of Dirty Entrepreneurs ($\kappa = 0.1$)

Notes: This figure compares the profits of dirty entrepreneurs under two wage scenarios: fixed wages (panel (a)) and flexible wages in general equilibrium (panel (b)). In both panels, productivity is held constant at its middle level (s_5). In panel (a), where the wage is fixed at the level corresponding to $\theta = 0$, profits increase as θ rises. In panel (b), with wages adjusting to their equilibrium levels, the profit differences across different values of θ are less pronounced. However, despite the contraction in profit variation, the earnings of dirty entrepreneurs still increase with θ.

Effect of Financial Frictions: Closed Economy

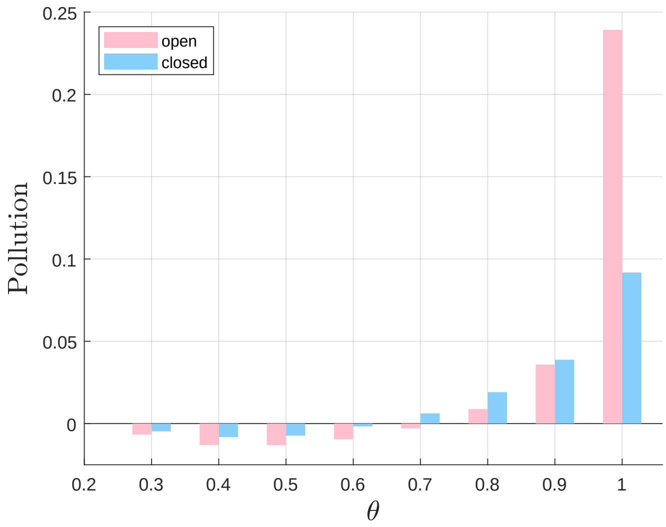
Table 6 reports the effects of financial development in a closed economy where interest rates adjust flexibly to clear the domestic capital market. The quadratic relationship between financial development and industrial pollution, as well as the proportion of output from polluting sectors, remains evident.

Table 6: The Effects of Financial Frictions: Closed Economy

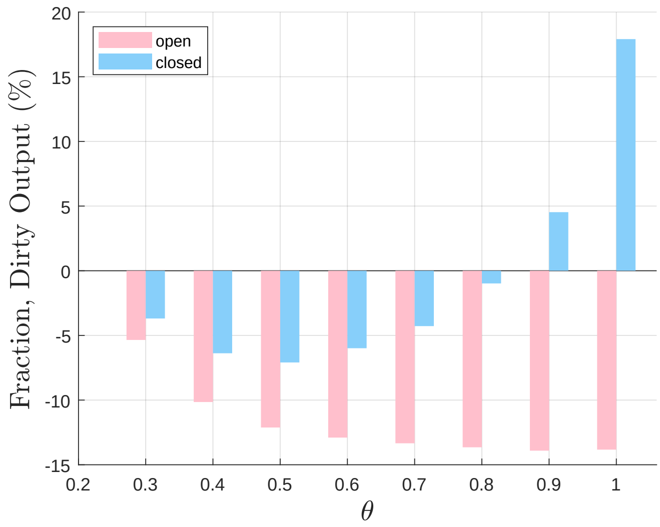
	$\theta = 0.2$	$\theta = 0.4$	$\theta = 0.5$	$\theta = 0.6$	$\theta = 0.8$	$\theta = 1$
Panel A: With Upfront Cost of Clean Technology ($\kappa = 1$)						
Wage	0.504	0.550	0.578	0.613	0.694	0.811
interest rate	-0.060	0.003	0.020	0.031	0.044	0.051
Fraction output dirty (%)	30.08	23.70	22.99	24.09	29.10	47.99
Fraction constrained (%)	100.00	89.16	77.54	74.75	37.54	0.00
Output	1.152	1.253	1.316	1.396	1.584	1.869
Pollution	0.0577	0.0495	0.0504	0.0560	0.0768	0.1495
Panel B: With Low Clean Technology Cost ($\kappa = 0.1$)						
Wage	0.538	0.591	0.615	0.644	0.715	0.902
interest rate	-0.060	-0.015	0.004	0.017	0.037	0.050
Fraction output dirty (%)	5.00	4.00	3.56	3.14	2.71	5.69
Fraction constrained (%)	100.00	94.45	84.13	73.21	48.09	0.00
Output	1.215	1.332	1.385	1.450	1.612	2.036
Pollution	0.0101	0.0089	0.0082	0.0076	0.0073	0.0193

Notes: This table reports the effects of financial development in closed economy where the interest rate is flexible to clear the capital market. The output and pollution are re-scaled by labor supply, hence the output can be explained as the overall labor productivity. The fraction of dirty output corresponds to the variable ϵ in equation (36). Fraction constrained is the share of entrepreneurs with binding credit constraints.

