Pollution-Shifting vs. Downscaling: How Financial Distress Affects the Green Transition *

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Preliminary

Abstract

Polluting practices can reduce costs in the short-term at the expense of exposing firms to significant environmental liability risk. This paper examines whether firms increase their pollution intensity as they become more financially distressed, akin to a risk-taking motive. We construct granular pollution measures for the oil and gas industry and empirically confirm the prominence of this channel therein. We then calibrate a rich dynamic model featuring endogenous default, clean and dirty capital, and financing frictions to study and quantify the relationship between financial distress and pollution. Our counterfactuals point to the limited impact of blanket divestment campaigns, as firms may scale down and pollution-shift their assets simultaneously. Tilting strategies are more effective at taming overall pollution.

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1 Introduction

How is the pollution intensity of corporate investment affected by firm financial distress? Insofar as dirty assets represent lower short-term costs and a higher risk exposure relative to clean ones, firms may have incentives to pollute more as they approach default. This hypothesized risk- or pollution-shifting channel may not only be costly for debt holders (Jensen and Meckling (1976)) but also for other stakeholders and the environment (Shavell (1986), Ohlrogge (2023)). Importantly, current divestment campaigns aimed at increasing financing costs of polluting firms and reducing their size (extensive margin) may prove to be counterproductive if this pollution-shifting effect (intensive margin) is more potent. In this paper, we examine the relationship between financial distress and the nature of corporate assets and investments and investigate the relevance of this mechanism empirically. We then develop a dynamic corporate model with endogenous default and clean vs. dirty asset choice to analyze firm behavior along *both* the extensive and intensive margins of pollution in light of debt or equity divestment campaigns and U.S. bankruptcy rules.

Investigating the relationship between financial distress and environmental practices is challenging, as it requires granular data on pollution and production. Further, financial distress could itself be correlated with unobserved forces, such as productivity differences across firms that could also affect pollution. Another challenge is to decompose pollution in its intensive and extensive margins. We attempt to address these challenges by using the oil and gas industry as our empirical setting. We first assemble a high-frequency and nearly exhaustive database of U.S.-located oil and gas projects completed between 2012 and 2022. We then develop a measure of gas flaring relying on recent advances in satellite imaging and remote sensing, and another based on administrative data on toxic releases. Together these two measures provide a comprehensive and granular picture of polluting practices within oil and gas companies. Further, we take advantage of key institutional features of this industry and use geographic variables to control for unobserved differences in technology or productivity between projects (Gilje and Taillard (2015), Gilje, Loutskina, and Murphy (2020).

The fossil fuel industry provides a particularly relevant setting for our research objective. First, it is responsible for significant air and water pollution, making it the largest source of greenhouse gas emissions in the United States.[1] Second, the capital structure of oil and gas companies involves high

[1]Environmental Integrity Project: https://environmentalintegrity.org.

leverage and financial distress. Third, this industry is at the epicenter of divestment campaigns with a stated objective of inflating its financing costs and reducing the scale of its operations. For instance, in October 2021, more than 1,485 institutions with $39.2 trillion in assets under management committed to divest from fossil fuels in what appeared to be the fastest-growing divestment movement in history. Such divestment has been encouraged through voluntary initiatives and recent regulatory proposals considering implementing green capital requirements or green repo.[2] Yet, the effectiveness of such policies remains heavily contested and debated within economists, investors, and policymakers.

Our empirical analysis relies on three complementary econometric perspectives that yield the same conclusion: pollution intensity increases with financial distress. First, we provide ample evidence of a positive and robust relationship between pollution and proxies for financial distress. Specifically, we plot the binscatters between our pollution measure and proxies for financial distress, such as size, leverage, Altman Z-score, estimated default probability. Second, we investigate how polluting practices evolve around a Chapter 11 filing in a dynamic event study window. The intuition of the test is that a Chapter 11 event may lead to a sizable reduction in default probability right after the filing. We show that the probability of pollution peaks just before a Chapter 11 filing and then decreases sharply immediately after. Third, we construct a measure of default probability at the monthly frequency. We then regress the pollution at the well-level on the lagged and forward default probabilities. We show that the relationship between pollution and default probability is the strongest for concomitant or one-month lag default probabilities.

Our analysis builds on the premise that pollution increases a firm's exposure to environmental liabilities and thus, increases the riskiness of its cash flows. One critical implication is that the relationship between pollution intensity and financial distress ought to be stronger when such risk heightens. We validate this premise, by using the Lawsuit Climate Survey. This survey reports corporate perceptions of the fairness and reasonableness of state liability systems, capturing firms' subjective ex-ante expectations about potential costs faced in a given state and thus variations in environmental liability risks. We split our sample into two, namely, one with projects in locations with high liability risk, and another with projects in locations with low liability risk. We then show that the relationship between the probability of default and pollution is stronger in the sample with high liability risk, consistent with our hypothesized pollution-shifting channel.

[2] Oehmke and Opp (2021), Drudi et al. (2021), Van Steenis (2019), and Board (2022).

Next we proceed to develop and calibrate a rich dynamic model with endogenous leverage, default, and pollution intensity to rationalize our empirical results and provide further intuition as to the underlying economic mechanism. Understanding how capital structure and distress feed back into the clean or dirty nature of investment is first-order, because pollution exposes firms to potentially large environmental liabilities, future regulatory burden, shift in workforce and consumer preferences, etc. Further, when such investment is irreversible, these decisions may have long-lasting effects. In the model, the choice of pollution intensity is endogenous and inherently dependent on firm capital structure, financial distress, and productivity. In turn, capital structure, financial distress, and ultimately default decisions depend on the firms' liability risk exposure, as captured by pollution intensity and size, and the magnitude and likelihood of implementing or enforcing regulatory pollution costs. This way, we can study the ex-ante implications on optimal leverage and capital structure and how investment decisions, jointly affect both capital structure and firm value and cost of debt.

We augment a standard discrete-time dynamic model of capital structure with two types of capital (clean vs. dirty) and an asset substitution motive. The model also features financing frictions through equity and debt issuance costs, which we use for analyzing the effects of divestment campaigns. The core mechanism relies on the mapping between pollution and risk exposure, which becomes more material as a firm approaches default.[3] Clean assets face a per-period operating cost. Conversely, dirty assets do not incur any operating cost, but are subject to a random liability shock. Thus, a firm's exposure to pollution liability risk may provide short-term earning benefits and higher investment growth, as it saves on operating costs, but it may also lead to higher credit risk and debt costs that become particularly critical following adverse productivity shocks. Depending on its distress level, a firm may have incentives to hedge against potential liability risk or amplify such risk.

We match empirical moments pertaining to the oil and gas industry and derived from our sample. Among others, the model is successful at replicating key moments such as: (i) leverage, (ii) default rate, (iii) value of equity and debt issuances, (iv) pollution intensity, and (v) the elasticity of pollution intensity to financial distress. We then revisit some of the arguments behind the impact of divestment campaigns by putting forward the distinct effects associated with the extensive (i.e., firm size) and

[3] Such mapping between pollution and risk exposure is inherent to a growing asset pricing literature (Bolton and Kacperczyk, 2021a,b; Zhang, 2023; Hsu, Li, and Tsou, 2023; Giglio et al., 2023). While the paper builds on this insight, our objective is rather about understanding how such risk exposure due to polluting assets interacts with investment dynamics and capital structure.

intensive (clean vs. dirty asset composition) margins of pollution in our quantitative analysis. We find that the relationship between financing costs and pollution is rather complex and depends on a firm's capital structure, financial health, and corresponding elasticities of both margins. In fact, our analysis highlights that, one may tend to overestimate significantly the effects of divestment campaigns and increased financing costs, absent any consideration for the intensive margin channel.

We investigate what happens when we increase equity or debt issuance costs or interest rates. The effects of issuance costs appear to be mostly counterproductive or modest at best. There are two reasons behind this surprising result. First, equity issuances are relatively small in terms of their value relative to firm size. Thus, small increases in corresponding costs may only have negligible effects by construction. Second, even when such costs are relatively large and significantly hamper their financing flexibility, we have two forces offsetting each other. Indeed, as firms may become more financially distressed, they experience a reduction in size on the one hand, but their pollution intensity also increases. Further, we found a non-monotonic relationship between pollution intensity and the magnitude of divestment campaigns. Whether the extensive or the intensive margin dominates depends on the calibration and the magnitude of the cost changes. These countervailing forces are also present for debt issuance costs or interest rates, albeit with larger magnitudes.

Overall, our analysis raises doubt as to the relevance of blanket divestment campaigns and point to their potentially limited impact. Further, it emphasizes that the presence of built-in incentives affecting directly pollution intensity choice, as it is the case debt- or asset-tilting strategies or sustainability-linked bonds can prove more effective.

Our work revolves around research strands on (i) corporate environmental decisions and financial frictions, (ii) asset substitution theory, (iii) dynamic capital structure models, and (iv) the oil and gas industry.

First, it contributes to the growing empirical literature connecting corporate environmental decisions to financing. This literature has so far focused mostly on investigating the role of financial constraints (Chava, 2014; Andersen, 2017; Cohn and Deryugina, 2018; De Haas and Popov, 2019; Levine et al., 2019; Xu and Kim, 2022). For example, Xu and Kim (2022) study how industrial pollution changes when firms face fewer financial constraints.

In contrast, we explore a complementary yet distinct channel associated with financial distress and risk-taking. In essence, our approach focuses on how the riskiness of polluting assets affect investment decisions, as opposed to the level of their fixed costs. In addition to our empirical analysis, one distinct feature of our work resides in providing theoretical foundations and calibrating a model to investigate quantitatively the effects of divestment campaigns.

Like us, two recent papers, Iovino, Thorsten, and Sauvagnat (2022) and Lanteri and Rampini (2023), also build models accounting for pollution choices. Iovino, Thorsten, and Sauvagnat (2022) focus on the relationship between corporate taxation and emission intensity, while Lanteri and Rampini (2023) investigate clean technology adoption in a theoretical setting featuring old vs. new forms of capital and financial constraints. In stark contrast, our approach focuses on the pollution-shifting motive stemming from financial distress. Further, we allow for endogenous size, capital structure, and default, for the feedback between pollution intensity choices and financing costs, and for debt and equity financing frictions. All these distinct features are critical to investigate holistically the implications of divestment campaigns on the extensive and intensive margins of pollution.

The extensive margin channel of pollution has been advanced as an argument in favor of divestment campaigns and investigated in several papers with mixed empirical findings (Barber, Morse, and Yasuda (2021), Berk and van Binsbergen (2021), Broccardo, Hart, and Zingales (2022), De Angelis, Tankov, and Zerbib (2022), Sachdeva et al. (2022), Green and Vallee (2022), Kacperczyk and Peydró (2022), Becht, Pajuste, and Toniolo (2023), Hartzmark and Shue (2023), and Gormsen, Huber, and Oh (2023)). In this context, our analysis brings to the forefront the relevance of both extensive and intensive margins, their corresponding elasticities, and potentially countervailing effects.

In particular, we view our analysis as complementary to recent work by Berk and van Binsbergen (2021) who highlight the potentially limited effects of divestment and Hartzmark and Shue (2023) who exploit cross-industries variations to show that an increase in the cost of capital can lead to an increase in pollution intensity. Like us, both of these papers point to potential shortcomings or raise doubts as to the effectiveness of divestment campaigns. Yet, very little research offers a rich quantitative setting to investigate their implications and assess their benefits. To our knowledge however, our paper is the first to study explicitly – both empirically and quantitatively – the effects and interactions among extensive and intensive margins jointly, the distinct roles of equity and debt divestment, and alternative policies such as debt tilting. Our quantitative analysis also enables us to show how a firm's pollution, which stems from the product of these two margins, is ultimately affected by interest rates, credit risk, and changes in debt and equity issuance costs. Overall, our results can be helpful to understand how changes in financing costs interact with pollution and to interpret how divestment campaign may affect firm behavior. One implication is that empirical researchers should carefully define whether they look at pollution intensity or total pollution, as its dynamics adhere to different economic mechanisms.

Our works also speaks to the literature on asset substitution and risk-shifting (Jensen and Meckling (1976)). As a firm approaches default, limited liability creates an incentive for firms to take on additional risks (Rauh (2009)). In particular, Gilje (2016) studies risk-shifting incentives in the oil and gas industry. Gilje (2016) defines risky investment as exploratory projects and development projects as safe investments. He shows that firms with more covenants, shorter debt maturity, and more bank debt are more likely to increase their development in safer projects, suggesting that bank monitoring reduces risk-shifting conflicts. We focus instead on a different classification of investment risk based on their embedded pollution.[4] Our dynamic model shares the insights of Purnanandam (2008), where firms with high continuation value have fewer incentives to risk-shift. Moreover, the ability to discharge environmental claims in bankruptcy incentivizes firms to take excessive environmental risks (Shavell, 1986; Feinstein, 1989; Ohlrogge, 2023). We show that the capital structure matters in understanding the overall impact of higher bankruptcy risks on this environmental risk-taking.

Our modelling approach builds on dynamic models of capital structure (e.g., Gomes (2001), Hennessy and Whited (2007), Gomes and Schmid (2010), Begenau and Salomao (2019)). One key novelty in our model resides in introducing two types of capital and an asset substitution motive and our focus on investigating quantitatively how capital structure and financial distress affect pollution choices.[5] Our setting differ, in that the firms gets to choose the share invested in green vs brown assets. In light of the persistence/partial irreversibility of such investment, the exposure to risk cannot be promptly adjusted. Further, creditors anticipate the effects of asset substitution/risk-taking and adjust the price of corporate debt ex-ante, mitigating shareholders' incentives to take on excessive risks.

[4] Two reasons could explain why debtholders (e.g., banks) do not fully monitor the environmental practices of their debtors. First, the U.S. legal system protects banks from the environmental liability of their debtors (Ohlrogge, 2020; Bellon, 2021). Second, asymmetric information and imperfect contracting could explain this absence of monitoring.

[5] The incentives for asset substitution and risk-taking have been mostly studied in continuous-time models building on Leland (1994), Leland and Toft (1996), or Leland (1998), which usually account for the level of risk of the firm's cash flow process. Falato et al. (2022) also consider a model of two capital types (tangible vs. intangible) in a different context, but do not model default nor asset substitution.

Finally, our paper also belongs to the broad literature of oil and gas companies and their investment dynamics in light of potential regulatory and transition risks. There are two opposite views. The neoclassical investment view suggests that higher future regulation uncertainty leads to lower production today (Baldwin, Cai, and Kuralbayeva, 2020; Bogmans, Pescatori, and Prifti, 2023). Conversely, the hoteling view – where operators find an optimal extraction path that maximizes their intertemporal profit – highlights that higher future policy uncertainty should lead to higher investment today (Sinn, 2012; Barnett, 2023). Our model shows that limited liability, a friction mostly omitted from these models, is also an important dimension to consider for our understanding of the interaction between risks and investment dynamics within the oil and gas industry, as lower earnings or higher financing costs lead to more distress and affect both pollution and production.[6]

The rest of the paper is organized as follows. Section 2 presents the data, Section 3 describes our empirical methodology, and Section 4 showcases our results. Section 5 develops our dynamic model, while Section 6 provides quantitative results and discusses counterfactuals. Section 7 concludes.

2 Background, Datasets, and Descriptive Statistics

The oil and gas extraction process creates an important number of environmental externalities. Our paper accounts for two complementary approaches for measuring pollution, namely: (i) flaring, and (ii) the use of toxic chemical in the fracturing process.

2.1 Flaring Practices

Flaring is the practice of burning the gas generated by an oil well, whenever oil and gas are co-products in the extraction process. In most cases, operators could decide to extract and develop both resources. However, extracting gas is only worthwhile in limited cases as operators must pay a high upfront cost for the purchase of a dehydrator and a compressor, and connect the well to a pipeline. When such upfront cost are above the present value of future cash flows stemming from gas extraction, it may be optimal to simply burn (i.e., flaring) or release (i.e., venting) the gas into the atmosphere. Flaring

[6] Consistent with our results linking financial distress to a decline in the extensive margin of oil and gas companies, Seleznev, Selezneva, and Melek (2021) show that financially constrained firms are less likely to complete wells that are already drilled, while Gilje and Taillard (2016) highlight that access to equity financing for public oil companies makes them more responsive to changes in investment opportunities.

involves burning natural gas, which releases uncombusted methane and carbon dioxide (CO2) into the atmosphere and contributes significantly to climate change. Certain oil and natural gas-rich nations like Yemen, Algeria, and Iraq could meet their national CO2 reduction targets under the UN Paris Agreement just by eliminating flaring (Elvidge et al. (2018)). Flaring is also a noteworthy contributor to global warming, although estimates are difficult to find, given the lack of uniform and verified reporting. Conservative measures suggest that worldwide flaring is estimated to burn 145 billion cubic meters of gas in 2018, which is equivalent to the total annual gas consumption of Central and South America. In the U.S., each day of flaring in the shale oil fields of North Dakota and South Texas burns 1.15 billion cubic feet of natural gas, which could provide power for 4 million homes. For all these reasons, the United Nation views flaring mitigation in the oil and gas industry as "Critical For Reaching 1.5°C Target" by the United Nations.[7]

Burning off natural gas, which is often mixed with other toxic chemicals, causes a nuisance that exposes firms to legal liabilities. Thus, flaring is often subject to regulation aiming at minimizing its negative impact on the environment. For example, in Texas, it requires an authorization, and in North Dakota, the type of flare that is allowed and its functioning is regulated. Moreover, this activity is likely subject to further taxation in multiple states. For instance, House Bill 1494, initiated by Rep. Vikki Goodwin, proposed a tax on the methane flared from oil and gas. This risk has in fact materialized late 2023 when the Federal state enacted a taxation of flaring activities through the methane emissions charge contained in the Inflation Reduction Act.[8] These regulations are also in line with a stream of international initiatives, such as the one from the World Bank, which launched the Zero Routine Flaring initiative (Bank (2015)).

Flaring produces a visible flame that can be detected with a satellite pyrometer. We use this insight to create a large sample covering flaring practices in the U.S., which is particularly valuable given the lack of federally-mandated reporting.[9] Recent advances in remote sensing allow us to recover a flaring measure, at the well level. We use the Visible Infrared Imaging Radiometer Suite (VIIRS) data produced by the Earth Observation Group (EOG), Payne Institute for Public Policy, Colorado School

[7] https://www.unep.org/explore-topics/energy/facts-about-methane.

[8] See the proposed rule on "Waste Emissions Charge for Petroleum and Natural Gas Systems" as of January 2024: https://www.epa.gov/system/files/documents/2024-01/wec-proposed-rule-fr_1-26-2024.pdf

[9] There is no administrative database on flaring practices at the federal level. Facilities located in Texas and North Dakota have to report their flaring practices at the state-level. However, flaring reporting is exposed to reporting bias, while the satellite measure is not.

of Mines. The data rely on the work of Elvidge et al. (2013) and Elvidge et al. (2015), who construct measures of radiation emitted by hot sources on Earth at night, relying on laws of physics such as Planck's radiation and Wien's displacement laws to recover the temperature of the hot point.[10]

We use the hot point's local temperature to identify the flaring practice, which emits a temperature between 950°C and 2250°C. This temperature is not to be mistaken with forest fires, which generally reach about 800°C. Further, we have access to data containing each well's longitude and latitude coordinates. Thus, we can use this information to investigate whether the temperature is within the flaring temperature range within 750 meters around the location of a given well. We then count total flaring detections between days 1 and 90 of production. One noteworthy limitation is that it is possible that multiple wells can be in close proximity of each other. In this case, we may not be able to disentangle the exact flaring source with a high degree of precision. As a result, we weigh flaring detections by the total number of wells captured in the scan. That is, if there are two wells within a detection point, then their flaring score is increased by 0.5 instead of 1, in order to ensure that less precise detections are assigned lower weights.

We extensively validate these satellite measures. First, we verify that the spatial and temporal patterns of our flaring measure are consistent with the geographical development of oil and gas basins. Second, the probability of observing a flare before well completion is extremely low (Figure 1 reports that this non-parametric probability is around 3%). However, such probability surges to about 15% within 90 days after well completion and then gradually declines, consistent with standard industry practices.[11]

2.2 Toxic Chemicals

Our second measure of pollution revolves around the release of toxic chemicals. Hydraulic fracturing consists of using high-pressure water mixed with toxic chemicals to generate small cracks in the rock to unleash the trapped oil and gas. The usage of toxic chemicals in this process is legal but controversial as it is exempt from the Safe Drinking Water Act (SDWA) regulation and several permitting and pollution control requirements from the Clean Water Act since the Energy Policy Act of 2005. However, ample evidence shows that releasing toxic chemicals can harm both human and animal health. These

[10] We recover the temperature through Planck's radiation law, which relates the spectral radiance to the wavelength and temperature of the material, and Wien's displacement law, which states that the wavelength of maximum spectral radiant emittance shifts to a shorter wavelength as the temperature increases.

[11] In unreported tests, we confirm that the results are robust to different ways of computing the flaring score.

chemicals can also pollute nearby water streams and groundwater tables, leak from a storage tank, and contaminate surface waters. While oil and gas operators face fewer ex-ante regulations than in other industries, they are still exposed to the same ex-post regulations through legal liabilities. In particular, releases of toxic chemicals other than diesel fuels expose operators to both CERCLA and tort liabilities.

The definition of toxicity closely follows Bellon (2020). Our measure of toxic chemicals builds on the Fracfocus database, which is matched to the production information using the unique regulatory ID of oil and gas wells (API14 number).

2.3 Production Datasets

Oil and gas firms follow a simple operational model: First, they acquire an acreage, a set of contractual rights to drill a well in a specific geographical area. Operators obtain these rights in exchange of a payment to the landowner. The payment usually takes the form of an upfront bonus and a royalty payment that depends on the fraction of oil and gas extracted. Second, the company drills a well, completes it, and extracts its resources.

One notable advantage of the U.S. oil and gas industry is that we can collect rich and granular administrative data at the well level. We rely on Enverus, which collects, processes, and cleans the data on oil and gas activities generated by county, state, and federal authorities. We use two datasets from this provider pertaining to well characteristics and production. The well characteristics provide information about the dates of initiation and completion of a well, its operator's name, its horizontal and vertical sizes, and its API14 number. It also provides the latitude and longitude coordinates of the well location, which identify the corresponding basin and allow us to match the data with our satellite-based flaring measures. The production dataset provides information on the quantity of oil and gas extracted on each well at the monthly frequency. It is also matched to the datasets on well characteristics and toxic chemicals using the API14 number. Finally, we complement these project-level datasets with firm-level balance-sheet information from COMPUSTAT, in addition to information from Chapter 11 filings for some of our tests.

2.4 Liability Measure

We use the Lawsuit Climate Survey, which reports corporate perceptions on the fairness and reasonableness of states' liability systems. One important advantage of this survey is its ability to capture ex-ante subjective expectations about potential legal liabilities faced in a given state and thus provide relevant variations in environmental liability risk. One caveat is that this survey is not conducted every year. We use the liability value of the preceding year whenever that is the case. We merge this dataset at the project level.

2.5 Sample and Descriptive Statistics

We construct two primary samples to perform our analysis. The first sample is at the project level. We restrict this sample to all publicly listed firms that can be matched to the project-level datasets. We have 78 unique firms that drilled the US onshore well between 2012 and 2022. We restrict the projects for which we can observe the pollution decision. This restriction gives us 78,044 unique projects.

Panel A of Table 1 provides descriptive statistics for this sample. Several facts emerge. Fewer than one out of three wells is polluted, according to our pollution measure, combining both flaring and toxic chemical releases. We define the cost of capital as interest (XINT) over debt (DLTT+DLC), and find that it averages 10%. This average is close to the discount rate in the SEC guidelines for valuing reserves. It is also similar to the discount rate in Décaire, Gilje, and Taillard (2020) and within the range of Kellogg (2014).

Firms in our sample are, on average, highly levered. Namely, an oil and gas project comes from a firm with an average leverage ratio of 0.73. However, there is significant dispersion, as the standard error equals 2.9. The average Altman Z-score equals 1.98, with an important dispersion. We define a firm as distressed if the Altman Z-score is below 1.8. According to this definition, 44% of the wells in the sample are operated by distressed firms. This is somewhat expected in light of the distress observed in the oil and gas industry following the significant decline in prices observed after 2014.

The second sample is at the firm-year level and contains the number of new wells firms drill annually. This sample aims to understand the production dimension of firms' decisions. On average, a firm starts about 131 new projects by year, with a standard deviation of 217. For some regressions, we aggregate the number of wells at the firm-basin level to add controls at the basin level.

3 Empirical Results

In this section, we explore two margins through which financial factors can affect a firm's pollution footprint, namely, (i) the clean or dirty nature of the production process or assets in place (i.e., intensive margin), and (ii) the production scale (i.e., extensive margin). The stylized facts we document have been individually studied in the literature, albeit not in the context of the oil and gas industry.

3.1 Financially Distressed Firms Pollute More

We first plot the binscatters of the relationship between pollution and proxies for financial distress. This stylized fact is consistent with the results in Kim and Xu (2021) and Gentet-Raskopf (2022). Plotting the relationship in a graph ensures that the relationship is monotonic and not driven by abnormal observations. Figure 2 shows the relationship between pollution and the Altman Z-score, while Figure 3 uses firm leverage. In both graphs, we can observe the same fact: financial distress is positively related to pollution. Moreover, the relationship becomes more precise and stronger once we control for the size of the company or location fixed effects. Overall, the results are consistent with more substantial financial distress pushing firms to pollute. We validate this visual evidence by estimating the strength of the relationship in a regression framework, which allows us to quantify the relationship and adds several fixed effects and time-varying controls. Specifically, Table 2 reports the regression estimates of our proxies for financial distress on our pollution measures. We measure financial distress in two ways: Panel A uses the Altman Z-score, and Panel B relies on log-leverage. As shown in Column (1) of panel A, an increase of one standard deviation of the sample Altman Z-score leads to a drop in pollution of 4.1%. As shown in Column (1) of panel B, a 1% increase in leverage is associated with 0.00036 pollution units, representing 0.11% of the baseline rate.

The relationship still holds once we add several controls and high-dimensional fixed effects. Specifically, we add a firm fixed effect to control for the possibility that larger firms might use less polluting technology and less leverage. We also include the firm total assets. We also add several spatial fixed effects interacted with a year fixed effect. The spatial fixed effects absorb potential unobserved heterogeneity that could create a spurious relationship between pollution and distress. For example, polluting firms could develop wells in less productive acreages, increasing firm financial fragility. Using location-fixed effects to control for differences in productivity is a common practice among papers that rely on the fracking industry as an empirical setting.

Next we show that the positive relationship between pollution and financial distress also holds if we decompose the effects by different types of pollution. Specifically, Columns (3) and (4) of Panels A and B investigate the relationship between Z-score (Panel A) and leverage (Panel B) on flaring. Similarly, Columns (5) and (6) show the same relationship, except that the dependent variable is now a dummy variable that takes a value equal to one if the firm uses at least one toxic chemical.

Finally, we perform several event studies that rely on a more precise time variation in the cost of capital. In particular, we first study the amount of pollution around Chapter 11 bankruptcy events. The idea is that firms face a lower expected cost of capital following a formal renegotiation. As a result, we should observe a drop in pollution following a Chapter 11 filing.

We empirically test this prediction. Figure 4 plots the average difference in the probability of polluting each year around a Chapter 11 filing after controlling for a firm, location, and year-fixed effect. The reference year is one year before the filing year for Chapter 11. We observe a sharp decrease in the probability of pollution after the Chapter 11 filing. Specifically, the firms are 30% less likely to pollute one year after Chapter 11 filing. After the filing, pollution levels may slightly increase over time, but never reach the same level as before. Three years after filing, firms are still around 15% cleaner. Overall, the tests indicate that companies with a lower chance of going bankrupt are more inclined to have a lower pollution level.

The second event study we perform relies on a higher frequency window. We compute monthly firm-level delisting events using the measure of Boualam, Gomes, and Ward (2020). Specifically, the approach uses annual rolling logit regression that captures the one-year probability of default, taking into both balance-sheet and market variables available up to a a certain point. We estimate the following equation for a given project k, made by firm i at time t and for $j = -6, -5, \ldots, 5, 6$:

$$\text{Pollution}_{kit} = \text{Lprob}_{i,t+j} + \text{FE}_{ikt} + \text{Controls}_{ikt} + \varepsilon_{ikt},$$

where Pollution is a dummy variable that takes the value of one if the well pollutes and zero otherwise. Controls_{ikt} is a set of firm and project characteristics namely firm size, sales, capx, Tobin's Q, the total liabilities, return on asset, and the first 6 month of oil and gas production. FE_{ikt} contains for a firm fixed effect, a location fixed effect, a basin-year fixed effect, and a month fixed effect. $\text{Lprob}_{i,t+j}$ is the estimating distress probability for firm i and for the month $t+j$.

Figure 5 plots the coefficients, where j goes from -6 to 6. The main insight is that the relationship between the distress probability and pollution intensity has an inverted U-shape that peaks one month before the well completion. Specifically, the impact of distress risk is low six months before the well is completed but gradually increases until one month before completion. Ultimately, this probability gradually falls. This event study confirms the view that default probability is a key driver behind firms' decision to pollute.

We then decompose the previous dynamic event study graph on two subsamples, to show that the relationship between pollution and distress is stronger when the potential liabilities associated with pollution are stronger. We use the Lawsuit Climate Survey, which reports the perceptions of US businesses of how fair and reasonable states' liability systems are to obtain variations in liability risks. The dots in red of Figure 6 show the impact of the probability of default on pollution for projects located in states with high perceived liability risks. The dots in gray plot the coefficients for the same regression, but on the sample of projects that are located in states with low perceived liability risks. Overall, we show that the relationship is entirely driven by projects located in states with high perceived liability risk. This empirical fact is consistent with a core prediction of our model, namely that the relationship between distress and pollution should be stronger when the potential liabilities associated with pollution are stronger.