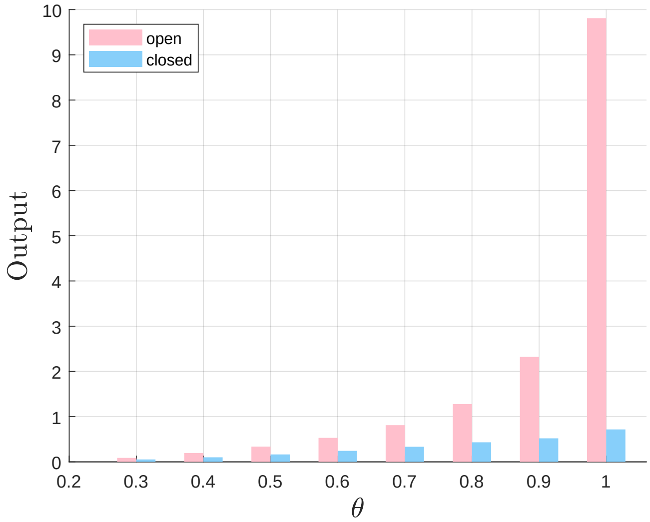
In both open and closed economies, the development of a relatively highly-developed financial market is detrimental to the environment. However, the magnitude of the effects on industrial pollution differs. Figure 10 compares the cumulative effects of financial development on pollution and its two key determinants—the fraction of dirty output and aggregate output—across both open and closed economies. Notably, these two factors have opposite effects. Compared to the open economy, financial development leads to a smaller increase in output but a larger increase in the share of dirty output in the closed economy.



(a) Pollution



(b) Fraction of Dirty Output



(c) Output

Figure 10: Cumulative Effects of Financial Development

Notes: This figure presents the cumulative effects of increasing θ on pollution, the fraction of dirty output, and total output. The baseline for comparison is set at $\theta = 0.2$. In this open economy scenario, the interest rate remains fixed at the general equilibrium level corresponding to $\theta = 0.2$, which is significantly lower than the 4 percent interest rate used in the benchmark analysis.

On the one hand, financial development results in a smaller increase in output in a closed economy due to higher interest rates, which dampen capital demand. This, in turn, leads to a relatively smaller increase in pollution. On the other hand, financial development also exacerbates the size of dirty production relative to clean production in a closed economy, driven by a reinforced *general equilibrium* effect. The profits of unconstrained entrepreneurs are reduced not only by higher wages but also by higher interest rates in general equilibrium. Moreover, as interest rates rise in response to financial development, the desired capital stock for unconstrained producers decreases, leading to fewer constrained dirty entrepreneurs. Consequently, in a closed economy, financial development results in more unconstrained dirty entrepreneurs, who require a longer time to accumulate sufficient net worth for adopting clean technology. Thus, financial development disproportionately supports dirty production in a closed economy. Together, these opposing effects determine the overall impact on pollution in a closed economy.

5 Concluding Remarks

This paper examines the impact of financial development on the green transition, primarily through its influence on clean technology adoption. Using a dynamic heterogeneous-agents general equilibrium model, I derive two key findings. First, financial development supports the green transition primarily in underdeveloped financial markets, while in more advanced markets, it can hinder progress. Second, the effect of financial development on clean production is contingent on the startup costs of clean technology; lower startup costs make financial development more conducive to green production.

There are several potential extensions of the current work, which I plan to explore in future research. Firstly, I will match up the theoretical model with data by estimating or calibrating environmental parameters and probably firm dynamic parameters in section 4.1. Secondly, I will utilize country-sector-level data to test my theoretical predictions empirically. Following the approach of De Haas and Popov (2022), I will modify their linear regression model by incorporating a quadratic term for the *financial development* variable. Thirdly, it is better to investigate whether environmental taxes or sustainable finance— alter the collateral requirements for clean technology investments—can mitigate the adverse effects of financial development on pollution. Finally, to align my empirical evidence more closely with the model, where firm productivity and net worth are key state variables, I should include *productivity* as an additional variable in my regressions in section 2, alongside the current financial constraint variable. I will also check the robustness of results in section 2 by using different measures of financial constraints.

A Appendix

A.1 Matching TRI with Compustat

I construct firm-level variables for *Production Waste*, *Total Release*, and *Total Abatement* by aggregating facility-level data for each year, using parent company names from the TRI database. To link these parent names to U.S. public companies in the Compustat database, I first clean the parent firm names in both databases using the *fedmatch* package in R. Subsequently, I apply Stata's fuzzy name-matching algorithm, *matchit*, which generates matching scores for all pairs of parent names in TRI and Compustat. These scores quantify the similarity between two names on a scale from zero to infinity, with a score of one indicating an exact match. I first give equal weight to each word and select all pairs with scores higher than 0.8 and manually check to ensure accuracy. To avoid inflated matching scores caused by common words such as "corporate" or "industry," I then reapply *matchit* using a weighting scheme that assigns lower weights to high-frequency words. After repeating the matching process, I combine the matched pairs from both methods to create the final dataset.