3.2 Financially Distressed Firms Produce Less

In this subsection, we show that a higher probability of default is associated with lower investment, as the cost of capital plausibly increases. We view this subsection as a validation exercise of our database, as there has been an enormous amount of literature, going back to at least Fazzari, Hubbard, and Petersen (1987), establishing that a company's distress affects its investment choices. We start by plotting the binscatter of the average number of projects per year for each firm as a function of proxies for financial distress. In Figure 7, we use the Altman Z-score as a proxy. In Figure 8, we use leverage. For both figures, we plot the raw relationship on the left, and the binscatter with controls is on the right. The controls include the size of the company. Overall, all figures show a clear negative relationship between the number of projects started and these two proxies of financial constraint. Table 3 shows the estimates in a regression framework. The dependent variable is the firm's number of new projects in a given year and basin.

Column (1) shows that when the firm is distressed, which we proxy by having an Altman Z-score below 1.8, firms reduce their number of projects per basin by 0.8 on average. Once we add a firm fixed effect and a basin year fixed effect in the specification, this coefficient drops to -0.19. These fixed effects absorb potential omitted variables, such as differences in investment opportunities that vary with financial distress. They are also likely to be "contaminated controls", because these controls also absorb the distress component that causes firms to reduce pollution. With these caveats in mind, the point estimate gives an economically significant range. There are a total of 65 basins, which is equivalent to a decrease of between 12 and 52 new projects. On average, a firm has 131 projects per year, so this reduction represents 11% and 39% of the total number of projects. The relationship also holds when we add the Z-score and the leverage. Overall, we replicate the known results that higher financial distress leads firms to reduce investment in our setting.

4 A Dynamic Model of Financial Distress and Pollution Intensity

We extend dynamic corporate finance models featuring endogenous leverage and default (e.g., Hennessy and Whited (2007), Gomes and Schmid (2010), Begenau and Salomao (2019), Gomes and Schmid (2021)) to account for a firm's pollution intensity, and the choice to invest in dirty or clean assets. The distinction between dirty and clean capital investments resides in the following: on the one hand, clean capital is subject to permanent operating costs, on the other hand, dirty capital does not incur any costs unless a stochastic pollution liability shock is realized. In this context, pollution intensity is a dynamic *and* persistent state variable, as investments are only partially reversible, and endogenously depends on current states of firm size, pollution intensity, capital structure, and idiosyncratic productivity.

Interestingly, this distinction in capital type generates a mechanism akin to risk-taking for financially-distressed firms. Conceptually, firms subject to financial distress may elect to either gradually become (i) heavy polluters by hiking their pollution intensity (risk-taking), or, instead, (ii) greener by reducing their pollution intensity and hence their exposure to environmental or regulatory costs and (risk-hedging), depending on their productivity levels and other balance-sheet characteristics.

We build an industry equilibrium with the objective to highlight this key economic channel linking pollution intensity choice to capital structure. We then calibrate the model and investigate its quantitative properties and implications through a series of counterfactual exercises.

4.1 Technology

We consider an economy populated with heterogeneous firms, producing the same final good. Firms are infinitely-lived pending no default. They operate a decreasing-return-to-scale technology ($\alpha < 1$), with idiosyncratic productivity shocks, $s_{j,t}$, governing the instantaneous flow of output for firm j at time t, as follows:

$$y_{j,t} = s_{j,t} k^{\alpha}. \tag{1}$$

We assume that the dynamics of these shocks follow a first-order autoregressive process with normal i.i.d. innovations, following:

$$\log(s') = \rho_s \log(s) + \sigma_s \varepsilon_s', \tag{2}$$

with $\varepsilon_s \sim \mathcal{N}(0,1)$.

4.2 Dirty vs. Clean Capital

Firms experience different idiosyncratic shock histories and, at each point in time, vary along the following dimensions: capital, k, pollution intensity (i.e., dirty vs. clean composition), η, and debt, b. Capital stock depreciates at a periodic rate, δ, irrespective of its type. We also assume a quadratic and asymmetric adjustment cost for capital such that:

$$g(k,k') = c\left(\frac{k' - (1-\delta)k}{k}\right)^2 k \tag{3}$$

$$c = c_0 \mathbb{1}_{\{k'-(1-\delta)k>0\}} + c_1 \mathbb{1}_{\{k'-(1-\delta)k<0\}}, \tag{4}$$

with $c_1 \geq c_0$. This assumption allows for smooth and gradual capital stock dynamics and a realistic firm size distribution. As it is common in the literature, the asymmetry in capital adjustment costs also entails that taking on additional leverage and a new investment that is only reversible partially is risky because firm downsizing in the aftermath of a negative shock becomes more costly and slow-moving.

Every period, firms invest in one capital type, namely, dirty (denoted with D) or clean (denoted with C) capital, and thus carry dynamic capital stocks k^D and k^C, and total capital $k = k^D + k^C$. The dirty vs. clean capital composition determines an endogenous capital pollution intensity, $\eta = \frac{k^D}{k^C + k^D} = \frac{k^D}{k} \in [0,1]$. Hence, our model allows to express firm pollution as the product of two complementary dimensions: (i) an intensive margin (i.e., pollution intensity), and (ii) an extensive margin (i.e., firm size).

Dirty and clean capital types require the same investment cost and provide the same per-period output, and thus are perfectly substitutable from a production perspective. However, they differ in terms of their maintenance and pollution-related costs, as in for example Oehmke and Opp (2022). The maintenance cost per unit of capital is denoted by $m > 0$, and is only incurred by clean assets. Conversely, dirty assets are subject to a potential pollution liability shock (e.g., carbon tax, environmental liabilities, regulatory costs), whose realization affects firms' net operating income permanently. This pollution liability is captured by a random variable, τ_C, which takes the value of ζ whenever the shock is realized and zero otherwise. It is assumed that $Prob[\tau_C = \zeta] = p$ and $Prob[\tau_C = 0] = 1 - p$, so as the expected time to shock realization is $\frac{1}{p}$. Once this shock is realized, we assume that it becomes a permanent institutional feature. Combined with the capital pollution intensity, this cost shock reflects firms' exposure to transition risk within the model.

4.3 Firm Earnings

We define the after-tax profits of the firm, Π, within a given period, as:

$$\Pi(k, \eta, b, s, \tau_C) \quad = \quad (1-\tau)\left[sk^\alpha - c_f - (\delta + m)k + \eta k(m - \tau_C) - b\right], \tag{5}$$

where τ is the effective tax rate on profits (adjusted for taxes on distribution and personal interest income) and c_f is a fixed operating cost. The term $\tau_C \eta k$ captures the potential losses due to operating dirty capital, upon the realization of the pollution liability shock, which can be interpreted as an endogenous depreciation of dirty capital.

4.4 External Financing

Firms can issue both equity and debt in order to finance their investment. Each type of financing is subject to an issuance cost, denoted by λ_e, and λ_b, respectively. We assume that both bond and equity holders are risk-neutral, with a discount factor, β. Firms issue one-period bonds at a discount, i.e., they raise $q^b b'$, with $q^b < 1$, and pay back the face value, b', in the next period. If the firm defaults, the creditors receive an amount equal to the liquidation value, that is independent of capital composition, $L(k,b) = \min(\phi \frac{k}{b}, 0.75)$, where $\phi > 0$ represents the recovery rate of the firm's assets. The recovery value is capped to 75% in order to ensure that issuing debt remains risky across all firm sizes, as in Begenau and Salomao (2019). In the benchmark setup, we assume that both dirty and clean capital have the same liquidation value.[12]

Default region and Debt Pricing. Limited liability is such that it is always beneficial for the equity holders to default whenever the firm's equity value, $V(k,\eta,b,s,\tau_C)$, dwindles below zero. We define a parameter region $\Delta(k,\eta,b)$ that specifies the default states such that:

$$\Delta(k,\eta,b) = \{(s,\tau_C), \text{ s.t. } V(k,\eta,b,s,\tau_C) \leq 0\}. \tag{6}$$

A firm in current state (k,η,b,s,τ_C) commands a market value for debt q^b, such that:

$$\begin{aligned} q^b(k,\eta,b,s,\tau_C) &= \beta \left[\iint_{(s',\tau_C') \notin \Delta(k,\eta,b)} ds\, d\tau_C' + \iint_{(s',\tau_C') \in \Delta(k,\eta,b)} L(k,b)\, ds\, d\tau_C' \right] \\ &= \beta \left[1 - p(k,\eta,b,s,\tau_C)(1 - L(k,b)) \right], \end{aligned} \tag{7}$$

where $p(k,\eta,b,s,\tau_C)$ represents the default probability one period ahead, taking into account all current state variables.

[12]The assumption of liquidation being independent of capital types is motivated by the environmental lender liability discharges benefiting debtholders. We relax this assumption later.

4.5 Equity Value and the Firm Optimization Problem

Let us now characterize the firm problem and policy decisions. The equity payouts are:

$$e(k,\eta,b,s,\tau_C) \;=\; \Pi(k,\eta,b,s,\tau_C)-(k'-(1-\delta)k)-g(k,k')-b+(1-\lambda_b)qb'+\tau(\delta k+rb). \quad (8)$$

The timeline is such that, at the beginning of each period and upon shock realizations, the firm chooses to continue or default such that:

$$V(k,\eta,b,s,\tau_C)=\max\left(0,V_C(k,\eta,b,s,\tau_C)\right). \tag{9}$$

Upon continuation, the firm chooses the size and composition of its investment and the corresponding financing source. Thus, conditional on survival, its continuation value is given by:

$$V_C(k,\eta,b,s,\tau_C)=\max_{k',\eta',b'}\left[(1+1_{e<0}\lambda_e)e+\beta\mathbb{E}_{s,\tau_C}[V(k',\eta',b',s',\tau_C')]\right], \tag{10}$$

where $1_{e<0}\lambda_e e$ represents equity issuance and corresponding costs when the firm payouts are negative, and the expectation in the right-hand side is taken over the conditional distributions of s and τ_c.

We assume – without loss of generality – that any investment is exclusively clean or dirty within a given period, and specify the dynamics of capital and its composition, given investment, i, and type, η_i as:

$$\begin{aligned} k' &= (1-\delta)k+i && (11)\\ \eta' &= \frac{\eta(1-\delta)k+\eta_i i}{(1-\delta)k+i} \\ &= \eta+\frac{(\eta_i-\eta)i}{(1-\delta)k+i}. && (12)\end{aligned}$$

We note that in the complete absence of pollution liabilities (i.e., probability is 0), a strictly positive maintenance cost for clean assets (i.e., $m>0$) implies that firms always choose to invest in dirty capital. Conversely, in the presence of a permanent pollution tax, such that $\tau_C>m$, clean capital is always preferred. The more interesting case resides in a setting with a stochastic pollution tax implementation and firm default. Indeed, away from default, firms' choice depends on $\mathbb{E}[\tau_C]$ vs. m. Conversely, under a high distress probability and the realization of a pollution cost shock tomorrow, τ_C', may lead to certain firms defaulting. Thus, distressed firms may have incentives to load on more dirty assets today (risk-taking), as long as $m > \mathbb{E}[\tau_C' | (k', \eta', b) \notin \Delta(k, \eta, b)]$.

4.6 Stationary Firm Distribution

We define the cross-sectional distribution of firms at the beginning or period t, as $\mu_t = \mu(k, \eta, b, s, \tau_C)$, over capital, k, pollution intensity, η, debt, b, given an idiosyncratic productivity, s, and an aggregate pollution liability shock, τ_C. Further, we define aggregate variables at the beginning of period t as:

$$
\begin{aligned}
F_t &= \int d\mu_t && \text{Mass of firms} \\
K_t &= \int k d\mu_t && \text{Aggregate capital} \\
I_t &= \int i d\mu_t && \text{Aggregate investment} \\
B_t &= \int b d\mu_t && \text{Aggregate debt} \\
\Upsilon_t &= \int \eta d\mu_t && \text{Aggregate pollution intensity} \\
P_t &= \int k\eta d\mu_t && \text{Aggregate pollution}
\end{aligned}
$$

4.7 Firm Entry

Firm entry allows for the replacement of defaulting firms and thus is necessary to ensure a stationary firm distribution in equilibrium. At the beginning of each period t, a mass of firms are created, with the following initial conditions: (i) no initial debt, $b = 0$, and (ii) an initial draw of the idiosyncratic shock $s_{j,t}$, from the long-run invariant distribution, $H(s)$, derived from (2). Entrant firms are assumed to start with an initial amount of capital $k_e = \gamma_k \bar{k}_t$, that is proportional to the average firm size, $\bar{k}_t = \frac{K_t}{F_t}$, and a pollution intensity level $\eta_e = 1$. Thus, given the initial firm conditions, only firms with sufficiently large productivity shocks may find it optimal to enter the market.

4.8 Equilibrium

A recursive competitive equilibrium consists of: (i) value function $V(k, \eta, b, s, \tau_c)$, (ii) policy functions $\Delta(k, \eta, b)$, $k'(k, \eta, b, s, \tau_c)$, $\eta'(k, \eta, b, s, \tau_c)$, and $b'(k, \eta, b, s, \tau_c)$, and (iii) distributions for incumbent and entrant firms, such that:

- Value function $V(k,\eta,b,s,\tau_c)$ and policy functions, $\Delta(k,\eta,b)$, $k'(k,\eta,b,s,\tau_c)$, $\eta'(k,\eta,b,s,\tau_c)$, and $b'(k,\eta,b,s,\tau_c)$ solve the firms problem.

- Given optimal policies, the law of motion for the distribution of firms satisfies:

$$\mu_{t+1}(k,\eta,b,s,\tau_C) = \int_S \int_{\bar{\Delta}(k,\eta,b)} d\mu_t(k,\eta,b,s,\tau_C) dG_s(s'|s) d\tau_C,$$

where $\bar{\Delta}(k,\eta,b)$ represents the continuation states. The firm distribution evolves as follows. Every period, a mass of firm defaults and exit the economy and are replaced by new entrants characterized by their initial size, debt and pollution intensity. Conversely, surviving incumbent firms evolve according to the realization of their productivity shocks over the next period and the corresponding optimal policy functions. Thus, at each period, the measure of firms for a given quintuplet state (k,η,b,s,τ_c) is determined by both entrant and incumbent firms.

5 Quantitative Application

Our model is calibrated to match moments and derive implications related to the oil and gas industry, in line with our empirical section. In this context, the clean vs. dirty asset choice corresponds to oil wells, being drilled and operated with or without gas flaring or toxic chemical release.

5.1 Model Parametrization

The model consists of 17 parameters for which we need to specify a value: one for preferences, four for institutional features, nine for technology, and three for the distinctive features of dirty and clean assets. We calibrate the model on a yearly basis and our target moments are derived from the oil and gas industry. A subset of seven parameters are set according to the literature or from direct empirical counterparts. The remaining ten parameters, namely: (i) investment adjustment cost, c_0; (ii) divestment adjustment cost, c_1; (iii) fixed operating cost, c_f; (iv) equity issuance cost, λ_e; (v) debt issuance cost, λ_b; (vi) operating costs of clean asset, m; (vii) probability of pollution liabilities, p; and three parameters governing the productivity process, $(\bar{s},\rho,\sigma)$, are calibrated to jointly match target moments.

Our calibration exercise is standard and proceeds as follows: first, we solve for the policy and value functions through a method combining value and policy function iteration. Models with endogenous default can be relatively difficult and time-consuming to solve. We follow the numerical dynamic programming approach in Gomes and Schmid (2010) and simultaneously updated both the value function and the price of debt through the iteration procedure.[13] The model solution relies on a discretization of the idiosyncratic shock process following Tauchen and Hussey (1991) and allowing for 7 states. Second, we simulate the model-implied moments and minimize the distance with their empirical counterparts. Table 5 reports set (Panel A) and calibrated (Panel B) parameters in our benchmark calibration.

Set parameters. We set the discount factor β to 0.976, corresponding to an annualized interest rate of about 2.5%. For the institutional parameters, we set the effective corporate tax, τ to 25%, the bankruptcy cost, ϕ to 0.4, consistent with an average recovery value on defaulted bonds of about 60%, in line with parameter values commonly used in the literature.

For the technology parameters, we use a decreasing-returning-to-scale parameter, α, of 0.65, which is within the range of values used in the literature, and an annual depreciation rate of 10%, consistent with the average NIPA depreciation rate and an operating lifespan of an oil well of about 10 years. Finally, we determine the AR(1) parameters associated with idiosyncratic shock dynamics using their empirical counterparts (revenue process).

The relative size, γ_k, of entrants are determined relying directly on their data counterparts. Finally, the maintenance cost of clean assets, m, is directly imputed based on our measurement net revenues of dirty vs. clean assets, as obtained from our sample of oil well projects.

Calibrated parameters. The remaining parameters are jointly calibrated so as model-implied moments, determined based on a panel consisting of 5,000 firms simulated over 30 years, are inline with their empirical counterpart targets. The calibrated parameters and corresponding target moments are relatively standard in the literature with two exceptions. First is the divestment adjustment cost for which the corresponding target is the ratio of the investment rate of the smallest size quartile over the average investment rate, as in Begenau and Salomao (2019).[14] Second is the probability of pollution

[13] Further computational details are relegated to the Online Appendix.

[14] The empirical average investment rate is determined at the extensive margin as follows: the average firm in our sample consists of about 575 oil wells, and initiate about 86 new well project per year. Assuming that oil wells are of homogeneous value, this represents an annual investment rate $i = \frac{86}{575} = 15.0\%$.

cost implementation, p, is identified through the average capital pollution intensity of firms in our sample.

5.2 Results

We begin by characterizing the policy functions and the key mechanism linking financial distress, capital, and debt choices, to pollution intensity. Further, we validate our quantitative exercise by discussing cross-sectional moments that were not targeted in our calibration. Finally, we examine the effects of interest rates, institutional parameters related to issuance costs and policy through comparative statics and counterfactual analyses. The model is solved for our benchmark calibration, in addition to alternative specifications described in our quantitative applications.

5.2.1 Optimal Policies and Mechanism

In light of our parameter specification, we characterize the optimal policies generated by the model. Corporate decisions involve an exogenous productivity shock, s, in addition to three endogenous states: capital, k, debt, b, and pollution intensity, η. Given the dynamic nature of the model and the autoregressive property of the idiosyncratic productivity shock, a firm's decision to continue or default, and its next-period characteristics, depend on all current variables.

One particularly novel aspect of our model is the pollution intensity decision, $\eta'(K, \eta, B, s, \tau_c)$ and its feedback to firm capital structure. Optimal policies are constructed, assuming that the liability shock remains null, by averaging over the top and bottom halves of current firm size, K (Panel A), or firm pollution intensity, η, (Panel B), and the productivity shock, s, using the steady-state distribution, μ.

Figure 11 reports select optimal policy functions pertaining to firm size, pollution intensity, and default probability. Panel A illustrates the behavior of small and large firms across the range of productivity values. We see that small firms tend to select higher pollution intensity relative to larger firms. This is particularly visible for lower productivity levels. Indeed, as firm face adverse productive shocks and approach financial distress, they have more incentives to load up in riskier polluting assets, as long as no pollution liability shock has been realized. Further, the increased pollution intensity is also associated with higher default probability.

Panel B reports optimal policies averaged over the top and bottom halves of of pollution intensity. We note that when productivity is sufficiently favorable, high pollution firms tend to relatively larger than low pollution firms. The intuition is straightforward. Absent any costly pollution liability shock, high pollution firms economize the clean asset operating cost, thus generating higher profits, and scaling up faster. However, adverse productivity shocks lead to the opposite behavior. High pollution firms are more exposed to financial distress and credit risk, rendering the financing to be more sensitive to productivity shocks. As a result, they scale down faster during unfavorable situations. Further, such scaling down is also accompanied with a larger increase in their pollution intensity, as depicted in the central plot in Panel B. This pollution-shifting behavior further exacerbate the firm default probability.

This result is in line with a risk-taking motive, driven by the equity holders' limited liability and financial constraints. Indeed, as firms become more constrained, they limit their operating costs, by increasing their pollution intensity. Due to financial distress, the expected firm value conditional on survival also impacts their pollution intensity choice as firms are willing to take on more transition risk exposure. It is also worth noting that the increase in pollution intensity for distressed firms is likely to be associated with the sale of clean assets, as opposed to dirty asset investments.[15]

5.2.2 Model Validation & Cross-sectional Moments

In order to generate sensible quantitative results about the relationship between corporate decisions and pollution, it is essential to validate the benchmark calibration by investigating both micro and macro moments. In this section, we explore the sensitivity of pollution intensity choice to firm size and financial distress measures. We then explore the cross-sectional moments implied by the model's steady-state firm distribution and compare them to their empirical counterparts.

Pollution sensitivity to default rates, size, leverage, and productivity. Figure 12 reports the relationship between firm variables such as (i) default probability, (ii) size, (iii) productivity, and (iv) leverage, and pollution intensity, tabulated as a share of dirty capital stock or dirty new investment. In line with the model policy functions, pollution intensity is negatively related to size, productivity, and leverage.

[15] Our model does not assume a fixed aggregate amount of clean or dirty capital. In this context, one could interpret the sold assets as simply scrapped or reallocated beyond the borders of our economy, and thus not contributing to its aggregate pollution.

In contrast, the relationship between default probability and pollution intensity exhibit a U-shape pattern. Indeed, firm with no immediate risk of default can initially take on more polluting assets, as long their expected costs are equal to or cheaper than clean assets. As such probability of default increases, firms may be inclined to hedge themselves again further negative pollution shocks and become greener. However, as firms become further distressed, their equity holders become more incentivized to take on more risks and thus operating more polluting assets as they "gamble for resurrection".

Figure 13 further examines the relationship between financial distress and pollution, as a function of firm size. It shows that the positive relationship between financial distress and pollution is mostly concentrated among the lowest size tercile. Moreover, it appears that the average firm pollution does increase overall for low to medium-size firms as the increase in pollution intensity accompanying financial distress is only partially compensated by the decline in firm size.

Cross-sectional moments. We also investigate the model performance in the cross-section. Table 6 reports the cross-sectional averages of model variables and their empirical counterparts. These moments provide additional modelling validation as they were not part of our calibration exercise. With the exception of the size distribution, which is more concentrated, the model generates values and patterns that are reasonably close to the data. In particular, default probabilities are decreasing with size and range from 12% for the bottom quartile to 2% for the top quartile. Pollution intensity also exhibits a decreasing pattern in line with the data, with values ranging from 0.35 to 0.23.

5.3 Counterfactual Analysis: Micro-level Effects

Table 7 reports counterfactual results pertaining to changes associated with (i) interest rates, (ii) debt and equity issuance costs, and (iii) pollution liability costs. The reported results represent long-run changes relative to the benchmark economy for firm size, debt, leverage, default rate, in addition to pollution intensity and average pollution. These changes are tabulated in logs on an equal-weight basis.

Interest Rates and Monetary Policy. How does pollution choice respond to changes in interest rates or monetary policy? Panel A highlights that a 100 basis point increase in interest rates is associated with potentially large and countervailing effects along the extensive and intensive margins of pollution. While the average firm size declines by about 17%, the average pollution intensity does increase by about 8%, consistent with the increase in default probability and the pollution-shifting mechanism. Indeed, an increase in borrowing costs implies lower debt capacity and firms scaling down. Further, earnings also dwindle leading to a further increase in credit spreads and pushing more companies toward financial distress. Ultimately, and as long as the pollution liability cost has not yet been realized, this leads firms to take on more risks and turn to more polluting assets. Overall, however, our results point to the extensive margin effect being more prominent, ultimately leading to an overall decline in average and aggregate pollution of about 9.3% and 4.1%, respectively.

Debt and Equity Issuance Costs. Next we investigate the effects associated with increased debt and equity issuance costs, which we interpret as being driven by investor preferences and investment exclusion campaigns. Our analysis highlights that the magnitude of the effects of these issuance costs depends necessarily on a firm capital structure and the relevance of such issuances. Indeed, we estimate that the annual equity and debt issuances represent a value (as a share of capital) of about 6% each, for the oil and gas firms in our sample.[16]

First, we show that an increase in equity issuance costs can only have modest effects on aggregate pollution. Indeed, Panel C reports that an increase of 1.5% in equity issuance costs (representing a doubling of the benchmark value), does not have any significant effect on size or pollution intensity. This result is consistent with dynamic corporate models noting the limited effects of equity issuances (Gomes and Schmid (2021)), and more generally the fact that such linear issuance equity, only have modest wealth effects.

However, as the equity issuance costs increase more significantly (+4.5%), such change can lead to a counterproductive increase in the average firm pollution of 1.5%. Such increase is due to the decline in average size of 0.9% combined with a larger increase in pollution intensity of 2.3%. Thus, our results can be viewed as providing a complementary perspective to the findings in Berk and van Binsbergen (2021) who argue that divestiture strategies do not appear to meaningfully affect the cost of capital of targeted firms and thus their investment decisions. Our point, is that even if such was the case, and captured by equity issuance costs, the fact that such issuances are relatively infrequent and represent only a small fraction of the firm financing needs, means that equity divestment campaigns may not be that effective.

[16] Understanding the impact of divestment campaigns in light of firm capital structure and the relevance of equity and debt financing is typically absent from the literature and deserves further research.

Next we move on to debt issuances which represent the major source of financing for oil and gas companies. Panel B shows that a 25 basis point increase in debt issuance costs is in fact associated with an increase in average firm pollution, albeit such effect remains negligible. This is due to offsetting effects from the extensive (-3.4%) and intensive (+4.1%) margins. In line with the interest rate counterfactual above, an increase in debt issuance costs, which are proportional to total debt stock in this setting, hamper firms' financial flexibility and ability to roll over debt and increase the overall cost of borrowing. Firms respond to such shock by scaling down and shifting toward more polluting assets. Firms with higher likelihood of default respond more aggressively relative to low distress firms.

Surprisingly however, a larger change in debt issuance costs (+0.75%) leads to the opposite conclusion (i.e., a 2.3% decline in average firm pollution) as the intensive margin effect subsides and the extensive margin effect ultimately dominates. The hump-shape pattern observed for pollution intensity deserves some attention. Pollution intensity initially first increases significantly due to the risk-shifting motive. When debt issuance costs becomes very large, firm debt issuance and leverage significantly decline, ultimately reducing such shifting incentives and the magnitude of the intensive margin effect.

Figure 14 plots the magnitude of these changes across a range of changes in debt issuance costs and interest rates. Ultimately, the relative elasticities of the intensive and extensive margins to default probability determine the sign of the aggregate effect.

Finally, in light of the substitution between equity and debt financing, a natural experiment is to investigate whether *joint* equity and debt divestment campaigns can be significantly more effective. Such approach – which has been overlooked in the existing literature – would ensure that financing costs increase across the board and prevent the substitution work around. Nonetheless, as Panel D illustrates, the combination of large debt and equity issuance costs only leads to a 4.9% average decline in pollution, as a result of a -8.3% in the extensive margin and an offsetting increase of 3.4% in pollution intensity for the average firm.

5.4 Regulatory Costs and Pollution Liabilities

We finally investigate the implications in the likelihood, p, and magnitude, τ, of pollution liabilities. Both dimensions affect the expected costs associated with polluting assets, and outcome variance. In contrast to previous policies, an increase in either aspect leads to a decline in *both* the intensive and extensive margins. Unsurprisingly, as the cost of polluting assets increases, firms grow at a slower rate and reduce their pollution intensity. In addition, these effects appear more significant for the magnitude of the pollution liability as opposed to its likelihood.

5.5 Extensions: Debt and Asset Tilting and Stranded Asset Policies

In this section, we augment the model to account for further manifestations of the differences in the treatment of green vs. dirty assets by analyzing alternative policies. Namely, we would like to investigate how debt holder tilting toward green firms or differentiated recovery values upon liquidation influence firm capital structure and capital choice.

5.5.1 Debt Tilting and Sustainability-Linked Bonds

We extend our model to account for potential effects stemming from debt holder tilting toward greener firms. We model such tilting by formulating a debt issuance cost that is linearly increasing in pollution intensity, $\tilde{\lambda}_b = (1+\theta_0\eta) \times \lambda_b$, with tilt multiple, $\theta_0 > 0$. Such debt tilting can be interpreted as a form of implicit greenium reflecting investor preferences and demand or as an explicit or negotiated monetary incentive, as it is, for example, the case for sustainability-linked bonds or loans.

Contrary to the blanket debt issuance cost increases discussed above, tilting provides firms with additional incentives to shift their investments toward greener assets. These assets now provide the additional benefit of lowering firms' debt issuance costs, and ultimately preserve their financial flexibility and reduce their likelihood of distress.

We start from the benchmark debt issuance cost value of 25 basis points and consider a linear increase that goes up to 100 basis points for a 100%-dirty firm. Such an increase represents a debt issuance cost gap of 10 to 15 basis points across firms in the bottom and highest pollution intensity quartiles in line with existing empirical estimates of the greenium.

Our results point to the effectiveness of this approach relative to a uniform increase in debt issuance costs. On the one hand, increases across the board do not provide firms with any virtuous incentives, as firms simply substitute from debt to equity issuance, all else equal. While such substitution may still lead to costlier financing and reduce firm size, such lack of financial flexibility comes with an increase in pollution intensity, as firms attempt to front-load their earnings, in light of the increase in default likelihood and thus lower discount factors. Conversely, tilting opens up a new adjustment channel as firms substituting dirty for clean assets benefit from improved financing conditions, with limited effect on their profitability, default rate, or growth.

In fact, as Panel B in Table 8 illustrates, tilted debt issuance costs lead to a decline in pollution of the order of 38-40%, which is mostly due to the intensive margins, as the average firm reduces its pollution intensity by over 36%.