A.2 Model Details

The equation for TFP across the $h-$type entrepreneurs is

$$S_t^h(r,w) = \left\{ \left[\frac{B^h(r,w)}{E^h(r,w)} \right]^{\alpha(1-\rho(h))(\sigma-1)} B^h(r,w) \right\}^{\frac{1}{\sigma-1}} \tag{38}$$

where both $B^h(r,w)$ and $E^h(r,w)$ are the integrals of productivity across $h-$type where individual productivities are weighted by the wedge between the shadow price of saving $(r+\delta+\mu^h(a,s_i))$ and the market price of capital $(r+\delta)$ in different ways:

$$B^h(r,w) = \sum_{j=1}^{N_p} \int_A \left[s_j \left(\frac{r+\delta}{r+\mu^h(a,s_i)+\delta} \right)^{\alpha} \right]^{(1-\rho(h))(\sigma-1)} dn^h(a,s_i)$$

$$E^h(r,w) = \sum_{j=1}^{N_p} \int_A \left[s_j \left(\frac{r+\delta}{r+\mu^h(a,s_i)+\delta} \right)^{\alpha} \right]^{(1-\rho(h))(\sigma-1)} \frac{r+\delta}{r+\mu^h(a,s_i)+\delta} dn^h(a,s_i)$$

In the efficient economy, $\mu(a, s_i) = 0$, $B^h(r, w)$ and $E^h(r, w)$ are equivalent and the TFP is equal to its efficient level. However, with financial frictions, both of them are smaller:

$$E^h(r,w) < B^h(r,w) < \overline{S_t}^h(r,w)$$

The share of labor income, capital income and pollution tax revenues are reported as follows:

$$\frac{wL_t}{Y_t} = \frac{\sigma - 1}{\sigma}(1 - \alpha)\left[1 - \rho\epsilon(r,w)\right] \tag{39}$$

$$\frac{(r+\delta)K_t}{Y_t} = \frac{\sigma - 1}{\sigma}\alpha\left[\frac{E^c(r,w)}{B^c(r,w)}(1 - \epsilon(r,w)) + \frac{E^d(r,w)}{B^d(r,w)}(1 - rho)\epsilon(r,w)\right] \tag{40}$$