5.5.2 Stranded Assets and Recovery Rates

Next we move on to investigating the role of liquidation value upon default of polluting assets. We assume the extreme case where polluting assets are stranded and worthless in the bankruptcy state. In light of our parameter setting, this assumption has relatively limited effects on firm pollution intensity choice and overall pollution. This is not surprising in light of our parameters and empirical moments matched from the oil and gas industry. Indeed, the average annual default probability is about 5%, and the benchmark recovery rate is around 60%. Given that the pollution intensity of the average firm is 28%, assigning a recovery rate of 0 to dirty assets only increases credit spreads by a negligible amount, all else equal.

5.5.3 Higher Asset Divestment Costs

Finally, we also assume that dirty assets require additional divestment costs relative to clean assets. Essentially, we consider here the preferences of potential asset buyers in the secondary market for capital, instead of the preferences of debt holders. We rewrite divestment costs as: $\tilde{c}_1 = (1 + \theta_1 \eta) \times c_1$, with multiple $\theta_1 > 0$ and re-solve for the model, all else equal. Higher divestment costs penalize firms in the aftermath of adverse shocks. As firms' ability to sell assets and scale down becomes severely compromised, this renders its pollution intensity more persistent (i.e., less reversible), and limits its operational and financial flexibility, potentially precipitating the firm toward bankruptcy. Thus, firms become ex-ante increasingly cautious when investing in dirty assets and choose lower pollution intensity. Panel D illustrates, that in the presence of divestment costs that are twice as high for polluting assets, average and aggregate pollution decline by 51%, and 32%, respectively.[17]

[17] While the firm could selectively choose to sell clean or dirty assets, we assume here that the divestment cost it is subject to is simply proportional to its current pollution intensity. We also keep the 0-recovery rate upon default for consistency.

6 Conclusion

To conclude, we use novel and granular project-level datasets from the oil and gas industry to show that proxies of financial distress lead to increased pollution and decreased production. Specifically, we plot the binscatters between the pollution measure and proxies for financial distress, such as size, leverage, and Altman Z-score. Second, we investigate how such polluting practices evolve around a Chapter 11 filing in a dynamic event study window. Finally, we construct a measure of default probability and plot the lead-lag relationship between this measure of default probability and pollution. We show that the relationship between pollution and default probability is the strongest for concomitant or one-month lag default probabilities.

We then construct a dynamic endogenous default model with two productive assets to study how a change in financial health affects pollution and production. In the model, the choice of pollution intensity is endogenous and inherently dependent on firm capital structure, financial distress, and productivity. Dirty capital does not incur operating costs unless a stochastic pollution liability shock is realized. As firms face limited liability, it becomes rational to increase pollution if they approach financial distress. Intuitively, the pollution liability is not paid if the firms file for bankruptcy, which truncates the ex-ante expected cost of polluting. We show that ESG divestment campaigns have different effects on firms because they change the capital structure of the firm and their incentive to risk-shift by polluting more.

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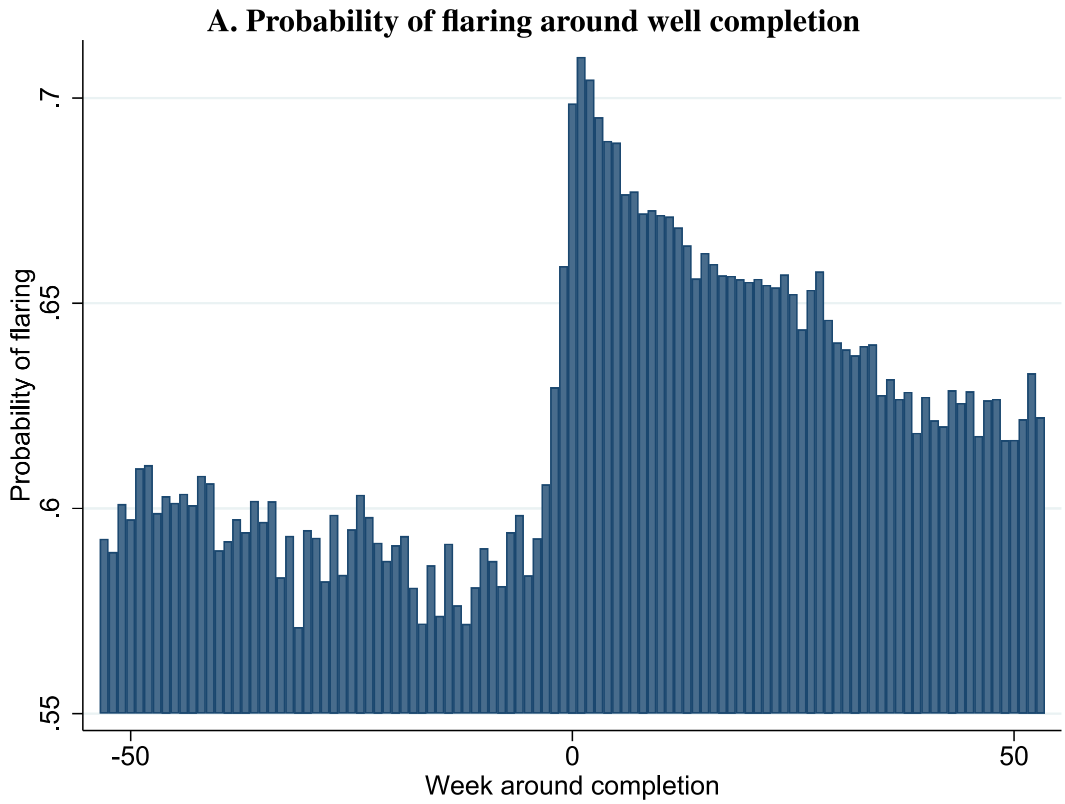
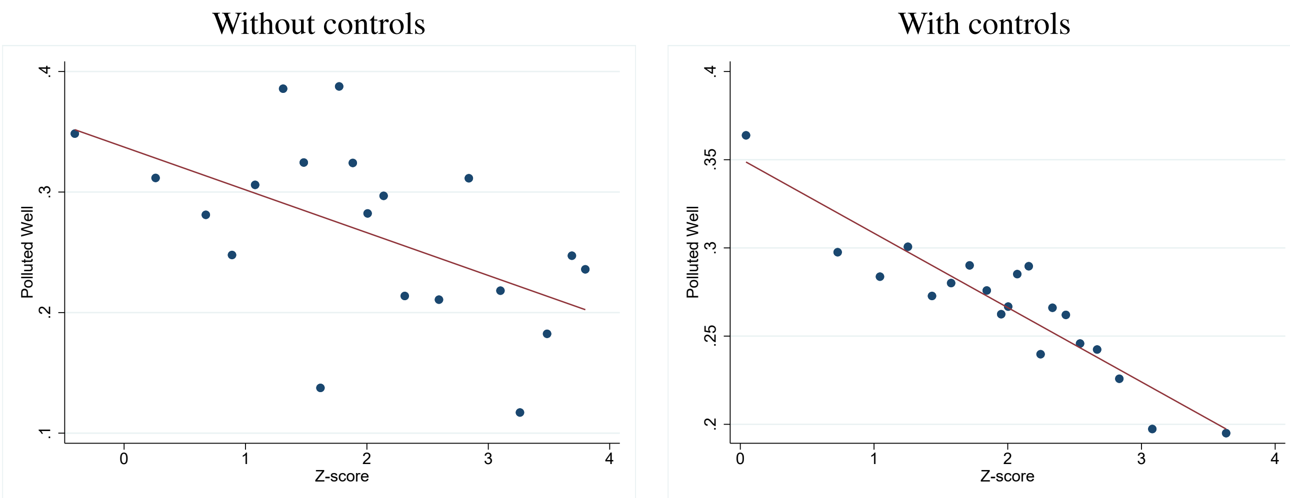
Tables / Figures

Figure 1: Validation of the Flaring Measure



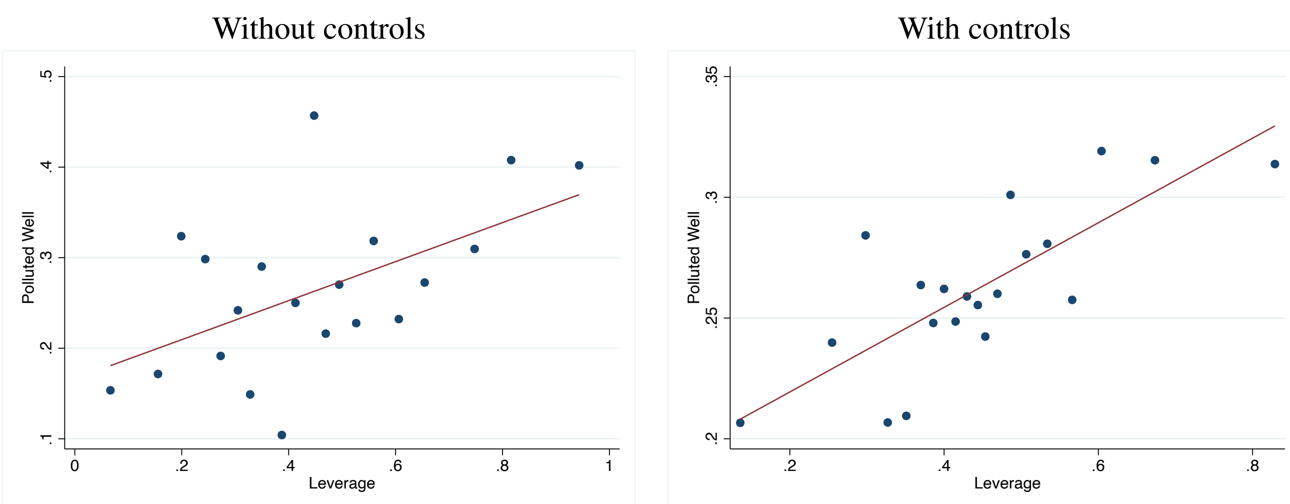
This graph plots the non-parametric probability of observing a flare before and after the well completion. We observe that the probability of flaring is low before the well is flaring; This probability increases just after the well is completed, and peaks at completion, and decreases with time. These patterns are consistent with the observed practice of flaring in the oil and gas, and confirm the usage of satellite imaging datasets to measure flaring practices.

Figure 2: Relationship between Pollution and Financial Distress



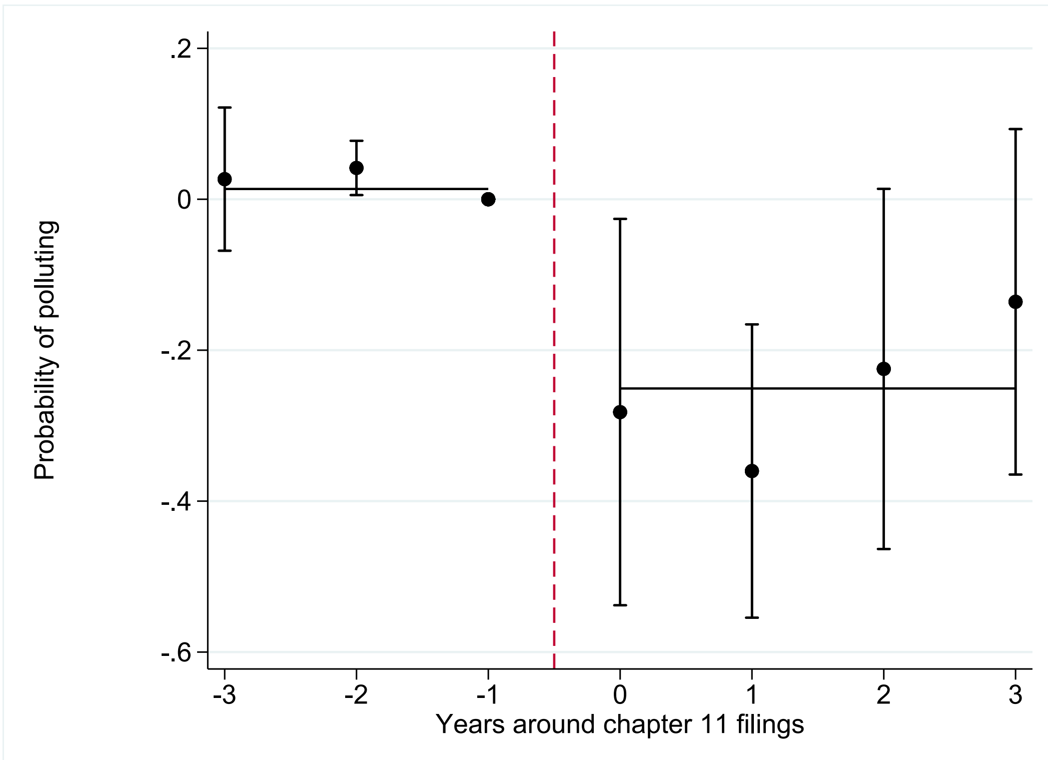
These graphs report the binned scatterplots of our pollution measure with the Altman z-score. Pollution is defined as a dummy variable that takes the value 1 if the well is either flaring or using toxic chemicals. Both graphs show a negative relationship between pollution and the z-score which is consistent with the idea that firms that are more financially distressed are more likely to pollute. In the graph located at the left, we show the relationship without any controls. In the graph located at the right, we show the relationship after the inclusion of a control for the size of the company and a location fixed effect.

Figure 3: Relationship between Pollution and Leverage



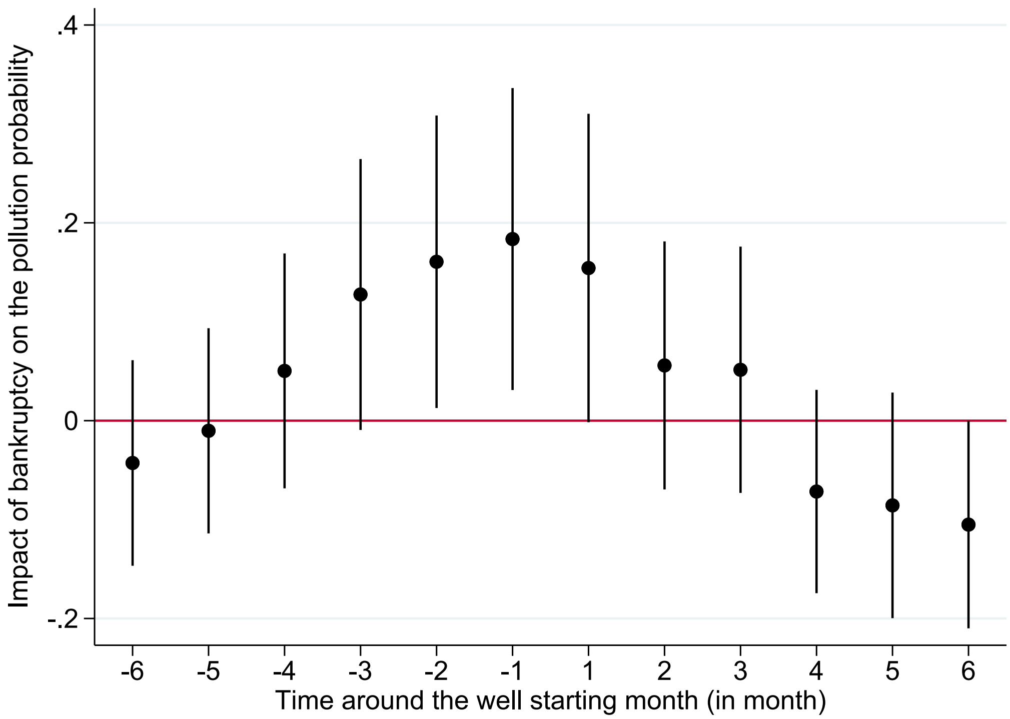
These graphs report the binned scatterplots between pollution and the firm's leverage. Pollution is defined as a dummy variable that takes the value 1 if the well is either flaring or using toxic chemicals. Both graphs show a positive relationship between pollution and firm's leverage, which is consistent with the idea that firms that are more financially distressed are more likely to pollute more. In the graph located at the left, we show the relationship without any controls. In the graph located at the right, we show the relationship after the inclusion of a control for the size of the company and a location fixed effect. We exclude outliers, i.e. firms for which the leverage is below 0 or above 1, and show in the econometric regressions that the relationship still hold in the full sample.

Figure 4: Dynamic Graph: Bankruptcy



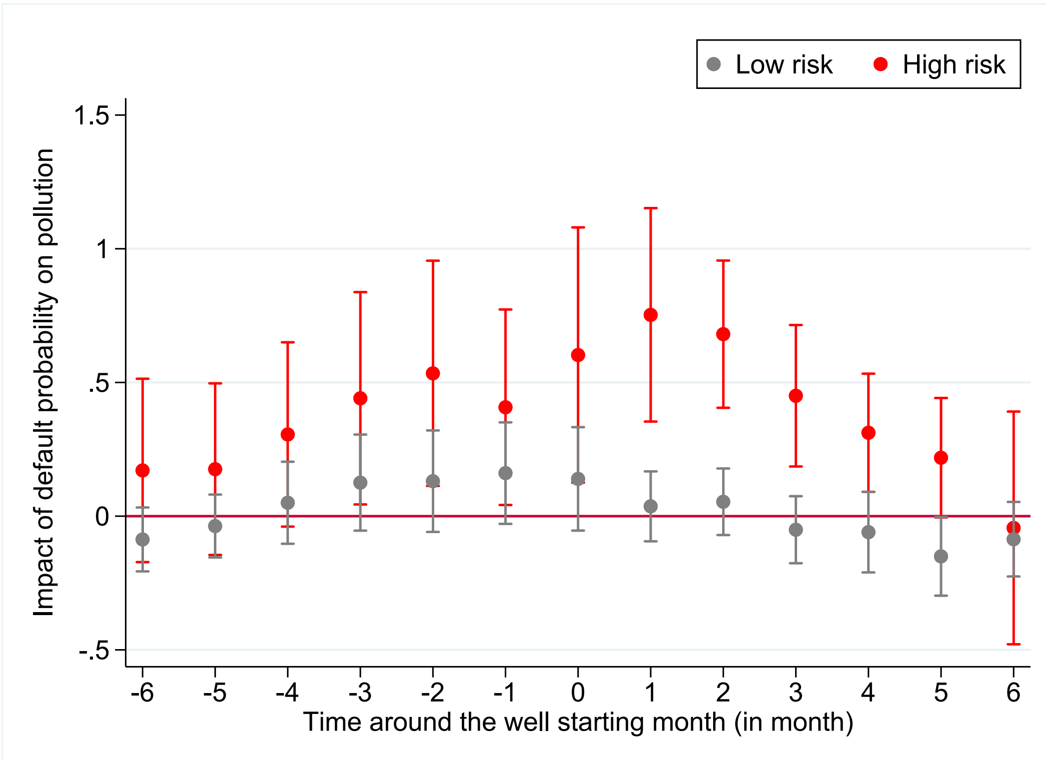
This graph studies the pollution practices and after a firm files for Chapter 11. The x-axis report the the years around chapter 11 filings. The y-axis represent the probability of pollution for firms that will or have filed for bankruptcy for the given year. This probability is estimated using a dynamic event windows in a difference-in-differences regression framework within the sample of firms that file for bankruptcy, where a firm, location, and year fixed effects are included.

Figure 5: Dynamic Graph: Around the Well Completion



This graph studies the pollution practices at the monthly frequency, for different lagged probability of default. Specifically, we compute monthly level of firm delisting events using an annual rolling logit regression that captures the probability of defaulting at any time within the next year, given the information available at the beginning of the year. We then regress our pollution measure of time t on the probability of default at time $t+j$, where j goes from -6 to 6. We add a set of control to the regression. These controls include a set of firm characteristics (namely firms' firm size, sales, capx, tobin Q, the total liabilities, return on asset, and the first 6 month of oil and gas production) and a firm fixed effect, a location fixed effect, a basin-year fixed effect, and a month fixed effect. We report the coefficients (y-axis) that measures the relationship between pollution and the monthly probability of delisting at time $t+j$, where j goes from -6 to 6 (x-axis).

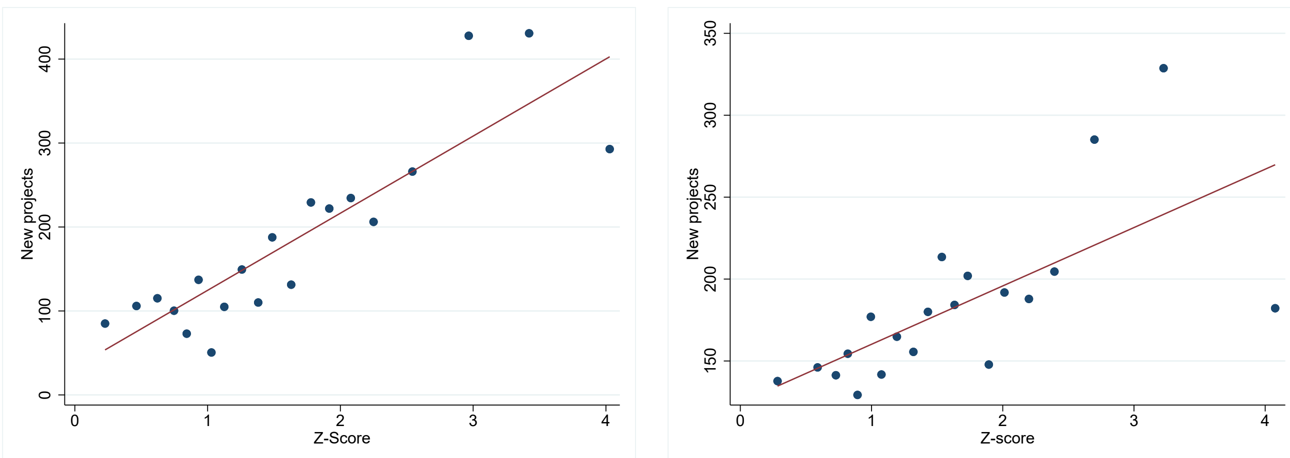
Figure 6: Dynamic Graph: Around the Well Completion



This graph studies the pollution practices at the monthly frequency, for different lagged probability of default. The relationship is estimated on different subsamples: in red, in the sample where the perceived liabilities of the location are above the sample median, and in gray, where these perceived liabilities are below the sample median. We compute monthly level of firm delisting events using an annual rolling logit regression that captures the probability of defaulting at any time within the next year, given the information available at the beginning of the year. We then regress our pollution measure of time t on the probability of default at time $t+j$, where j goes from -6 to 6. We add a set of control to the regression. These controls include a set of firm characteristics (namely firms' firm size, sales, capx, tobin Q, the total liabilities, return on asset, and the first 6 month of oil and gas production) and a firm fixed effect, a location fixed effect, a basin-year fixed effect, and a month fixed effect. We report the coefficients (y-axis) that measures the relationship between pollution and the monthly probability of delisting at time $t+j$, where j goes from -6 to 6 (x-axis).

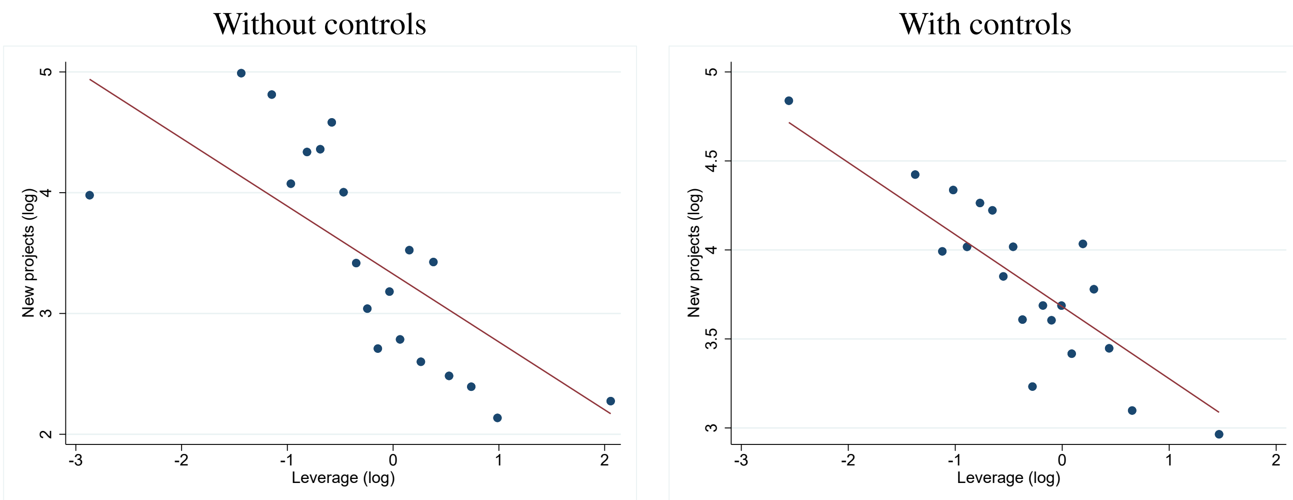
Figure 7: Relationship between New Projects and Financial Distress

Without controls | With controls



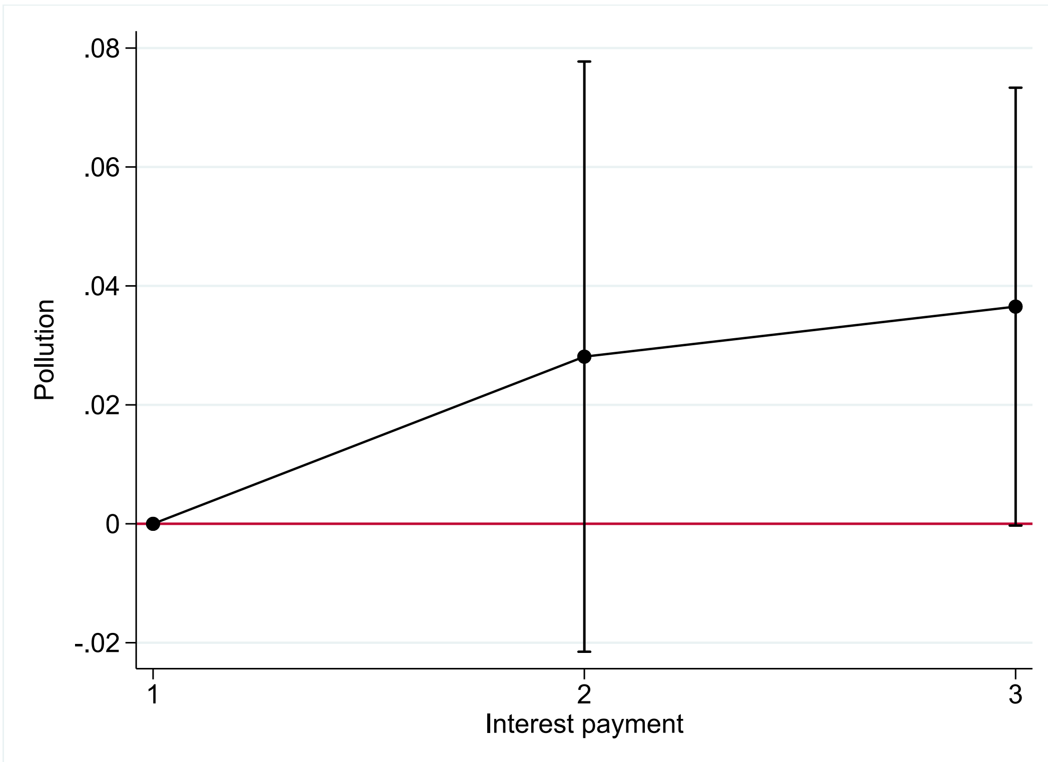
These graphs plot the binscatter of the number of new projects, aggregated at the basin level, with the Altman z-score. Both graphs show a positive relationship between the number of new projects and the z-score which is consistent with the idea that firms that are more financially distressed are more likely to invest in fewer new projects. In the graph located at the left, we show the relationship without any controls. In the graph located at the right, we show the relationship after the inclusion of a control for the size of the company. Both binscatters are estimated on the sample of all oil projects.

Figure 8: Relationship between New Projects and Leverage



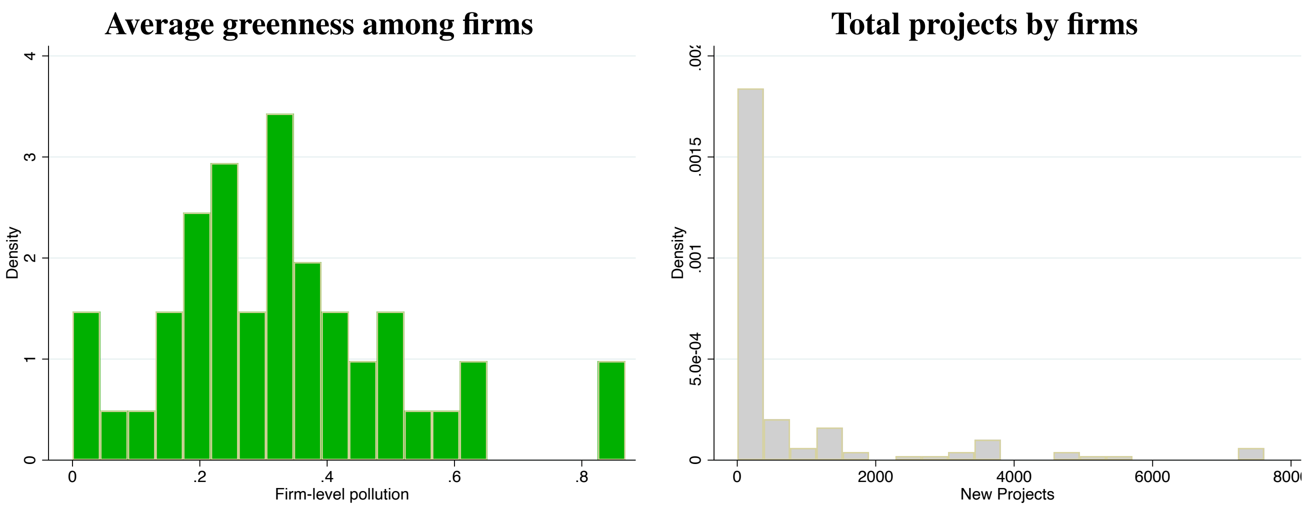
These graphs plot the binscatter of the number of new projects, aggregated at the basin level, with the Altman z-score. Both graphs show a positive relationship between the number of new projects and the z-score which is consistent with the idea that firms that are more financially distressed are more likely to invest in fewer new projects. In the graph located at the left, we show the relationship without any controls. In the graph located at the right, we show the relationship after the inclusion of a control for the size of the company. Both binscatters are estimated on the sample of all oil projects.