$$\frac{\tau Z_t}{Y_t} = \frac{\sigma - 1}{\sigma}\rho\epsilon(r,w) \tag{41}$$

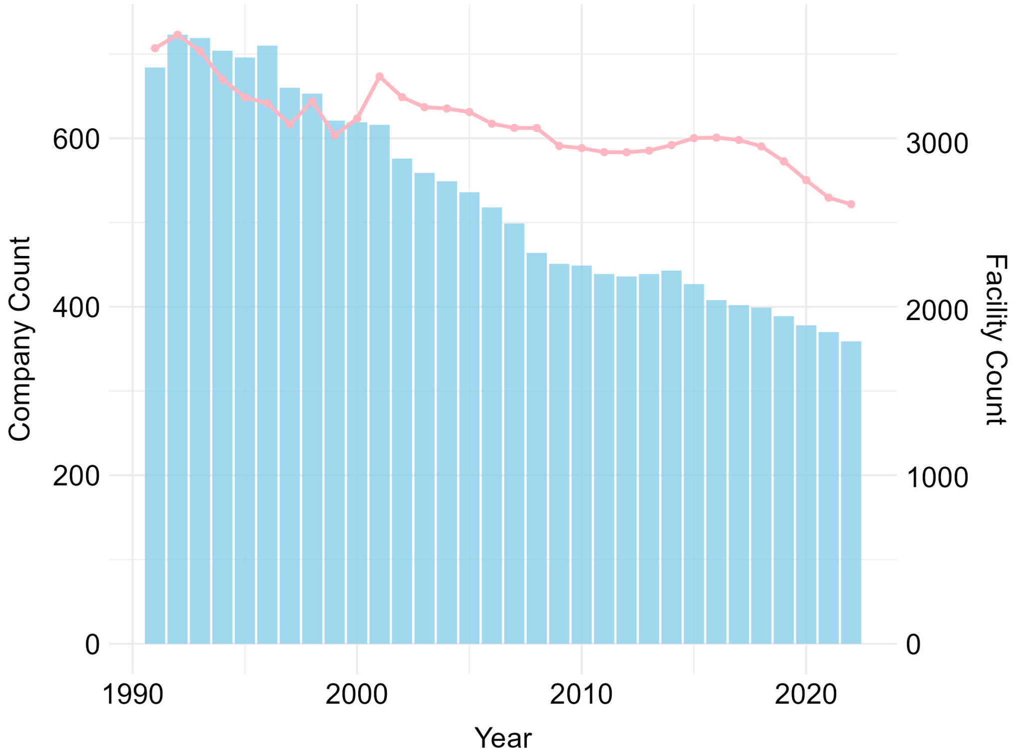


Figure A.1: Sample Number of Companies (Bar) and Facilities (Line), 1991-2022

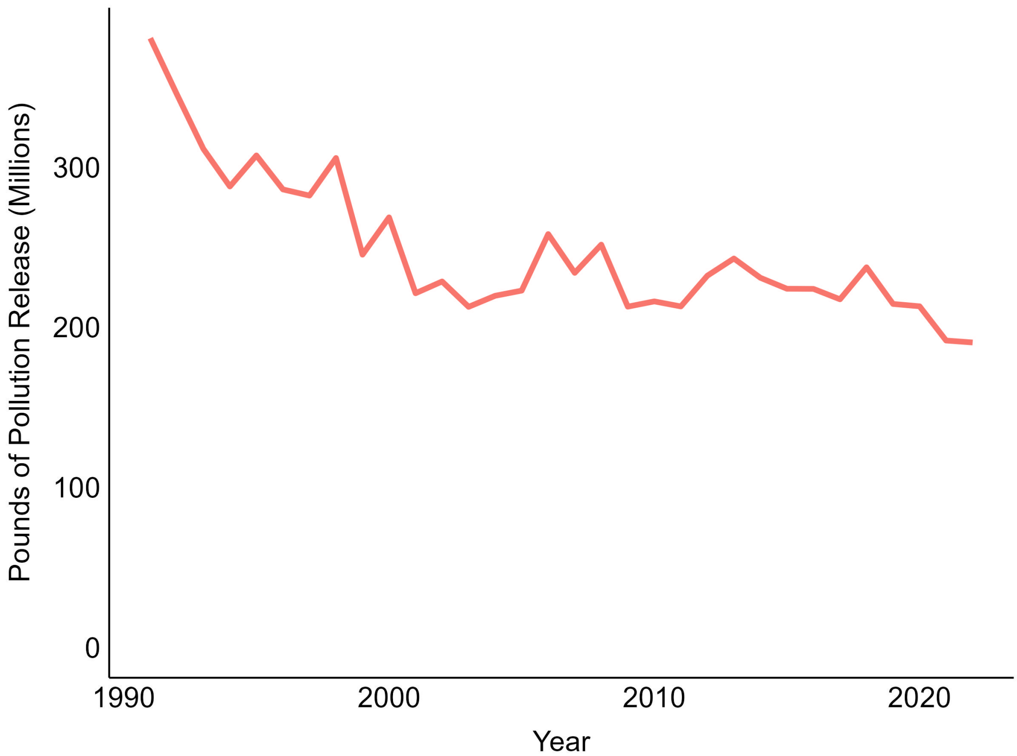


Figure A.2: Total Toxic Release, 1991-2022

Notes: This figure presents the time series of toxic release of all companies in the sample for a period running from 1991 through 2022. We exclude top 1% companies with highest toxic release during the sample period.

Figure A.3: Clean Technology Adoption Rate, 1991-2022

Notes: This figure presents the time series of the share of facilities who adopt clean technology each year from 1991 through 2022.

Table A.1: Financial Constraint, Emission Intensity and Abatement Ratio

	log (1 + emission intensity)			abatement ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
log(asset)	-0.2661***	-0.2753***	-0.2819***	0.0190***	0.0222***	0.0202***
	(0.0202)	(0.0197)	(0.0187)	(0.0031)	(0.0027)	(0.0026)
Observations	16,895	16,895	16,895	16,888	16,888	16,888
Asjusted R2	0.0777	0.1998	0.3083	0.0591	0.1748	0.2944
Year FE	Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes
State-Year FE			Yes			Yes

Table A.2: Clean Technology Adoption

	log(1+adoption frequency)			log (1 + generation intensity)		
	(1)	(2)	(3)	(1)	(2)	(3)
log(asset)	0.0234***	0.0158***	0.0161***	-0.3784***	-0.3740***	-0.3874***
	(0.0035)	(0.0037)	(0.0037)	(0.0209)	(0.0197)	(0.0186)
Observations	99,559	99,559	99,559	16,895	16,895	16,895
Asjusted R2	0.0205	0.0463	0.0835	0.0782	0.2059	0.3147
Year FE	Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes
State-Year FE			Yes			Yes
Controls	Yes	Yes	Yes			

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