Figure 9: Relationship between Pollution and Interest Payments



This graph shows the relationship between pollution and interest payments. Pollution is defined as a dummy variable that takes the value 1 if the well is either flaring or using toxic chemicals. We divide the sample into three groups of equal size. The first group has the lowest interest payment and the third group has the highest interest payment. The second group are the observations that were not in the first and third group. We then run a regression between between the dummy variable of pollution on each of these group variables. We add a firm fixed effect a year fixed effect and include a location fixed effect. We report each of the coefficients on this graph. Specifically, the x-axis reports the group dummy, and the y-axis reports its point estimate with the confidence interval at the 10% level.

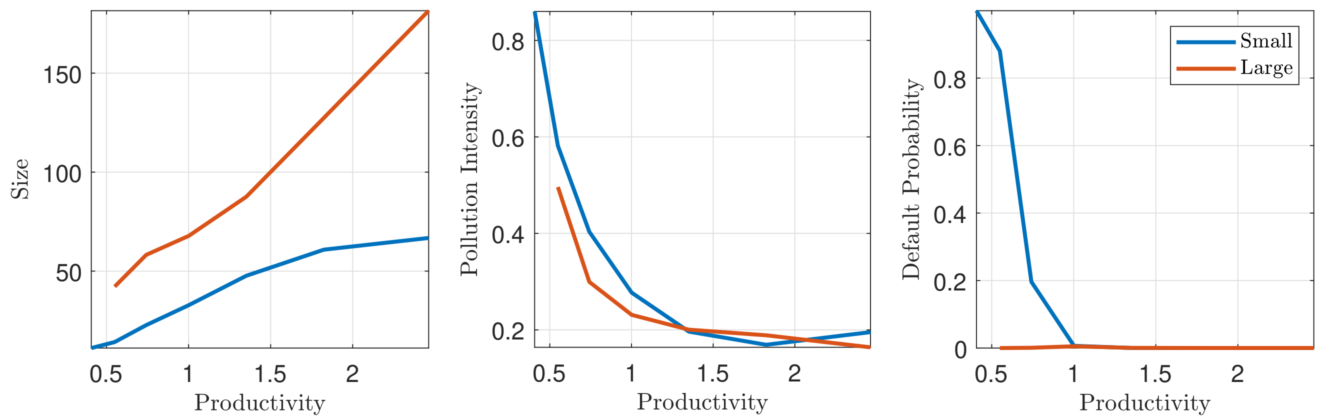
Figure 10: Distributions of Green Firms and Projects



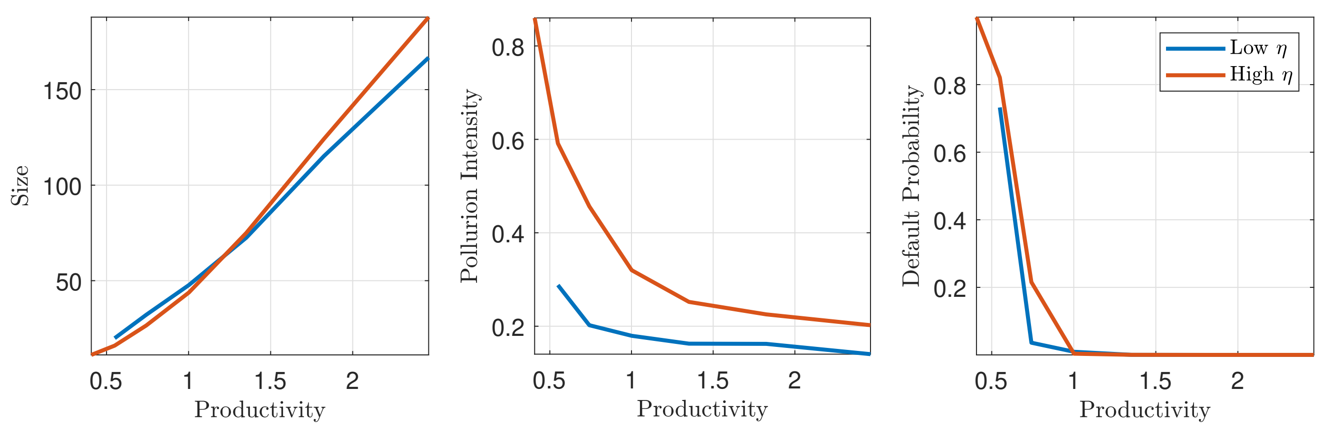
The graph on the left plots the average greenness among firms, which is the fraction of wells that were either using toxic chemicals or flaring between 2012 and 2022 in our sample. To limit the influence of outliers, we drop the firms that had fewer than 100 projects between 2012 and 2022. The graph on the right plots the distribution of the total number of projects per firm during our sample time period.

Figure 11: Optimal Policies for Size, Pollution Intensity, and Default Probability

A. Small vs. Large Firms

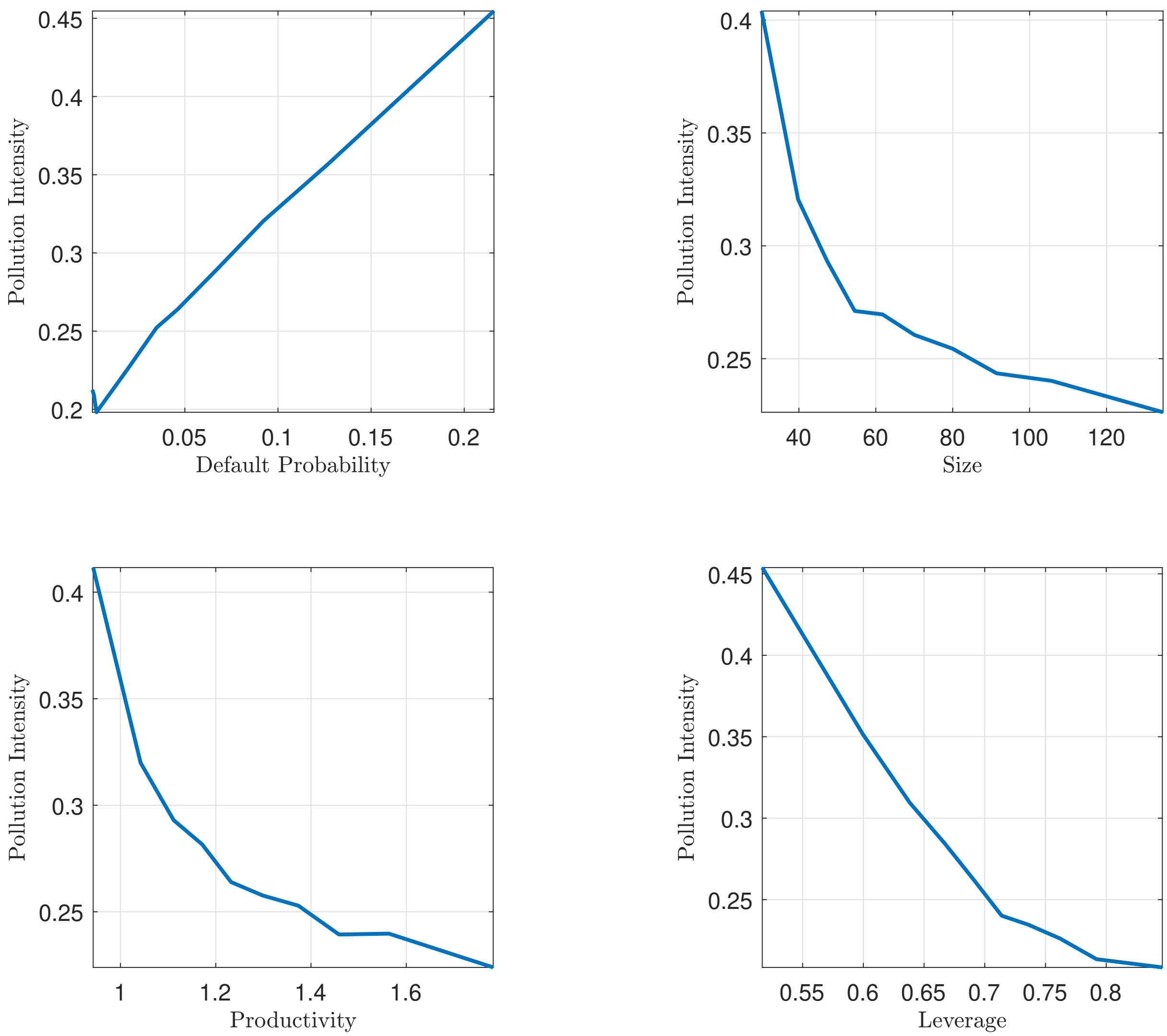


B. Low vs. High Pollution Intensity Firms



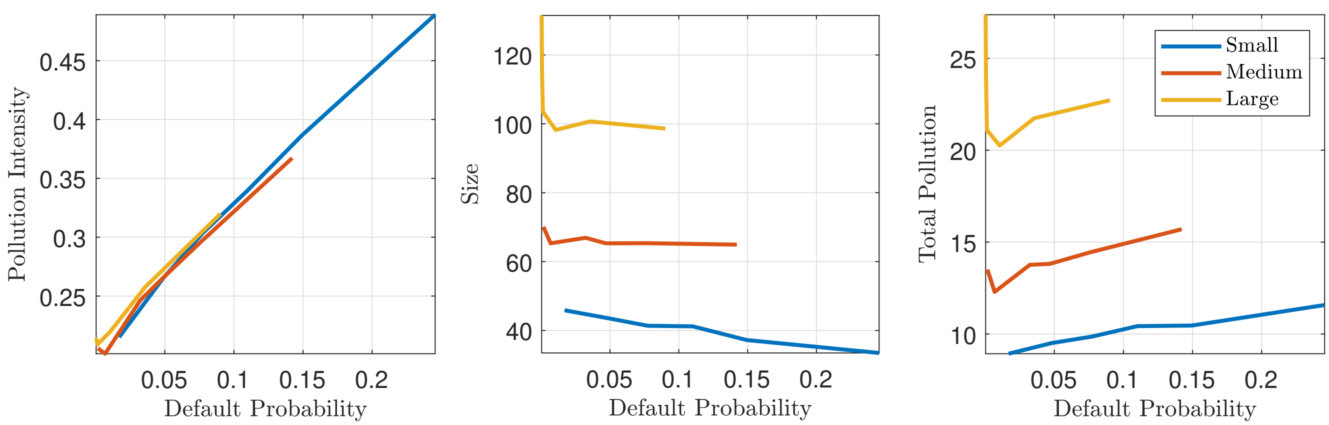
This figure plots optimal next-period size and pollution intensity, and corresponding default probability. Panel A displays optimal policies for small vs. large firms, while Panel B displays optimal policies for low vs. high pollution intensity firms. Optimal policy functions are tabulated based on the model steady state distribution, conditioning on current productivity shock. The parameter values for the benchmark calibration are reported in Table 5.

Figure 12: Financial Distress and Pollution Intensity - Model



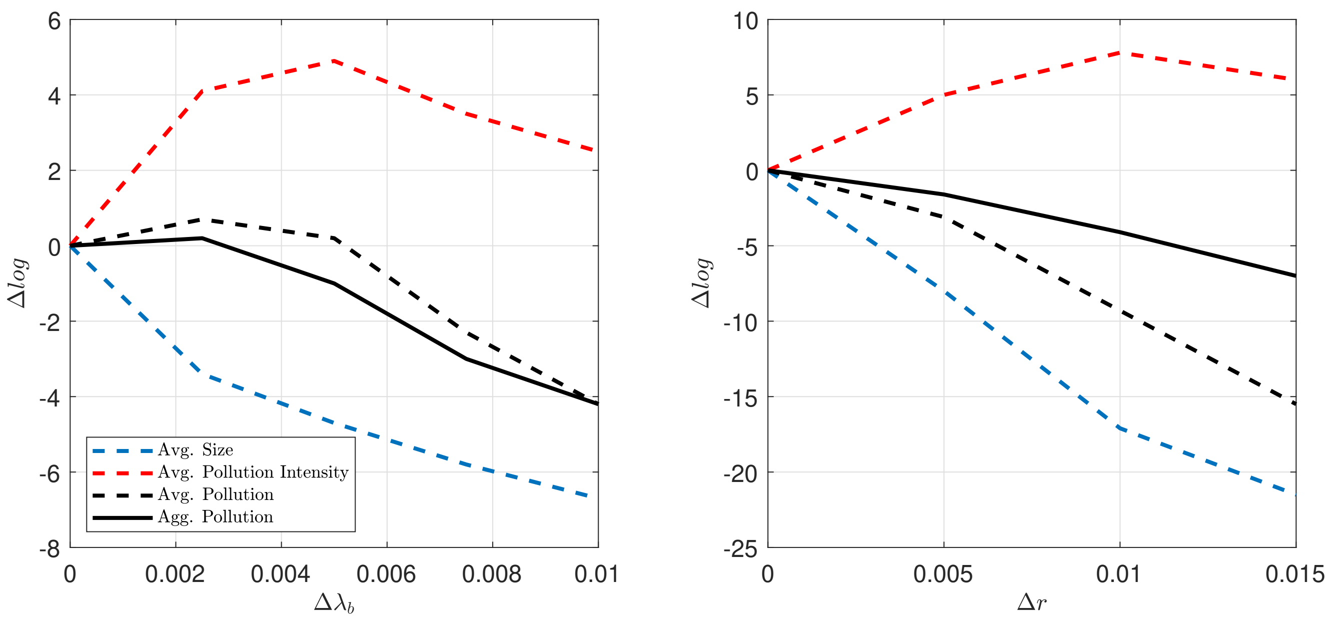
This figure shows the relationship between financial distress, as measured by the default probability, key firm variables (i.e., size, productivity, and leverage), and pollution intensity. Blue solid lines represent pollution intensity, as a share of total capital, while the red dashed lines represent pollution intensity, as a share of new investment. The parameter values are reported in Table 5. The results are obtained using a panel of 5,000 firms simulated over 30 years.

Figure 13: Size, Financial Distress and the Intensive and Extensive Margins of Pollution - Model



This figure shows the relationship between firm size, financial distress, and the intensive (i.e., pollution intensity), extensive (i.e., firm size) margins of pollution, in addition to total pollution. Firms are sorted into three equal size categories (small (blue), medium (red), large (yellow)) and four equal default probabilities bins. The parameter values are reported in Table 5. The results are obtained using a panel of 5,000 firms simulated over 30 years.

Figure 14: Extensive and Intensive Margin Pollution Effects of Debt Issuance costs and Interest Rates



This figure shows the effects (tabulated as log-changes) of an increase in debt issuance costs (left panel) and interest rates (right panel) on average (i) firm size (blue line), (ii) pollution intensity (red line), pollution (dashed black line), and (iv) aggregate pollution (solid black line). The parameter values are reported in Table 5. The results are obtained using a panel of 5,000 firms simulated over 30 years.

Table 1: Descriptive Statistics

A. All wells

	count	mean	sd	p10	p50	p90
Pollution	78044	0.270	0.444	0.000	0.000	1.000
First 6 Oil	78044	58329.698	57065.426	0.000	46109.000	135302.000
First 6 Gas	78044	322581.661	602714.752	10465.000	121645.500	785210.000
CAPEX	78044	6183.538	8085.394	497.214	3054.882	16163.000
Assets - Total	78044	59436.333	93166.150	2159.037	20245.000	239790.000
Leverage	78044	0.730	2.907	0.189	0.475	1.380
Distress	77664	0.439	0.496	0.000	0.000	1.000
Z-score	77664	1.979	1.137	0.536	1.950	3.599
Cost of capital	77023	0.106	0.778	0.021	0.049	0.072

B. Project-level database

	count	mean	sd	p10	p50	p90
Projects	1057	131.248	217.746	1.000	30.000	430.000

These tables report the descriptive statistics of our sample. Specifically, Panel A reports the descriptive statistics based on the sample of public corporation where we can observe the pollution of the well. Panel B describes the project-level database, where the number of new projects are aggregated at the basin-year level for all public corporations.

Table 2: Pollution and Distress

Panel A:

	Pollution$_{it}$		Flaring$_{it}$		Number of toxic chemicals$_{it} > 0$	
	(1)	(2)	(3)	(4)	(5)	(6)
Z-score (std)	-0.041*	-0.024**	-0.006**	-0.003*	-0.036*	-0.023*
	(0.021)	(0.011)	(0.003)	(0.002)	(0.021)	(0.012)
Assets - Total		-0.000**		-0.000**		-0.000*
		(0.000)		(0.000)		(0.000)
Observations	77,664	75,947	77,664	75,947	77,664	75,947
R-squared	0.0083	0.54	0.0030	0.55	0.0067	0.54
Firm FE$_i$		x		x		x
Basin FE$_i \times$ year FE$_t$		x		x		x
Location$_j \times$ year FE$_t$		x		x		x

Panel B:

	Pollution$_{it}$		Flaring$_{it}$		Number of toxic chemicals$_{it} > 0$	
	(1)	(2)	(3)	(4)	(5)	(6)
Leverage (log)	0.036**	0.016***	0.002	0.002*	0.035**	0.015***
	(0.015)	(0.005)	(0.001)	(0.001)	(0.014)	(0.005)
Assets - Total		-0.000*		-0.000*		-0.000*
		(0.000)		(0.000)		(0.000)
Observations	76,594	74,898	76,594	74,898	76,594	74,898
R-squared	0.0061	0.54	0.00032	0.55	0.0058	0.54
Firm FE$_i$		x		x		x
Basin FE$_i \times$ year FE$_t$		x		x		x
Location$_j \times$ year FE$_t$		x		x		x

This table reports the regression that measures the link between flaring practices and distress. Panel A (Panel B) uses the Altman Z-score (The log leverage, respectively) as a proxy for financial distress. Pollution is defined as a dummy variable that takes the value 1 if the well is either flared or using toxic chemicals. The dependent variable Flaring is a dummy variable that takes the value 1 if the well is flared with high intensity and 0 otherwise. Number of toxic chemicals$_{it} > 0$ is a dummy variable that takes the value 1 if the well is using at least one toxic chemical. Z-score (std) is the firm's Altman Z-score that has been standardized to have a mean 0 and a variance 1.

Table 3: New Projects and Distress

	New Project					
	(1)	(2)	(3)	(4)	(5)	(6)
Distress	-0.851*			-0.192*		
	(0.438)			(0.103)		
Z-score (std)		0.436**			0.065	
		(0.220)			(0.068)	
Leverage (log)			-0.475***			-0.117**
			(0.171)			(0.057)
Observations	86,658	86,658	94,908	85,345	85,345	93,470
R-squared	0.00060	0.00066	0.0011	0.063	0.063	0.061
Basin $\times$ Year FE				x	x	x
Firm FE				x	x	x

This table reports the regression that measures the link between new projects and distress. The dependent variable is new project, which is the summation of all new projects in a basin for a given year. Z-score (std) is the firm's Altman Z-score that has been standardized to have a mean 0 and a variance 1.

Table 4: Bankruptcy and Pollution

	Pollution	
Post Bankruptcy (Chapter 11)	-0.296**	-0.170***
	(0.125)	(0.036)
Observations	4,298	4,273
R-squared	0.35	0.46
Firm FE$_i$	x	x
year FE$_t$	x	x
Basin FE$_i \times$ year FE$_t$		x
Location FE$_t$	x	x

This table reports the relationship between chapter 11 and pollution. Specifically, firms that have renegotiated their debts through a chapter 11 are less likely to pollute. Pollution is defined as a dummy variable that takes the value 1 if the well is either flared or using toxic chemicals.

Table 5: Parameter Values

Parameter	Value	Description	Target		
A. Set Parameters					
β	0.976	Discount factor	2.5% risk free rate		
α	0.65	DRS parameter	Literature		
δ	0.1	Depreciation rate	NIPA depreciation		
τ	0.25	Effective corporate tax rate	Gomes and Schmid (2021)		
ϕ	0.4	Bankruptcy cost	Gomes and Schmid (2021)		
ζ	0.25	Magnitude of pollution liability			
γ_k	0.25	Relative size of entrants	Data		
B. Calibrated Parameters					
				Data	Model
$\bar{s}$	1.65	Aggregate productivity level	Sales-to-asset ratio	0.40	0.20
ρ_s	0.85	Persistence of idiosyncratic shock	autocorr. of sales ratio	0.37	0.69
σ_s	0.45	Volatility of idiosyncratic shock	std. dev. of sales ratio	0.12	0.07
c_0	0.1	Investment adjustment cost	Avg. Inv. rate	0.13	0.12
c_1	0.5	Divestiture adjustment cost	Size 1 Inv. rate/Avg. Inv. rate	0.90	0.91
c_f	6	Fixed operating cost	Default rate	0.05	0.06
λ_e	0.015	Equity issuance cost	Equity issuance frequency	0.25	0.19
λ_b	0.0025	Debt issuance cost	Avg. Leverage	0.40	0.73
m	0.06	Clean asset operating cost	Avg. pollution intensity	0.27	0.28
p	0.125	Proba. of pollution liability	Pollution elasticity to default proba.	0.20	0.14

This table reports set and calibrated parameter values for the model. All moments are reported on an equal-weighted basis. The model pollution elasticity to default probability is constructed based on a linear regression without intercept. Model moments are obtained using a panel of 5,000 firms simulated over 30 years.

Table 6: Cross-Sectional Moments

Asset	Size		Investment		Leverage		Def. Proba.		Poll. Intensity	
%tile	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
0%-25%	8.2	37.2	0.15	0.10	0.79	0.59		0.12	0.41	0.35
25%-50%	56.3	56.3	0.15	0.12	0.91	0.67		0.06	0.42	0.27
50%-75%	157.6	77.7	0.12	0.12	0.78	0.72		0.04	0.31	0.26
75%-100%	565.9	115.1	0.13	0.11	0.56	0.80		0.02	0.25	0.23

This table reports the cross-sectional moments. The parameter values are reported in Table 5. All numbers are tabulated as time series averages of asset percentile levels. The results are obtained using a panel of 5,000 firms simulated over 30 years.

Table 7: Long-run Effects of Interest Rates, Issuance Costs, and Regulatory Costs

	Size	Debt	Leverage	Default rate	Poll. intensity	Avg. poll.	Agg. poll.
Benchmark	71.37	56.87	0.70	0.06	0.28	15.63	$7.8\ 10^4$
A. Interest rates							
$\Delta r \ = 0.01$	-17.1%	-39.6%	-14.5%	29.3%	7.8%	-9.3%	-4.1%
B. Debt Issuance Costs							
$\Delta\lambda_b = 0.0025$	-3.4%	-19.7%	-14.8%	0.7%	4.1%	0.7%	0.2%
$\Delta\lambda_b = 0.0075$	-5.8%	-265.8%	-253.7%	2.8%	3.5%	-2.3%	-3.0%
C. Equity Issuance Costs							
$\Delta\lambda_e = 0.015$	0.2%	-3.2%	-3.6%	-1.5%	-0.1%	0.0%	0.3%
$\Delta\lambda_e = 0.045$	-0.9%	-10.5%	-8.9%	1.3%	2.3%	1.5%	1.3%
D. Debt + Equity Issuance Costs							
$\Delta\lambda_b$ & $\Delta\lambda_e$	-8.1%	-169.0%	-155.0%	6.8%	2.8%	-5.2%	-5.0%
D. Regulatory Costs							
$\Delta p \ = 0.025$	-3.4%	-3.1%	0.5%	0.6%	-55.6%	-59.0%	-53.5%
$\Delta\tau \ = 0.05$	-2.4%	-3.6%	-0.7%	1%	-42.6%	-40.2%	-38.8%

This table reports the long-run effects (tabulated as log-changes) due to changes in (i) interest rates, (ii) issuance costs, and (iii) regulatory costs. In Panel D, we use $\Delta\lambda_b = 0.0075$ & $\Delta\lambda_e = 0.045$. The parameter values are reported in Table 5. The results are obtained using a panel of 5,000 firms simulated over 30 years.

Table 8: Long-run Effects of Alternative Policies: Tilting and Liquidation Values

	Size	Debt	Leverage	Default rate	Poll. intensity	Avg. poll.	Agg. poll
Benchmark	71.37	56.87	0.70	0.06	0.28	15.63	7.8 10^4
A. Uniform Debt Issuance Costs							
$\Delta\lambda_b = 0.0075$	-5.8%	-265.8%	-253.7%	2.8%	3.5%	-2.3%	-3.0%
B. Tilted Debt Issuance Costs							
$\tilde{\lambda}_b$	-3.2%	-7.7%	-3.9%	0.3%	-36.6%	-39.9%	-38.5%
C. No Recovery Value Upon Default for Dirty Assets							
$\tilde{L}(K,B)$	-2.6%	0.5%	-0.4%	-5.3%	-0.7%	-3.2%	-1.5%
D. No Recovery Value Upon Default + Higher Divestment Costs for Dirty Assets							
$\tilde{L}(K,B)$ & $\tilde{c}_1$	-3.5%	1.3%	1.4%	-1.5%	-47.2%	-50.7%	-31.6%

This table reports the long-run effects (tabulated as log-changes) due to (i) a uniform 100 basis point increase in debt issuance costs, (ii) debt tilting, (iii) liquidation value, and (iv) asset divestment costs. In Panel B, debt issuance costs are: $\tilde{\lambda}_b = (1+\theta_0\eta)\lambda_b$. In Panel C, liquidation value is: $\tilde{L}(K,B) = \min(0.75, (1-\phi)(1-\eta)\frac{K}{B})$. In Panel D, divestment costs are: $\tilde{c}_1 = (1+\theta_1)c_1$. The parameter values are reported in Table 5, and the tilting parameters, $\theta_0 = 3$, and $\theta_1 = 1$. The results are obtained using a panel of 5,000 firms simulated over 30 years.

Online Appendix

Table 9: Financial Distress Sort

A. Z-score

%tile	Z-score	# Projects	Assets	Leverage	Poll. Intensity	Project Share	Poll. Share
0%-25%	2.04	1212	51.57	0.24	0.32	31.1	30.5
25%-50%	1.56	1536	51.80	0.53	0.31	37.4	35.6
50%-75%	0.92	832	17.28	0.83	0.35	20.3	21.8
75%-100%	0.72	462	10.74	1.42	0.35	11.3	12.1

B. Distress Probability

%tile	Distress Prob.	# Projects	Assets	Leverage	Poll. Intensity	Project Share	Poll. Share
0%-25%	0.03	2089	63.07		0.27	47.5	40.1
25%-50%	0.17	1238	10.89		0.34	26.5	28.6
50%-75%	1.05	893	4.30		0.37	19.1	22.5
75%-100%	8.03	327	1.95		0.37	7.0	8.2

This table reports cross-sectional moments.

Table 10: Correlations

corr(X, Pollution)	Size		Leverage		Credit spread	
	Data	Model	Data	Model	Data	Model
		-0.92		-0.03		0.20
corr(X, Def. Proba)	New Investment		Inv Type			
	Data	Model	Data	Model		
		-0.58		0.04		

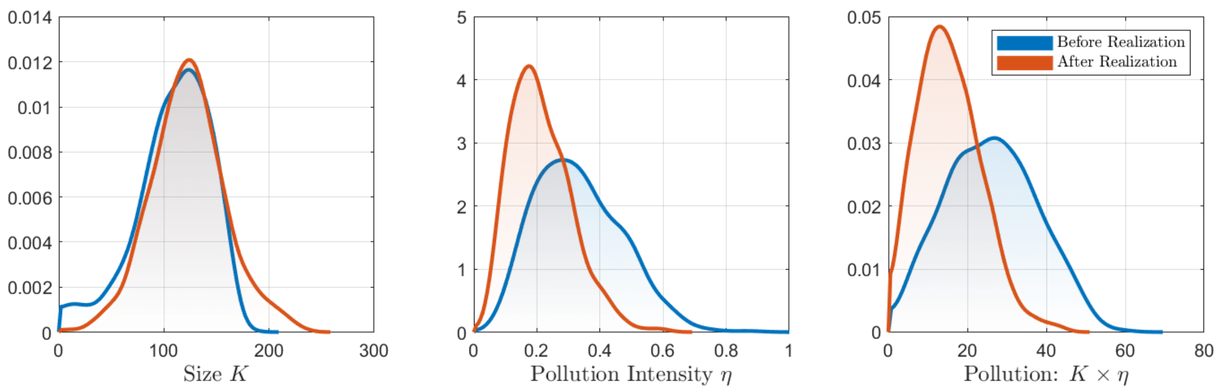
This table reports set and calibrated parameter values for the model.

Table 11: Sensitivity of Pollution to Default Probability

	(1) Pollution (model)	(2) Pollution (data)
Default probability	0.154**	0.163*
		(0.097)
Observations	1,567	72,888
R-squared	0.52	0.31
Basin × Year FE	-	x
time-varying controls	x	x
Firm FE	x	x
Time FE	x	x

This table reports the regression of the investment in dirty assets on the probability of default, for both the data simulated by the model and the real dataset.

Figure 15: Firm Distributions Before and After Cost Shock Realization



These figures report the change in the distributions pertaining to: (i) firm size, (ii) pollution intensity, and (iii) aggregate pollution, before and after the realization of a pollution liability shock. The parameter values are reported in Table 5. The results are obtained using a panel of 5,000 firms simulated over 30 years.